



# Population-weighted exposure to green spaces tied to lower COVID-19 mortality rates: A nationwide dose-response study in the USA



Yuwen Yang<sup>a,b</sup>, Yi Lu<sup>c</sup>, Bin Jiang<sup>a,b,\*</sup>

<sup>a</sup> Urban Environments and Human Health Lab, HKUrbanLabs, Faculty of Architecture, The University of Hong Kong, Hong Kong SAR

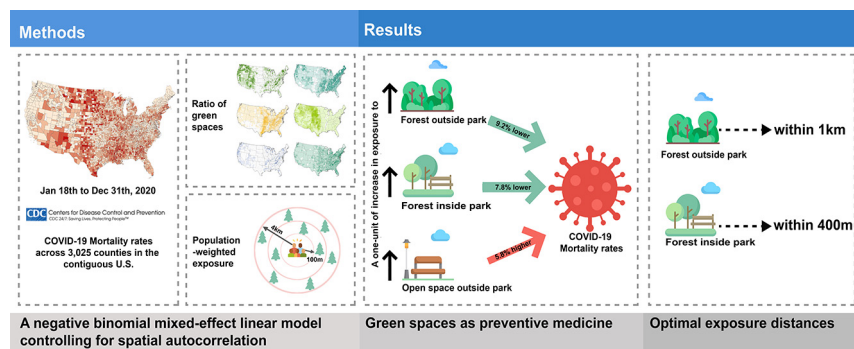
<sup>b</sup> Division of Landscape Architecture, Department of Architecture, The University of Hong Kong, Hong Kong SAR

<sup>c</sup> Department of Architecture and Civil Engineering, College of Engineering, City University of Hong Kong, Hong Kong SAR

## HIGHLIGHTS

- Greater exposure to forest significantly tied to lower COVID-19 mortality rates.
- Forest outside park yielded a larger effect size than forest inside park.
- Exposure to open space yielded mixed associations with COVID-19 mortality rates.
- Optimal buffer distances for exposure to key green spaces were identified.
- A framework on the causal links between green space exposure and mortality rates.

## GRAPHICAL ABSTRACT



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## ABSTRACT

The COVID-19 pandemic has caused a huge loss of human life globally. However, few studies investigated the link between exposure to green space and risk of COVID-19 mortality rate, while also distinguishing the effects of various types of green space, considering the spatial distribution of human population and green space, and identifying the optimal buffer distances of nearby green space. It is critical and pressing to fill these significant knowledge gaps to protect and promote billions of people's health and life across the world.

This study adopted a negative binomial generalized linear mixed-effects model to examine the association between the ratios of various types of green space, population-weighted exposure to those various types of green space, and COVID-19 mortality rates across 3025 counties in the USA, adjusted for sociodemographic, pre-existing chronic disease, policy and regulation, behavioral, and environmental factors.

The findings show that greater exposure to forest was associated with lower COVID-19 mortality rates, while developed open space had mixed associations with COVID-19 mortality rates. *Forest outside park* had the largest effect size across all buffer distances, followed by *forest inside park*. The optimal exposure buffer distance was 1 km for *forest outside park*, with per one-unit of increase in exposure associated with a 9.9 % decrease in COVID-19 mortality rates (95 % confidence interval (CI): 6.9 %–12.8 %). The optimal exposure buffer distance of *forest inside park* was 400 m, with per one-unit of increase in exposure associated with a 4.7 % decrease in mortality rates (95 % CI: 2.4 %–6.9 %). The results suggest that greater exposure to green spaces, especially to nearby forests, may mitigate the risk of COVID-19 mortality. Although findings of an ecological study cannot be directly used to guide medical interventions, this study may pave a critical new way for future research and practice across multiple disciplines.

\* Corresponding author at: The University of Hong Kong, RM614, 6/F, Knowles Building, Pok fu lam Road, Hong Kong.  
E-mail address: [jiangbin@hku.hk](mailto:jiangbin@hku.hk) (B. Jiang).

## 1. Introduction

Since its outbreak in 2019, Coronavirus disease (COVID-19) has spread rapidly throughout the world, leading to numerous infections and deaths. In the United States, COVID-19 was largely responsible for the 17.7 % increase in total deaths from 2019 to 2020 and was the third leading cause of death after heart disease and cancer (Ahmad et al., 2021). Moreover, by the end of 2020, there had been an estimated 348,600 deaths attributed to COVID-19 in the USA; by February 2021, this had increased to an estimated 933,000 deaths (John Hopkins University & Medicine, 2021; Viglione, 2020). Further, it was estimated that COVID-19 has reduced life expectancy in the USA by 1.13 years annually (Andrasfay and Goldman, 2021).

The COVID-19 pandemic also overwhelmed healthcare systems and caused substantial economic losses in the USA. The testing for SARS-CoV-2 infections and treating cases of COVID-19 created pressure on testing facilities and hospitals (Dyer, 2020; Miller et al., 2020). The large numbers of patients who were critically ill with COVID-19 or other severe health conditions exacerbated by COVID-19 led to shortages of beds in intensive care units (ICUs) compounded by other critical health conditions (Halpern and Tan, 2020). It has been estimated that by 2030 the cumulative economic costs associated with the COVID-19 pandemic due to premature deaths, unemployment, and decreased business revenue will be equivalent to US\$ 1.4 trillion in gross domestic product (Cutler and Summers, 2020; Chen et al., 2021).

Accumulating evidence suggests links between nature, the built environment, and COVID-19 mortality rates. Exposure to air pollution (Ali and Islam, 2020; Konstantinou et al., 2021; Liang et al., 2020), crowded housing (Brandén et al., 2020; Hu et al., 2021; van Ingen et al., 2021), and lower average temperature (Benedetti et al., 2020; Wu et al., 2020) have been found to increase deaths from COVID-19. However, despite the manifold salutary effects that exposure to nature has on human health, the relationship between green space and COVID-19 mortality rates has received far less attention (Jiang et al., 2021b; Klompaker et al., 2021; Lu et al., 2021a).

### 1.1. How may exposure to green space alleviate COVID-19 mortality rates?

An overwhelming number of empirical studies have shown that exposure to green space can improve both physical and mental health (Jiang et al., 2014; Lu et al., 2021a, b). In particular, studies have demonstrated that contact with green space enhances the human body's capacity against viruses by increasing Natural Killer (NK) and T cells and cytotoxic activities (Li, 2010), reducing inflammation (Kuo, 2015; Ribeiro et al., 2019), and replenishing gut microbiota (Parajuli, 2019; Parajuli et al., 2020; Roslund et al., 2020). Moreover, compared to non-critically ill COVID-19 patients, hospitalized COVID-19 patients with severe or fatal cases exhibit immune interference (e.g., abnormal low NK and T cell counts and exaggerated cytotoxic activities) (Castelli et al., 2020; Qin et al., 2020), hyper-inflammation or a "cytokine storm," (i.e., delayed but ultimately elevated concentrations of pro-inflammatory cytokines) (Paranjpe et al., 2020; Potempa et al., 2020; Yang et al., 2020), and decreased diversity in their gut microbiota (Dhar and Mohanty, 2020). Thus, contact with green space has the potential to reduce the severity of COVID-19 illness and death.

### 1.2. A critical knowledge gap: the relationship between different types of green space and COVID-19 mortality rates

Several studies have found a significant association between green space and COVID-19 mortality rates in the USA, where green space is defined as the total area of vegetation within a boundary (e.g., Normalized Difference Vegetation Index (NDVI) or Leaf Area Index (LAI)) (Klompaker et al., 2021; Lee et al., 2021; Russette et al., 2021). However, these studies have not distinguished between open space, forest, grassland/herbaceous, and hay/pasture areas, and nor have they compared the effects of green space inside and outside parks on COVID-19 health outcomes. These aspects are important to examine, as there is evidence that the effect of green space

on health varies with the type of green space and whether it is inside or outside a park (Akpınar et al., 2016; Ekkel and de Vries, 2017; Kim and Miller, 2019; Johnson et al., 2021). For instance, green space and parks have been found to be negatively associated with COVID-19 infection rates (Wang et al., 2021a, b; Johnson et al., 2021), whereas park mobility and green space with better accessibility have been found to be positively associated with COVID-19 infection rates (Pan et al., 2021; DePhillipo et al., 2021). Thus, it remains unclear whether and to what extent different types of green space affect the COVID-19 mortality rates.

In addition, studies have estimated the amount of greenness in a county but have ignored the spatial distribution of green space in relation to population and urban fabric (Klompaker et al., 2021; Russette et al., 2021). This should be remedied, as the accuracy of the widely used metric for greenness can be greatly improved by considering the spatial relationships between the location of green space and population distributions (Ben et al., 2019). Furthermore, although deciles of greenness were used to assess the dose-response associations (Russette et al., 2021), the dose-response associations for different types of green space within various buffer distances remain unclear. Many studies have suggested that the effect of green space on people's health is dependent on its distance from people, such that its positive effects on health effect may decrease beyond a certain threshold distance (Coombes et al., 2010; Grahn and Stigsdotter, 2003; Nielsen and Hansen, 2007). Nevertheless, it is not known whether nearby greenspace has a significantly stronger negative association with mortality risk than distant green space or, if so, which distances between people and green space are optimal for decreasing COVID-19 mortality risk. These critical knowledge gaps must be filled to enable policymakers and urban planners to develop evidence-based urban greening solutions and policies to enhance public health in the current and future pandemics.

### 1.3. Research questions

In this study, we investigated the associations between the ratio of the areas of six types of green space to overall county area, population-weighted exposure to these six types of green space at various buffer distances, and full-year COVID-19 mortality rates, controlling for covariates. We sought to answer the following three research questions. (1) What are the associations between the ratio of six types of green space area to overall county area and COVID-19 mortality rates? (2) What are the associations between population-weighted exposure to six types of green space and COVID-19 mortality rates at various buffer distances? (3) For the types of green space that are significantly associated with COVID-19 mortality rates, which exposure distances have the strongest associations?

## 2. Methods

We combined COVID-19 mortality data, sociodemographic characteristic data, healthcare and SARS-CoV-2 testing data, pre-existing chronic disease data, policy and regulation data, behavioral data, and environmental factors from diverse sources for 3025 counties in the USA. The green space exposures were calculated in ArcGIS 10.6.1 and Google Earth Engine (GEE) platform. A negative binomial generalized linear mixed-effects model was used to evaluate the association between the ratio of each of the six types of green space to COVID-19 mortality rates in the USA from January 22 to December 31, 2020, adjusted for the above-mentioned factors. Then, we examined the associations between the population-weighted exposure to six types of green space at various buffer distances up to 4 km and COVID-19 mortality rates, adjusted for covariates.

### 2.1. Data

#### 2.1.1. Data of COVID-19 mortality

COVID-19 mortality data are publicly available on the websites of the US Centers for Disease Control and Prevention (CDC) and State government (Kolak et al., 2021). We defined the COVID-19 mortality rates as the cumulative number of COVID-19 deaths per 100,000 people for each of 3025

counties from January 22, 2020 to December 31, 2020 (Fig. 1). We set the end of our research period to the end of 2020 to eliminate the possible confounding effect from large-scale vaccination, which had a significant effect on COVID-19 mortality rates (see Supplementary Table 1 for descriptive statistics of COVID-19 mortality data).

### 2.1.2. Data of exposure to green spaces

We assessed green space exposure using two metrics. The first metric quantified the ratio of each of the six types of green space to the total area of a county. We extracted the four land covers with dominant natural elements—forest, grassland/herbaceous, pasture/hay, and developed open space—from the 2016 *National Land Cover Database* (NLCD). As defined in Supplementary Table 2, the forest consists of areas of deciduous, evergreen, and mixed forest that are dominated by large trees; grassland/herbaceous consists of areas dominated by herbaceous plants; hay/pasture consists of areas dominated by grasses; and developed open space consists of vegetated areas within developed settings (NLCD, 2016). We also distinguished open space and forest within a park from open space and forest outside a park using the USA Parks boundaries derived from the USA Parks data from the Environmental Systems Research Institute (ESRI, 2021). We then used ArcGIS to calculate the ratios of the six types of green space—forest inside park; forest outside park; hay/pasture; grassland/herbaceous; developed open space inside park; and developed open space outside park—to the total area of a county (Fig. 2).

The second metric used GEE to quantify the population-weighted exposure to green space at various distances from human settlements (Gorelick et al., 2017). This metric measures the mean area (m<sup>2</sup>) per person of exposure to green space within a certain buffer distance. We extracted the above-mentioned six types of green space using the 2016 NLCD dataset (Yang et al., 2018) and USA Parks boundary (ESRI, 2021), and located the spatial distribution of residents in the USA using the 2020 WorldPop Global Project Population Dataset (Sorichetta et al., 2015) in the GEE. The 2020 WorldPop Dataset depicts the estimated number of people residing in each 100 × 100-m grid cell matched to their associated administrative units (WorldPop, 2020). Then, the 30-m resolution NLCD, 2016 Landsat imagery

was re-projected to match the 100-m spatial resolution of the WorldPop Dataset in GEE. This enabled the population-weighted exposure to green space within various buffer sizes in each county to be calculated using the following Eq. (1) (Chen et al., 2022),

$$FE = \frac{\sum_{i=1}^N P_i \times F_i^b}{\sum_{i=1}^N P_i} \quad (1)$$

where  $P_i$  represents the population of the  $i^{\text{th}}$  grid,  $F_i^b$  represents the land cover of the  $i^{\text{th}}$  grid at a buffer size of  $b$  meters,  $N$  denotes the total number of grids for a given county, and  $FE$  is the estimated level of green space exposure for the given county (see Supplementary Table 3 for descriptive data on green space exposure). This metric considers the spatial relationship between population distributions and provision of green space and, unlike previous studies, gives proportionally greater weight to green space where more people reside, which previous studies fail to address (Chen et al., 2022). We estimated population-weighted exposures to green space within 4 km, as studies have suggested few walking activities occur beyond 4 km from a given person's location (Yang and Diez-Roux, 2012). Accordingly, we set buffer intervals of 200-m for less than or equal to 2 km and 500-m for 2–4 km.

### 2.1.3. Potential covariates

We select multiple types of potential covariates in the statistical analysis. Many studies have identified the sociodemographic, chronic disease, behavioral, healthcare, and environmental factors linked to COVID-19 mortality. Thus, we obtained the county-level sociodemographic, healthcare, and SARS-CoV-2 testing data from the US Census Bureau (US Census Bureau, 2019) and the US COVID Atlas of the Center for Spatial Data Science (Kolak et al., 2021). These county-level data consist of population density, the percentage of households with children headed by a single woman; the proportion of non-Hispanic black, white, and Hispanic people; the proportion of residents older than 65; median household income; Gini index of income inequality; poverty rate; median housing value; unemployment rate; the proportion of residents without a high school diploma and without a college degree; percentage of the population without health insurance

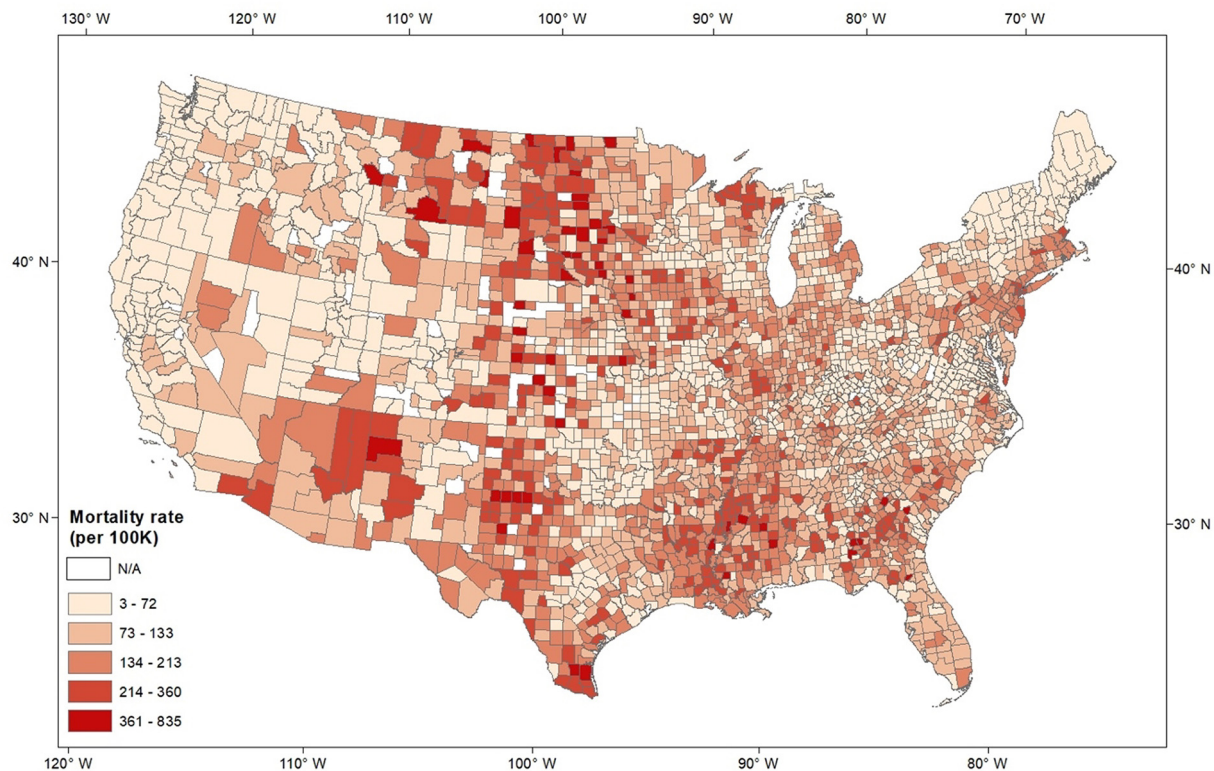


Fig. 1. County-level COVID-19 deaths per 100,000 people in the USA from January 18 to December 31, 2020.



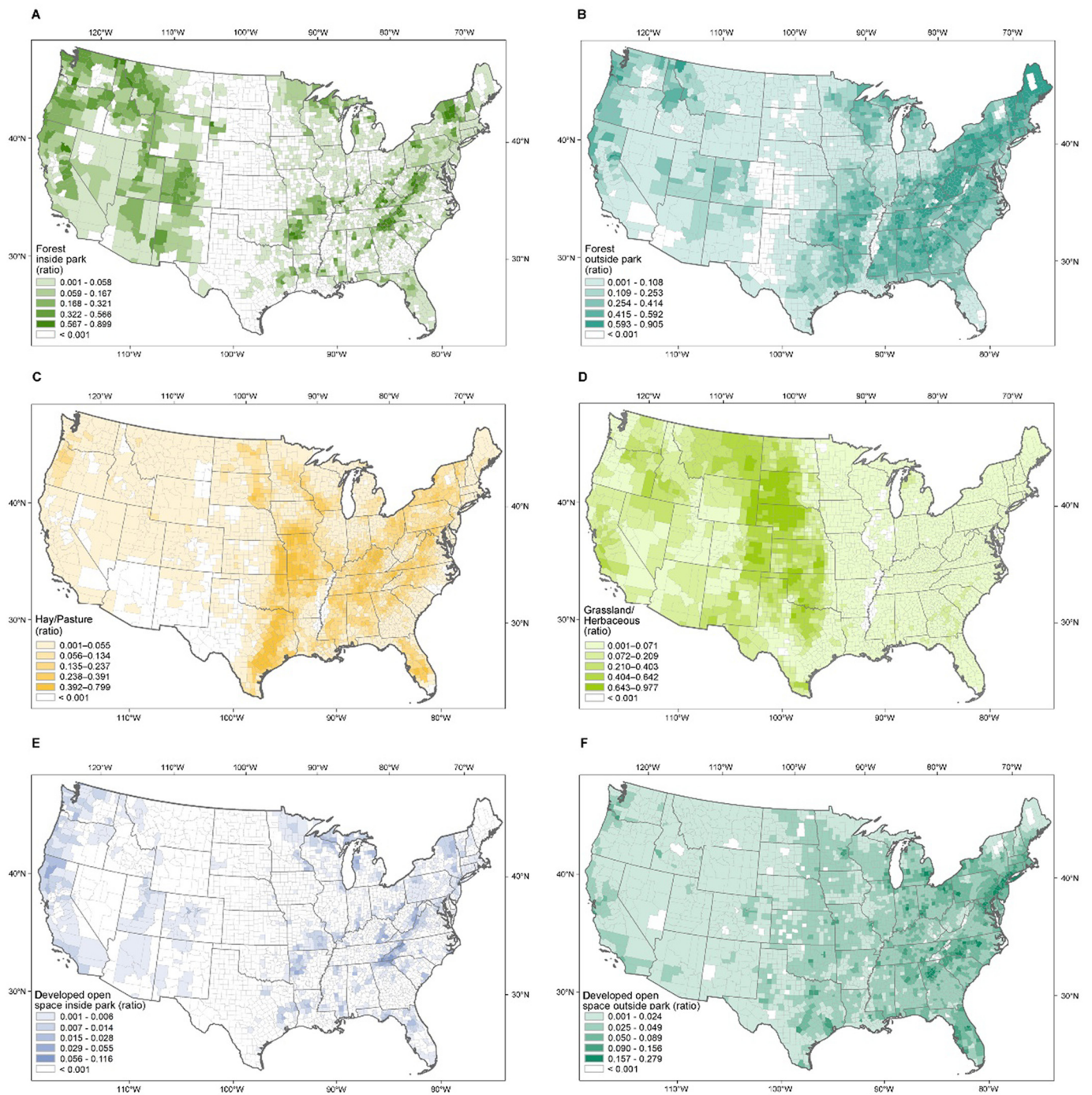


Fig. 2. Ratios of the six types of green space to the total area of each county across the USA. (A) forest inside park (B) forest outside park; (C) hay/pasture; (D) grassland/herbaceous; (E) developed open space inside park; (F) developed open space outside park.

coverage, and SARS-CoV-2 testing rates (see definitions and data source in Supplementary Table 4). We include rates of pre-existing chronic diseases that have been shown to affect COVID-19 mortality risk: rates of hypertension, heart failure, stroke mortality, diabetes, and obesity (CDC, 2021). Moreover, we included policy and regulation factors: stay-at-home order intensity, public mask mandates, and bar and restaurant closing and reopening orders (Chernozhukov et al., 2021; VoPham et al., 2020). Further, we include the following behavior risk factors: the proportion of current smokers and the proportion of essential workers, the proportion of workers who commuted to work by public transportation, walking, and private cars, respectively; the proportion of leisure-time physical inactivity; and the median maximum-distance traveled, and foot traffic to various out-

of-home activities. Last, we select environmental risk factors that include the concentration of particulate matter (PM) (i.e., 2.5- $\mu$ m PM (PM<sub>2.5</sub>) and 10- $\mu$ m PM (PM<sub>10</sub>)), temperature, relative humidity, precipitation, wind speed, and transportation density. The descriptive statistics of covariates and data sources are given in Supplementary Tables 1 and 4.

## 2.2. Statistical analysis

In the main model, we used a negative binomial generalized linear mixed-effects model to evaluate the associations between the ratios of each of the six types of green space and COVID-19 mortality rates, which provides an appropriate error structure for fitting our over-dispersed count

data. We employed state in analyses as a random effect to account for state-level variability and non-independence in our data and spatial autocorrelations. We also adjusted the analyses for a range of covariates. We applied restricted maximum likelihood estimation with a negative binomial link function. The variance inflation factor (VIF) test was used to identify multi-collinearity between the independent variables. Variables with a VIF greater than or equal to 4 were excluded from our models (O'Brien, 2007).

To identify the optimal exposure distance for significant types of green space, we used a negative binomial generalized linear mixed-effects model to evaluate associations between population-weighted exposures to the six types of green space and COVID-19 mortality rates at various distances. These analyses used the same sets of covariates as the main model, and state was again used as a random effect. All of the explanatory variables were centered and scaled.

The Moran's  $I$  test was used to assess the county-level spatial autocorrelations of COVID-19 mortality residuals, where a Moran's  $I$  of 0.21 indicated the presence of spatial autocorrelation ( $p < 0.0001$ ). A Moran's  $I$  value of 0 indicates a lack of spatial autocorrelation, and positive values indicate clustering of similar values. The analyses were performed in R v.4.1.2 (Team, 2015), and Moran's  $I$  test was performed using the package 'spdep' (Bivand and Wong, 2018), and the negative binomial mixed-effects models were performed using the package lme4 (Bates et al., 2014).

### 2.3. Model validation

Due to the presence of spatial autocorrelation at the county level (Moran's  $I = 0.21$ ,  $p < 0.0001$ ), we built additional spatial autoregressive models (SAR) to validate the results of the negative binomial mixed effects model. We used the queen's criterion to build the neighbors matrix and the Akaike Information Criterion (AIC) values to compare the spatial error model, spatial lag model, and spatial Durbin model. The spatial error model had the lowest AIC values, which suggests that spatial dependence occurs in the error term. The model validation confirmed the negative associations between *forest inside park*, *forest outside park*, pasture, and COVID-19 mortality rates (See results of the SAR models in Supplementary Table 5). Given the structure of our data, model coefficients and the magnitude of the effects, it was appropriate to interpret our results using a negative binomial generalized linear mixed-effects model.

## 3. Results

### 3.1. Associations between the ratios of each of the six types of green space and COVID-19 mortality rates

In the main model (ratio of green spaces and COVID-19 mortality rates), we found that after controlling for all covariates, more *forest inside park* and *forest outside park* were significantly associated with lower COVID-19 mortality rates ( $p < 0.0001$ ); while more *open space outside park* was significantly associated with higher COVID-19 mortality rates ( $p < 0.01$ ); grassland/herbaceous, hay/pasture and *open space inside park* were not significant, after controlling for all covariates (Fig. 3). *Forest outside park* had the greatest effect size ( $\beta = -0.097$ ), which was slightly larger than that of *forest inside park* ( $\beta = -0.082$ ). We found per one-unit of increase in *forest outside park* was associated with a mortality rate ratio (MRR) of 0.908 (95 % CI: 0.879, 0.937); per one-unit of increase in *forest inside park* was associated with a MRR of 0.922 (95 % CI: 0.888, 0.957); and per one-unit of increase in *developed open space outside park* was associated with a MRR of 1.058 (95 % CI: 1.023, 1.095). The  $\beta$  values, 95 % CIs, and  $p$ -values are given in Supplementary Table 6 and the MRRs for all the covariates included in the main model are given in Supplementary Table 7.

### 3.2. Associations of population-weighted exposures to green space with COVID-19 mortality rates at various buffer distances

We also found that greater population-weighted exposure to *forest inside park*, *forest outside park* and pasture were significantly associated with lower

COVID-19 mortality rates at various buffer distances, while population-weighted exposure to grassland/herbaceous, hay/pasture, *open space inside park*, *open space outside park* were not significant. First, greater population-weighted exposure to *forest inside park* was associated with lower COVID-19 mortality rates at buffer distances from 100 to 400 m and from 1800 m to 4 km, with the lowest COVID-19 mortality rates occurring at 4 km ( $\beta = -0.050$ ). The effect size increased as buffer distance increased, though the increase remains limited ( $\beta = -0.048$  at 400 m and  $\beta = -0.050$  at 4 km, equating to a 4 % increase) (Fig. 4). With per one-unit of increase in exposure to *forest in park* at 4 km resulted in a MRR of 0.951 (95 % CI: 0.930, 0.973).

Second, greater population-weighted exposure to *forest outside park* was consistently associated with lower COVID-19 mortality rates across all buffer distances, with the lowest COVID-19 mortality rate occurring at 1 km ( $\beta = -0.104$ ). The effect size increased as the buffer distance increased from 100 m to 1 km and decreased as the buffer distance increased beyond 1 km (Fig. 5). We found a MRR of 0.901 (95 % CI: 0.872, 0.931) with per unit increase in exposure to *forest outside park* at 1 km. Third, greater population-weighted exposure to *pasture* was associated with a lower COVID-19 mortality rates from 2500 m to 4 km with increasing effect size, with the greatest reduction in COVID-19 mortality rate occurring at 4 km ( $\beta = -0.036$ ). With per one-unit of increase in exposure to *pasture* at 4 km resulted in a MRR of 0.965 (95 % CI: 0.941, 0.990).

## 4. Discussion

We found that more forest was significantly associated with lower COVID-19 mortality rates, whereas more developed open space had a mixed association with COVID-19 mortality rates. The association between population-weighted exposure to *forest outside park* and reduced COVID-19 mortality rates had the largest effect size across all buffer distances, followed by *forest inside park*. Further, the effect size of population-weighted exposure to *forest outside park* increased up until a buffer distance of 1 km and then decreased. The effect size of population-weighted exposure to *forest inside park* increased as buffer size increased and was greatest at 4 km, although only slightly greater than the effect size at 400 m.

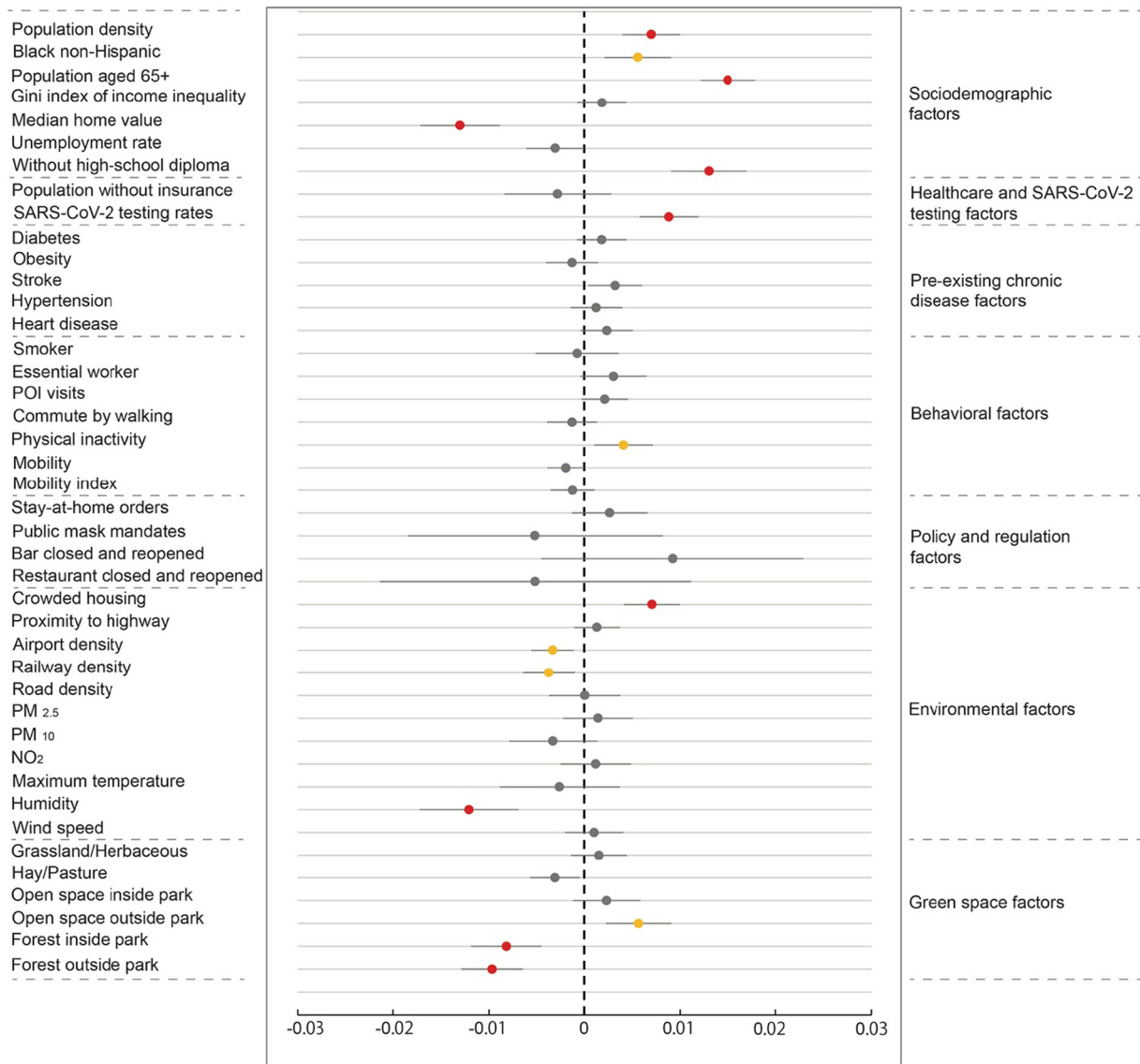
We acknowledge that causal relationships cannot be inferred from this ecological study. However, given the large amount of theoretical and empirical evidence, we argue that it is reasonable to interpret the observed associations as potential causal mechanisms. In this discussion, we proposed a framework of potential causal mechanisms to explain that *forest outside park* had a larger effect size than *forest inside park* on COVID-19 mortality rates, and that developed open space had mixed associations with COVID-19 mortality rates. We also provide explanations for optimal exposure buffer size for significant greenspace types. Lastly, we discussed the contributions of our findings to the field and provide suggestions for future research.

### 4.1. Potential mechanisms for observed significant associations

#### 4.1.1. How may exposure to green space alleviate COVID-19 mortality risk?

We found that exposure to forest and pasture was associated with lower COVID-19 mortality rates in the USA after controlling for covariates, which aligns with the findings of previous studies (Klomp maker et al., 2021; Lee et al., 2021; Russette et al., 2021). It has been suggested that green space may lower COVID-19 mortality risk if it boosts biological processes that help people fight against prognosis of COVID-19 (Andersen et al., 2021; Roslund et al., 2020), thereby decreasing their risk of death. Therefore, we posit that contact with green space may reduce COVID-19 mortality rates by increasing exposure to biogenic volatile organic compounds (VOCs) and environmental microbiota, decreasing psychological stress and exposure to air pollution, and increasing physical activity (Fig. 6).

Contact with forests increases exposure to phytoncides (e.g., terpenes, limonene, and pinene), which are biogenic VOCs synthesized and emitted into the air by trees. These VOCs may compensate for reduced concentrations of NK cells, boost NK defenses, and dampen excess inflammatory responses in severely affected patients (Market et al., 2020; Osman et al., 2020). It is



**Fig. 3.** Exposure to forest is significantly associated with lower COVID-19 mortality rates after controlling for covariates. Coefficient values represent effect sizes for the associations between the mortality rates of COVID-19 (cases per 100,000 people) and the ratio of grassland/herbaceous, hay/pasture, open space in park, open space outside park, forest inside park, and forest outside park to the total area of a given county in the USA. Coefficient values are represented as dots, 95 % CIs are represented as bars, and significant variables are shown in three colors: gray =  $p \geq 0.01$ ; yellow =  $p < 0.01$ ; red =  $p < 0.0001$ .

known that “forest bathing” increases NK cell counts and activity (Li, 2010; Li et al., 2008; Li et al., 2007; Tsao et al., 2018), which results in the activation of receptors that recognize virus-infected cells and trigger cytotoxicity processes (Market et al., 2020; Yokoyama, 2005). Exposure to nearby greenspaces has also been associated with reduced inflammation levels, which predicts the severity of disease in those with COVID-19 and their survival (Del Valle et al., 2020; Mandel et al., 2020; Ribeiro et al., 2019).

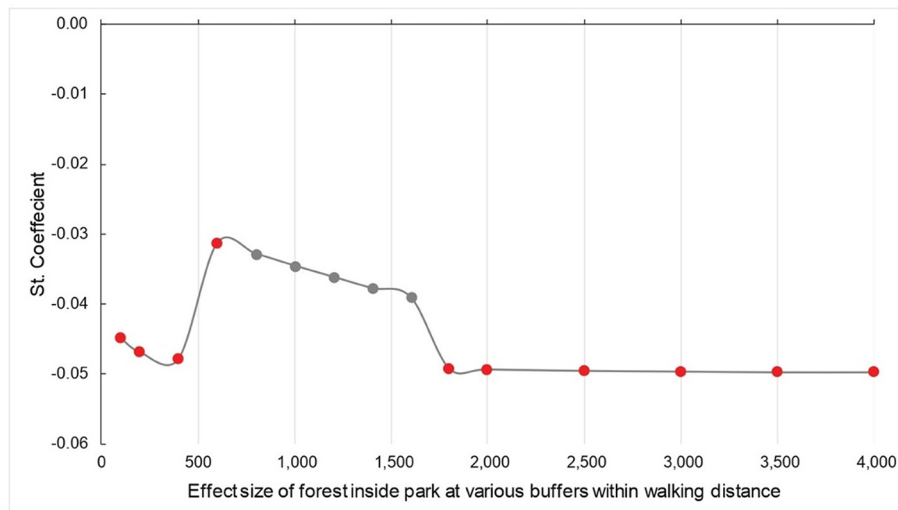
Exposure to forest and pasture may improve the disturbed gut microbe condition of COVID-19 patients (Dhar and Mohanty, 2020; Donati et al., 2020; Yeoh et al., 2021; Zuo et al., 2020). Though human's gut microbial composition is shaped by the interplay of multiple factors, such as diet and genetics (Claesson et al., 2012), the microbiome from surrounding green environments can transfer to humans (Grönroos et al., 2019; Parajuli et al., 2018; Parajuli et al., 2020). Moreover, exposure to forested and grassed areas diversifies gut microbiota profiles (Roslund et al., 2020).

Forests can also decrease people's exposure to air pollutants (Nowak et al., 2014). This is important, as air pollution is associated with delays in recovery and more fatal conditions in COVID-19 patients (Domingo

and Rovira, 2020). This may be attributable to air pollution modifying respiratory immune responses, perturbing anti-microbial responses, and triggering the release of inflammatory cytokines (Bauer et al., 2012; Ciencewicki and Jaspers, 2007; Glencross et al., 2020). It also may be attributable to a reduction in stress due to visual or physical contact with forests (Gidlow et al., 2016; Jiang et al., 2014; Lee et al., 2011; Ulrich et al., 1991), as psychological stress is linked to dysregulation of the immune system and increased pro-inflammatory cytokines level (Gouin et al., 2012; Morey et al., 2015; Steptoe et al., 2007).

In addition, physical activities such as walking or cycling have spiked in greenspace since the outbreak of the pandemic (Geng et al., 2021; Lu et al., 2021a, b; Venter et al., 2020; Venter et al., 2021). Researchers suggest physical activities may boost immune responses (Amatriain-Fernández et al., 2020; Fernandez et al., 2018; Nieman and Wentz, 2019) and mitigate systemic inflammation (Biddle et al., 2019; DeSantis et al., 2012; Nieman and Wentz, 2019). Physical activity also reduces the risk of obesity, which is a precursor to a range of chronic diseases that increases the risk of COVID-19 mortality (Bastien et al., 2014; Calle and Thun, 2004; Chan et al., 1994; Klang et al., 2020).





**Fig. 4.** Effect size of population-weighted exposure to *forest inside park* within 4 km on COVID-19 mortality rates. Coefficient values represent effect sizes in a negative binomial mixed effects model of the relationship between mortality of COVID-19 mortality rates (death count per 100,000 people) and population-weighted exposure to *forest inside park*. Coefficient values are represented as dots, gray =  $p > 0.05$ ; red =  $p < 0.0001$ .

**4.1.2. Why may open space have a mixed association with COVID-19 mortality rates?**

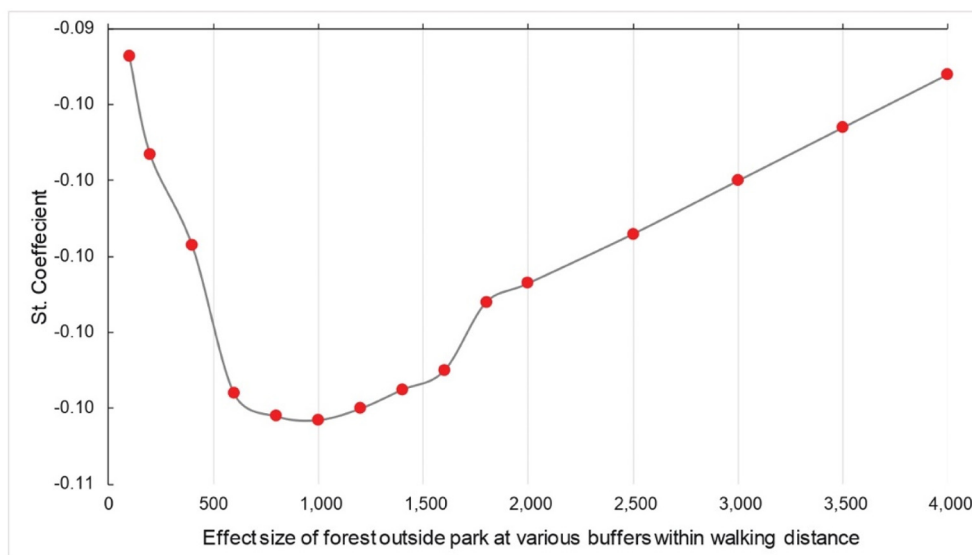
We found that the ratio of *open space outside park* was associated with higher COVID-19 mortality rates, whereas the ratio of *open space in park* was not significant. This suggests that exposure to open space may not be effective or even increase the COVID-19 mortality rate. These counterintuitive findings have not been clearly presented and interpreted by previous studies. Based on the literature, we believe that the increased infection in open space outside parks due to difficulty in achieving safe physical distancing may lead to higher mortality rates, despite the aforementioned health benefits of exposure to green space.

Open space is defined as “areas with a mixture of some constructed materials, but mostly vegetation in the form of lawn grasses (NLCD, 2016).” These areas most commonly include large-lot single-family housing units, parks, and vegetation planted in developed settings. Thus, while open spaces can provide health benefits by promoting physical activity, social interaction, and reducing exposure to air pollutants (Lu et al., 2021a, b), the low supply of

open space per capita in urban areas makes it hard to achieve safe physical distancing. In addition, park shutdown policies may also have increased gatherings in *open spaces outside park* (e.g., streets, plazas, and backyards). Although the risk of spreading the SARS-CoV-2 is much lower in outdoor environments (Bulfone et al., 2021), people who participate in certain social activities outdoors, such as chatting or partying, are at higher risk of spreading the virus (Domènech-Montoliu et al., 2021; Peng et al., 2022). Therefore, the increased SARS-CoV-2 infection risk in *open space outside park* may have led to higher COVID-19 mortality rates. Nevertheless, more evidence is needed to delineate the mechanisms underlying the mixed effects of exposure to open space on COVID-19 mortality rates.

**4.1.3. Why may forest outside park have a stronger effect than forest inside park on COVID-19 mortality rate?**

We found that the effect size of *forest outside park* was larger than that of *forest inside park* with respect to decreasing COVID-19 mortality rates after accounting for other covariates. This finding aligns with previous studies



**Fig. 5.** Effect size of population-weighted exposure to *forest outside park* within 4 km on COVID-19 mortality rates. Coefficient values represent effect sizes from a negative binomial mixed effects model of the relationship between mortality of COVID-19 mortality rates (deaths count per 100,000 people) and population-weighted exposure to *forest outside park*. Coefficient values are represented as dots, red =  $p < 0.0001$ .

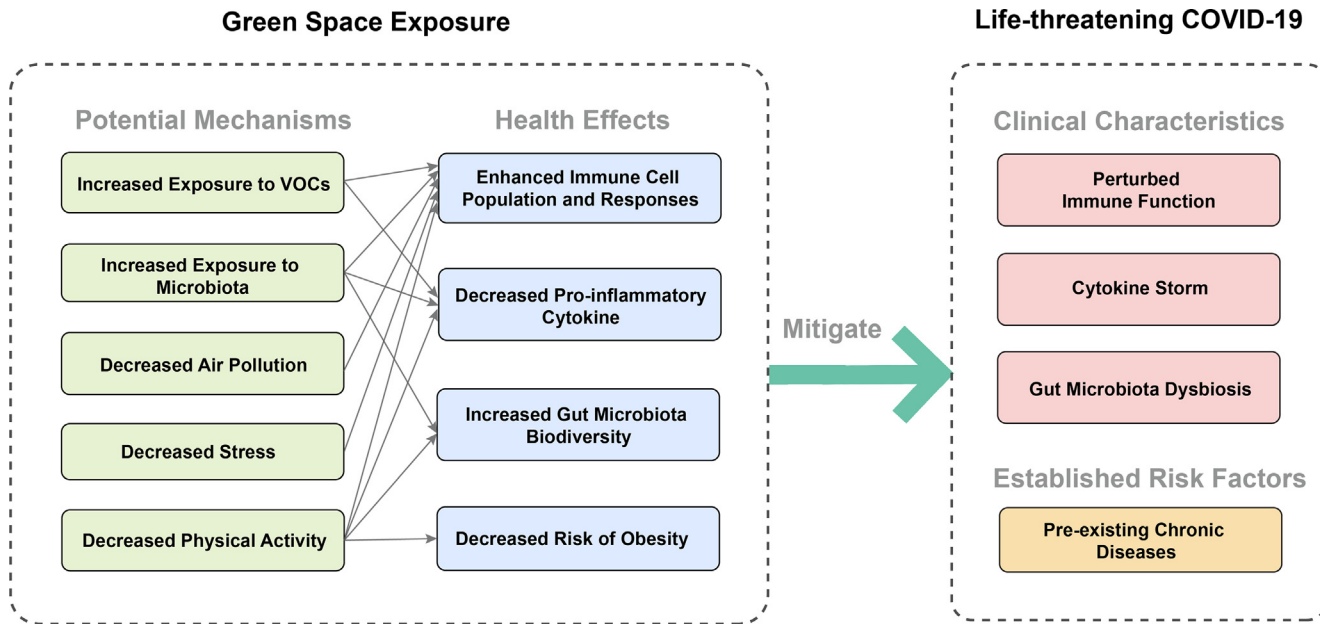


Fig. 6. Framework of potential causal mechanisms to explain negative associations between exposure to green space and COVID-19 mortality rates.

that have found a stronger health-promoting effect of outside-park areas than inside-park areas (Reid et al., 2017; Allard-Poesi et al., 2022). First, this may be due to the differences in the provision of forest inside and outside park areas; that is, the US population has a ten times greater within-walking-distance exposure to *forest inside park* than to *forest outside park* (Fig. 7). Second, social activities in parks may increase the risk of close contact and inhaling droplets from infected people (DePhillipo et al., 2021; Praharaj & Hoon, 2022), thereby increasing SARS-CoV-2 infection risk. Thus, the increased infection risk associated with social interactions in parks may have offset the other health benefits of exposure to *forests inside park* on COVID-19 mortality rates. Third, the health effect of exposure to *forest inside park* may have been weakened in part due to policies in some states that closed parks to reduce COVID-19 spread risk (Volenec et al., 2021; Smith et al., 2021).

4.1.4. Optimal exposure buffer distance: what is it and why?

We found that the effect size of population-weighted exposure to *forest outside park* on COVID-19 mortality rates increased with larger buffer distance and reached a maximum at 1 km. This suggests that exposure to *forest outside park* within 1 km is more effective than exposure to *forest outside park* at a greater walking distance. This may be because nearby forests are visited more often than forests located further away, as the frequency of visits to greenspaces declines as distance to green space increases (Coombes et al., 2010), and 1120 m (0.7 miles) is the mean walking distance in the U.S. (Yang and Diez-Roux, 2012).

We also found that the effect size of *forest inside park* reached a maximum at 4 km, although the effect size is close to that at 400 m (a 2 % increase). This suggests that the effect of *forest inside park* is less sensitive to buffer size within walking distance. Studies suggest people walk much

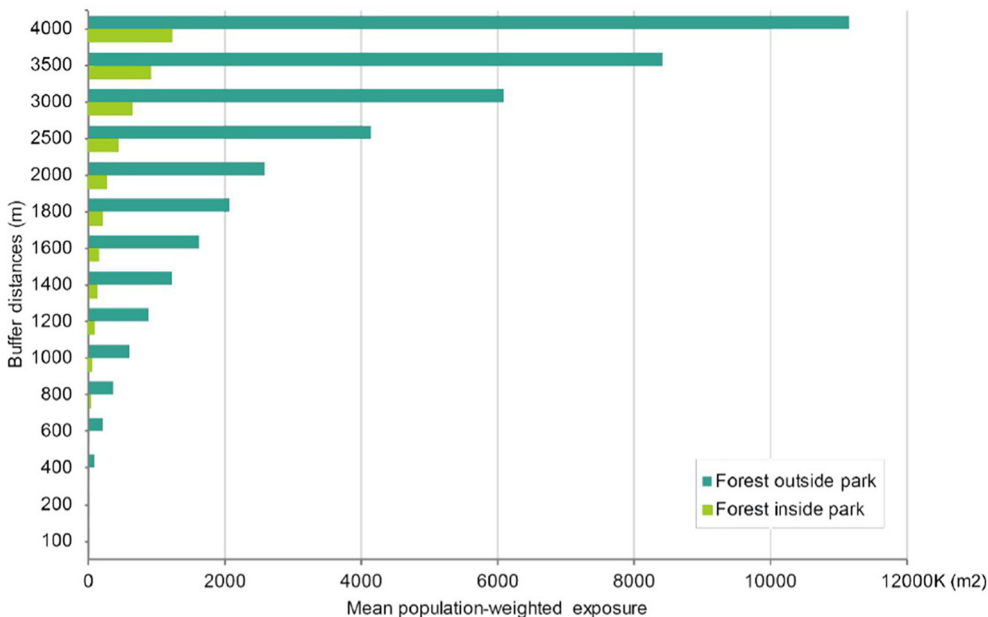


Fig. 7. Mean population-weighted exposure to *forest inside park* and *forest outside park* within 4 km. The bar represents the average population-weighted exposure to forest at the county level within each buffer distance.



longer distances for recreation purposes than other purposes (Yang and Diez-Roux, 2012). Thus, considering the effect size and previous literature on walking behaviors, we conclude that the optimal exposure buffer distance for *forest outside park* to be 1 km and the optimal exposure buffer distance for *forest inside park* to be 400 m.

#### 4.1.5. Significance of other covariates

In the main model, we also found that air pollution and pre-existing chronic disease variables were not significantly associated with COVID-19 mortality rates, which contradicts the findings of previous studies (Liang et al., 2020; Mehra et al., 2020; Smith et al., 2021; Wu et al., 2020). The main reason may be that green space partially offset the effects of air pollution and pre-existing chronic diseases on COVID-19 mortality rates in the main model (Fig. 3), given that air pollution and pre-existing chronic disease variables were significantly associated with COVID-19 mortality rates in models when other covariates are not adjusted (Supplementary Table 8). Those significant associations become much weaker or disappear when covariates are adjusted in the main model. Further, correlation analysis shows that air pollution variables ( $PM_{2.5}$ ,  $PM_{10}$ , and  $NO_2$ ) and pre-existing chronic disease variables (diabetes, obesity, stroke, hypertension, and heart disease) were significantly correlated with green spaces variables (Supplementary Table 9), which suggests that green space may dilute the significant effect of the air pollution and pre-existing chronic diseases factors on COVID-19 mortality rates in the main model. This is also consistent with green space's effects on reducing air pollution (Nowak et al., 2014; Nowak et al., 2018) and the risk of chronic diseases (Kondo et al., 2018; Yang et al., 2021). Lastly, the nonsignificant result may also be due to the 0.01 threshold value we used to indicate significance, which is stricter than the 0.05 threshold value used by other studies. Nevertheless, we focus on measuring the relationship between exposure to green spaces and COVID-19 mortality rates, adjusting for multiple categories of covariates. A full range of investigations on various variables should be conducted by future researchers in multiple fields, and we strongly suggest that the effect of green spaces should not be neglected in these future studies.

#### 4.2. Contributions and implications

To the best of our knowledge, this is the first nationwide study to distinguish relationships between different types of greenspaces and COVID-19 mortality rates using one of the largest countries as the research site. The large geographical scope, the diverse environmental and demographical characteristics, and the large sampling size ensured the generalizability of our findings and make this study a strong reference for future studies at the regional and global scales. We included population-weighted measure as an indicator of exposure to greenspace, as this enables the quantification of greenspaces by locating green spaces and human populations and gives proportionally greater weight to areas where more people live. Therefore, this new approach provides a more accurate estimation of people's real exposure to green spaces than not population-weighted measures (Chen et al., 2022). In addition, we investigated the dose-response associations between different types of green spaces at various buffer distances and COVID-19 mortality rates, which allowed us to identify an optimal effect distance that was previously lacking in the literature. Lastly, our framework has generated new knowledge that enhances our understanding of the potential causal relationship between exposure to green space and COVID-19 mortality rates.

#### 4.3. Limitations and future research opportunities

We acknowledge that this study has several limitations, which pose opportunities for future research. First, this is an ecological study that uses data at the county level. Despite the population-weighted measure considering green space located in residents' immediate surroundings, it is based on aggregated data. Future studies could use individual-level data to confirm the association and use experiments to confirm the causal mechanisms (Jiang et al., 2021a, b).

Moreover, the unit of analysis is county due to the data availability of COVID-19 mortality and other confounding variables. Though county data are widely used in nationwide studies, future studies should use finer-grained data (i.e., data at the census tract or block level) to enhance the accuracy and reliability of findings (Richardson et al., 2012). In addition, we used state as a random effect in the model to account for spatial autocorrelation; we suggest that future studies should control for spatial autocorrelation at finer geographic scales to further reduce bias. Further, this study used two-dimension green space indicators, which might have inaccuracies in estimating diverse combinations of different types of green space (Giannico et al., 2022). Future studies could overcome this limitation by incorporating 3D indicators (e.g., volumes of different types of vegetation). Lastly, this study investigated associations by using the whole-year data collected in 2020, but the situation has become much more complicated after 2021 due to the constant evolution of SARS-CoV-2 and implications of various vaccinations. Future research should examine these aspects.

## 5. Conclusion

Our findings demonstrate that greater exposure to green spaces, especially nearby forests, was significantly associated with a lower level of COVID-19 mortality rates while controlling for multiple categories of covariates. We interpret these significant associations by integrating theoretical and causal evidence provided by previous studies, to develop a framework of potential causal mechanisms.

This study is an initial research effort and future studies should use individual-level data to confirm the significance of the relationship between exposure to green space and reduced COVID-19 mortality rates. We are hopeful that this study can open a new avenue of research, allowing future researchers and professionals to consider green space planning as an effective strategy to mitigate the effects of the COVID-19 pandemic and those of other public health crises caused by infectious respiratory diseases. We argue that green space is not a decorative and trivial element but a critical civil infrastructure that protects people's health and well-being.

#### CRediT authorship contribution statement

**Yuwen Yang:** Data curation, Formal analysis, Investigation, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing. **Yi Lu:** Methodology, Resources, Funding acquisition, Writing – review & editing. **Bin Jiang:** Conceptualization, Project administration, Investigation, Methodology, Supervision, Funding acquisition, Resources, Visualization, Writing – original draft, Writing – review & editing.

#### Data availability

Data will be made available on request.

#### 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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## Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.scitotenv.2022.158333>.

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