GeoHealth

RESEARCH ARTICLE

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Key Points:

- A meta-analysis is conducted to synthesize the evidence of the benefits of greenspaces against COVID-19
- Greenspaces are linked to fewer COVID-19 infections and related mortalities

Supporting Information:

Supporting Information may be found in the online version of this article.

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A Global Meta-Analysis of the Effects of Greenspaces on COVID-19 Infection and Mortality Rates

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Abstract The COVID-19 outbreak in 2020 resulted in rapidly rising infection rates with high associated mortality rates. In response, several epidemiological studies aimed to define ways in which the spread and severity of COVID-19 can be curbed. As a result, there is a steady increase in the evidence linking greenspaces and COVID-19 impact. However, the evidence of the benefits of greenspaces or greenness to human wellbeing in the context of COVID-19 is fragmented and sometimes contradictory. This calls for a meta-analysis of existing studies to clarify the matter. Here, we identified 621 studies across the world on the matter, which were then filtered down to 13 relevant studies for meta-analysis, covering Africa, Asia, Europe, and the USA. These studies were meta-analyzed, with the impacts of greenness on COVID-19 infection rate quantified using regression estimates whereas impacts on mortality rates were measured using mortality rate ratios. We found evidence of significant negative correlations between greenness and both COVID-19 infection and mortality rates. We further found that the impacts on COVID-19 infection and related mortality are moderated by year of publication, greenness metrics, sample size, health and political covariates. This clarification has far-reaching implications for policy development toward the establishment and management of green infrastructure for the benefit of human wellbeing.

Plain Language Summary The research on whether greenspaces help people's health during COVID-19 is unclear and sometimes has conflicting results. To address this, we conducted a detailed study of this body of knowledge. First, we found 621 studies from around the world and narrowed them down to 13 that fit our research questions, from places like Africa, Asia, Europe, and the USA. We then consolidated the results of these studies to see how greenspaces affected the number of COVID-19 cases and deaths. Our analysis showed that more greenspaces are linked to fewer COVID-19 cases and deaths. We also found that other factors such as when the study was conducted, how they measured greenness, and other health and political factors have a strong impact on the results of each study. These findings are important because they can help guide policies on creating and taking care of greenspaces to improve people's health.

1. Introduction

The global human population is changing rapidly following an exponential growth path, putting tremendous pressures on natural resources. Currently, it is approximately 7.9 billion people (UN DESA, 2021) and is predicted to reach above 9 billion by 2050 and 11 billion by 2100 (Bongaarts, 2016). In response, nature fights back in various ways to bring down global population to a sustainable level. One of these ways is through global pandemics, for example, COVID-19 pandemic.

Indeed, the world has been witnessing the COVID-19 pandemic since 2020, with over half a million infection cases and over 20,000 deaths reported at the start of the pandemic (WHO, 2020). In 2022, these figures grew tremendously, reaching over 600 million cumulative cases with over 6 million cumulative deaths (WHO, 2022). Since humans have been using plants to treat various diseases over centuries, various studies, using different metrics of greenness (the total amount of vegetation in an area), were conducted across the globe to investigate whether greenspaces or greenness may act as buffer infrastructure against the spread of COVID-19 infection rates and severity. We use interchangeably "greenness" or "greenspaces" in the present study to mean the total plant diversity or vegetation in a given delimited area. These plants altogether may form a natural or man-made habitat which may be used by humans for various purposes, including recreative activities as well as passive (meditation) or active (physical) exercises (Huang et al., 2021; Pan et al., 2021; Zhang et al., 2017).

However, the findings reported in these studies are mixed (Spotswood et al., 2021; Yang et al., 2022; Zhai et al., 2022). For example, Spotswood et al. (2021) found that a 0.1 increase in Normalized Difference Vegetation Index (NDVI) corresponds to a 4.1% reduction in the COVID-19 incidence rate ratio in the USA. A similar pattern was observed using street-level indicators of greenness (Nguyen et al., 2020). The mitigating effects of greenness have also been reported elsewhere: in China and India, an increase in greenness shows a significant negative correlation with the spread of COVID-19 infections and mortalities (Peng et al., 2022; Sikarwar et al., 2023). These negative effects may be interpreted as follows: activities of the Natural Killer cells in the human body are boosted with frequent exposure to vegetation (Q. Li, 2010; WHO, 2020)—NK cells, as part of the immune system, attack to eliminate virus-infected cells in human body (Vivier et al., 2008). Also, by safeguarding against air pollution, vegetation, thus greenspaces, contributes to lower health risks that may aggravate the severity of COVID-19 infection (Q. X. Chen et al., 2020; Lin et al., 2019). Additionally, greenspaces often provide spacious environments for physical exercises, recreation, and social events with reduced chances of person-to-person contact (Huang et al., 2021; Pan et al., 2021). As opposed to these negative correlations between greenness and COVID-19 infection rates, reports of positive correlations are also documented. For example, Pan et al. (2021) found that urban greenspaces were associated with an increase in the spread of COVID-19 infections (see also Huang et al., 2021).

These mixed findings could be linked to the differences in how COVID-19 severity was measured, for example, as hospitalization rates, mortality rates, admission rates to intensive care unit (ICU), etc. Additional sources of differences in findings may be linked to differences in sample sizes, types and number of covariates analyzed, and choices of statistical tests (Labib et al., 2020; Zhang & Tan, 2019). Furthermore, the mixed findings may also be related to differences in how greenness was measured in different studies. Indeed, greenness was variously measured as street trees, botanical gardens, natural forests and grasslands, and residential gardens or as amount of greenness captured in NDVI or EVI (Enhanced Vegetation Index) or as quality of greenspaces (K. Chen et al., 2023; Huang et al., 2021; Jiang et al., 2022; Nguyen et al., 2020; Spotswood et al., 2021). For example, Huang et al. (2021) measured greenness as “green space density” which is the proportion of specific vegetation types in a given spatial unit which they correlated with COVID-19 infection risk measured as “venue density” (number of buildings visited by confirmed COVID-19 positive cases). Since greenspaces are attraction sites, they may have attracted an increasing number of visitors, thus increasing the infection risks, and leading to a positive correlation between greenness and infection rates (Huang et al., 2021). Finally, the mixed findings may also be linked to the use of various confounding factors in the model of COVID-19 infection and mortality rates. These factors may be age (Bajaj et al., 2021), ethnicity (Mathur et al., 2021), and poverty levels (Hussey et al., 2021), among others.

The emergence of conflicting findings presents a challenge with regard to the generalization of the benefits of greenness or vegetation to human wellbeing in the context of the COVID-19 pandemic. In such context, a meta-analysis of existing evidence is an opportunity to integrate all reported effects of greenness on COVID-19 infection rates and severity to investigate whether generalization is possible. Scientifically rigorous methodologies are increasingly adopted in various studies to improve the validity of findings and lower between-study heterogeneity. These include the use of larger sample sizes, the use of multiple predictors, choices of relevant statistical tests and covariates, and use of fine spatial scales (Hussey et al., 2021; H. Li et al., 2022; Lin et al., 2023; Lu et al., 2021). Regardless of these advances, consolidation of measured effect sizes and determination of between-study heterogeneity is still needed. To date, several studies have investigated the relationships between the provision and quantity of greenness and its effects on the spread and severity of COVID-19 (K. Chen et al., 2023; Sikarwar et al., 2023; Spotswood et al., 2021; Yang et al., 2022). However, in the context of conflictual findings reported, a meta-analysis imposes itself or becomes an obligation if we are to clarify how greenness or greenspaces could be of values to human in the context of COVID-19 pandemic. In the present study, our main objective is to provide such clarifications.

2. Materials and Methods

2.1. Ethics Statement

There was no need for any ethics application since this is a meta-analysis.

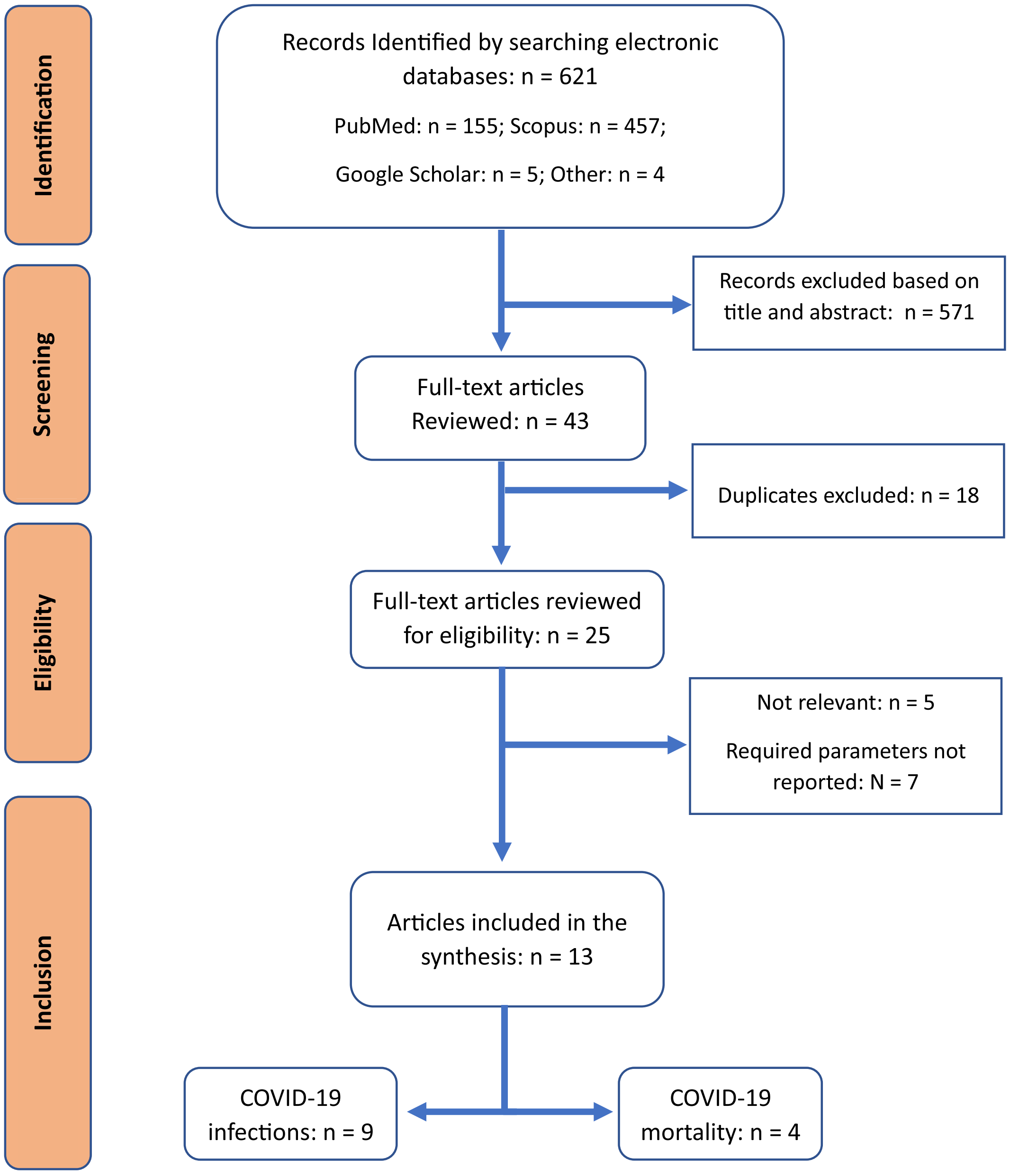

Figure 1. The PRISMA flow diagram for literature search and screening.

2.2. Study Selection

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRIMSA) guidelines (Page et al., 2021; Figure 1) were followed to search for literature that focuses on green infrastructure and its impact on COVID-19. All search results were reviewed for relevance based on their title and abstract to be considered for meta-analysis; Figure 1. Furthermore, reference lists of all included articles were reviewed to identify studies that meet the inclusion criteria.

2.3. Search Strategy

Three databases and data search platforms were identified for this study: PubMed, Scopus, and Google Scholar. These platforms were selected based on the global, multidisciplinary research that they host and the ability to apply advanced literature search. Literature search was limited to PubMed, Scopus, and Google Scholar. The following search string was used to search for literature on 17 April 2023: (“Greenspace” or “green space” or “greenery” or “greenness” or “vegetation” or “trees” or “forest” or “grass” or “grassland”) and (“COVID-19” or “SARS-CoV-2” or “coronavirus” or “COVID”). We did not apply any restrictions on the publication date in the search.

2.4. Eligibility Criteria

Inclusion criteria for this study were as follows: (a) original research that investigates the effects of green spaces on COVID-19 infections and related mortalities; (b) full-text is available; (c) publication is in English; (d) required statistical parameters for meta-analysis are reported in the main article or Supporting Information S1 (i.e., regression estimates for predicting COVID-19 infections, and mortality rate ratios (MRR) for predicting COVID-19 mortalities). Exclusion criteria were review or commentary articles, articles without required parameters, and articles not in English (see Figure 1).

2.5. Data Extraction and Analysis

A predetermined template was used to collect study characteristics which are surname of first author, year of publication, country of study, measure of green infrastructure, temporal extent of study, sample size, measure of COVID-19, effect type, effect size, standard error or confidence interval (CI), and list of covariates. All data analyzed in this study are available as Supporting Information S1.

All analyses were conducted in R version 4.2.3 (R Core Team, 2021; see R script in https://doi.org/10.6084/m9.figshare.26855890.v1). Two separate meta-analyses were conducted, focusing on the impacts of greenness on COVID-19 infections (meta-analysis 1) and COVID-19 mortalities (meta-analysis 2). Regression estimates were used as pre-calculated effect type when analyzing COVID-19 infections, and MRR were used as pre-calculated effect type when analyzing COVID-19 mortalities. Subsequently, subgroup analyses were applied to the same data to test the effects of predictor variables, sample size, and selection of covariates. Random models were selected in each analysis using the metagen function found in the “Metafor” R library (Viechtbauer, 2010).

Outcomes are reported as pooled regression estimates for COVID-19 infections and as pooled MRR for COVID-19 deaths. Furthermore, in each case, a 95% CI, t-value, and p-values are reported with $p < 0.005$ considered as an indicator of statistical significance. Between-studies heterogeneity was quantified using Higgins and Thompson's I^2 statistic (Higgins & Thompson, 2002) with the I^2 value of less than 25%, 50%, and 75% indicating low, moderate, or high heterogeneity, respectively. Heterogeneity variance and prediction interval were also reported to measure the extent of between-study heterogeneity. Publication bias was tested using the Funnel approach (Sterne & Egger, 2001) and the Orwin's fail-safe number (Orwin, 1983).

3. Results

3.1. Characteristics of Studies Included in the Meta-Analysis

A total of 621 studies across the world (Figure 2a) were identified through the search of Scopus, PubMed, and Google Scholar platforms. After removing irrelevant and duplicate studies, 25 studies remained, covering Africa, Asia, Europe, and the USA (Figure 2b). A review of the 25 full-text articles resulted in the removal of 12 studies that were either review/commentary in nature or did not report the statistical parameters required for a meta-analysis.

The characteristics of all valid studies are summarized in Table 1. Nine studies that tested the relationships between greenness and COVID-19 infections and four studies that investigated the relationships between greenness and COVID-19 mortality rates were included in the final synthesis. Most of the studies (nine out of 13) were conducted in the United States of America (USA) whereas China, England, India, and South Africa each had one study (Figure 2b). A total of 7 out of 13 studies used more than one predictor of COVID-19 impact in each study with NDVI and abundance of greenness (greenness provision) as the mostly used measures of greenness (Figure 3a). Because multiple predictors are used in a single study, a total of 45 different correlations between infection rates and greenness were tested in all 13 studies, whereas 14 correlations between mortality rates and greenness were modeled in four studies of COVID-19, implying that statistical parameters of 59 different correlations were included in our meta-analysis. We classified covariates into five broad groups: climatic, demographic, economic, health, and political. All 13 studies considered at least one demographic covariate in their

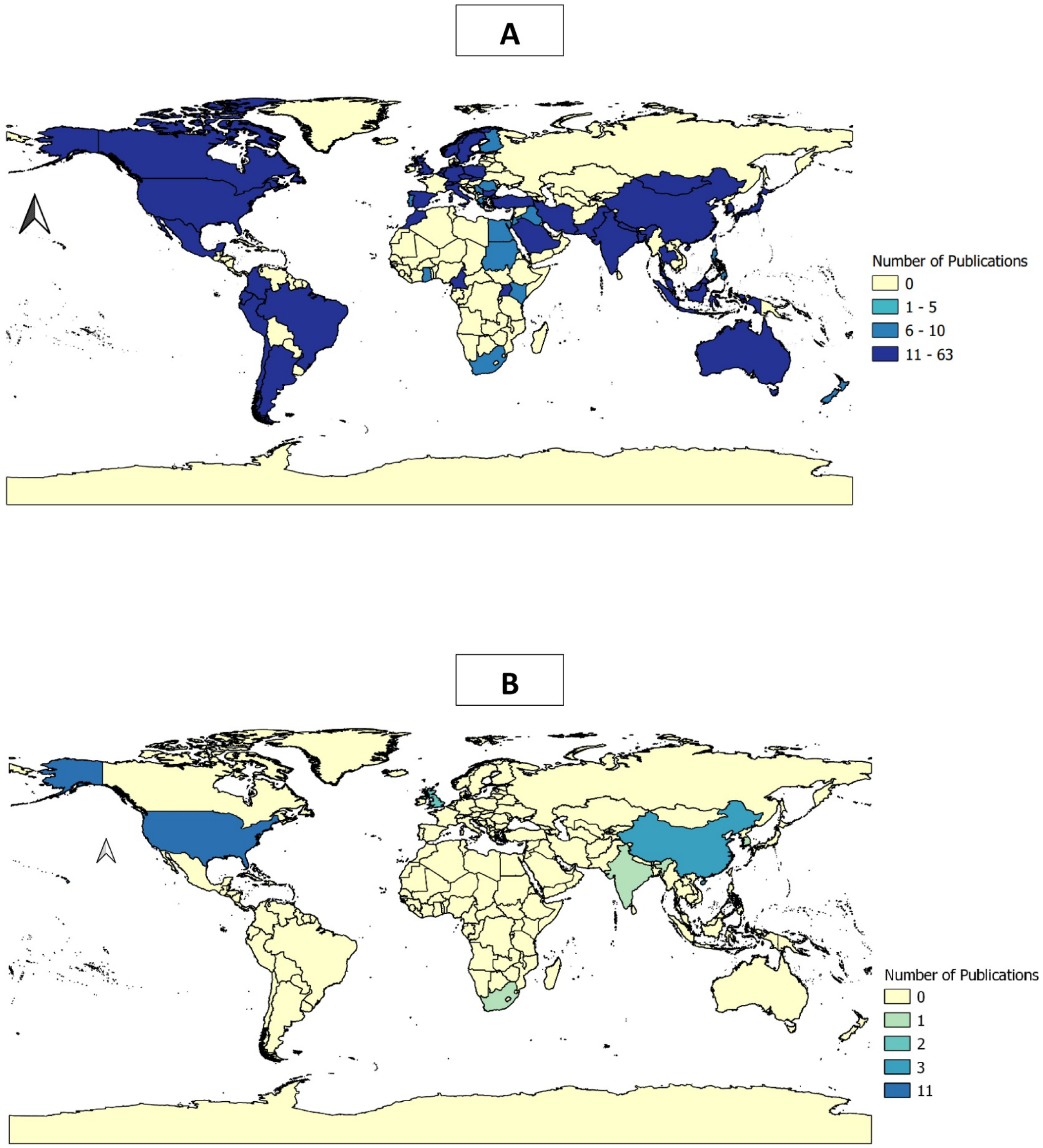

Figure 2. (a) Geographical distribution of the 621 studies that were retrieved during the literature search. (b) The geographical distribution of the 25 studies that focus on the link between green spaces and COVID-19 impact (N.B: the 25 studies are inclusive of studies that may not fit the inclusion criteria of the meta-analysis).

analyses, and only four studies included climatic, demographic, economic, health, and political covariates (Figure 3b).

3.2. Greenness and COVID-19 Infections

We found a statistically significant negative effect of greenness on COVID-19 infections ($\beta = -0.08$, 95% CI: -0.1396 to -0.0252; $t = -2.90$; $p = 0.006$) with a prediction interval of [-0.3601 to 0.1954] (95% CI) (Figure 4). Between-study heterogeneity variance was estimated at $\tau^2 = 0.0184$ (95% CI: 0.0185 to -0.0813), with an I^2 value of 94.1% (95% CI: 92.9%–95.1%). Subgroup analyses revealed that between-study heterogeneity can be attributed to year of publication ($X^2 = 8.24$; $p = 0.02$), choice of predictors ($X^2 = 129.68$; $p < 0.01$), and use of political covariates ($X^2 = 8.27$; $p < 0.01$) (see Table 2 and Figures S1–S6 in Supporting Information S1).

Table 1
Characteristics of All Studies Included in the Present Meta-Analysis

Study (1st author, year)	Country	Measure of green infrastructure	Temporal extent	Sample size	Measure of COVID-19 impact	Covariates
Grigsby-Toussaint and Shin (2022)	United States of America	• Normalized Difference Vegetation Index • Tree Canopy	1 October 2020	3,108	Positive cases per 1,000 people	• Rural population; Total population; Socioeconomic status; Household composition and disability; Minority status and language; Housing and transportation; Particulate matter ($PM_{2.5}$); Precipitation; Temperature; Wind speed
Jiang et al. (2022)	United States of America	• Open space inside park • Open space outside park • Forest inside park • Forest outside park • Shrub and scrub • Herbaceous • Hay and pasture	22 January–31 December 2020	3,108	Infection rate	• Socioeconomic and demographic factors; Healthcare and testing factors; Pre-existing chronic disease factors; Politics and policy factors; Behavioral factors; Environmental Factors
Johnson et al. (2021)	England	• Median frequency of parks within a 1 km^2 radius around households • Available green space per person (m^2) within the local authority	1 March 2020–30 November 2020	299	Infection rate	• Lag case rate; Population density; Population clustering; Mobility; Case average; Baseline health; Percentage over 70; Percentage unemployed
Klompmaker et al. (2021)	United States of America	• Mean values of Normalized Difference Vegetation Index	1 April 2020–31 May 2020	3,089	COVID-19 death rate (per 100,000)	• Population density; % poverty; % owner occupied housing; % less than high school education; % black; % Hispanic; % 65+ years of age; % 45–64 years of age; %14–44 years of age; Median home value; Median household income; % obese; % current smokers; Days since stay-at-home order; Days since non-essential businesses closure; Days since nursing homes visitor ban; Days since first case; Rate of hospital beds; Rate of tests; Average summer temperature; Average winter temperature; Average summer relative humidity; Average winter relative humidity; $PM_{2.5}$; Urban counties; Counties with issuance of stay-at-home order; Counties with 10< cases
Lin et al. (2023)	United States of America	Population-density-weighted NDVI	April 2021	3,040	Count of COVID-19 infections	• Particulate matter ($PM_{2.5}$); Temperature; % unemployment; % poverty; GINI; % not proficient in English; % bachelor; % females; % white; % 60 and older; % below 18; % rent; Average household size; % severe housing problems; % children in single-parent households; % limited access to

Table 1
Continued

Study (1st author, year)	Country	Measure of green infrastructure	Temporal extent	Sample size	Measure of COVID-19 impact	Covariates
						healthy food; Social associations; % adult obesity; % adult diabetes; % physical inactivity; %excessive drinking
Lu et al. (2021)	United States of America	• Developed open space • Forest • Shrub and scrub • Grassland and herbaceous • Pasture and hay • Cultivated crops • Woody wetlands • Emergent herbaceous wetlands	10 July 2020	135	Number of COVID-19 cases per 100,000 people	• Population density; Female population ratio; Different in black-white population; Different in black-white adult population; Household size; Households with broadband; Median household income; Healthcare receipts; Number of firms; coronary heart disease; death rate; Heart failure death rate; Diagnosed diabetes rate
Peng et al. (2022)	China	• Mean value of Normalized Difference Vegetation Index	1 January 2020–29 February 2020	266	Number of COVID-19 cases per 100,000 people	• Population density; Older people %; Gender ratio; Education years; Urbanization rate; GDP per capita; Hospital beds; Number of doctors; Government Response Index; Intra-city movement intensity; $PM_{2.5}$; NO_2; CO; Temperature; Relative humidity
Phogole and Yessoufou (2023)	South Africa	• Mean value of Enhanced Vegetation Index • Forest • Grassland	4 June 2022	4,429 226	Count number of COVID-19 cases per total population in a unit area	• Aged 65 years or older; Surface area; Revenue per capita
Russette et al. (2021)	United states of South Africa	• Leaf area index	21 January 2020–29 July 2020	3,049	Count number of COVID-19 deaths	• Total population; Over 60%; No high school diploma or equivalent; Medical aid; Overcrowding; Black %; Native American %; Physical inactivity
Sikarwar et al. (2023)	India	• Normalized Difference Vegetation Index	1 May 2020	640	Count number of COVID-19 deaths	• $PM_{2.5}$; Temperature and rainfall; Total population; Population density; Proportion of older adults and their sex ratio; Rural population; Household crowding; Material deprivation
Spotswood et al. (2021)	United States of America	• Normalized Difference Vegetative Index • Park proximity	1–30 September 2020	2,652	Number of COVID-19 cases per 100,000 people	• Proportion of non-white people; Income; Age; Population density; Days since first case
Yang et al. (2022)	United States of America	• Forest inside park • Forest outside park • Grassland/Herbaceous • Pasture/hay • Open space inside park • Open space outside park	22 January 2020–31 December 2020	3,025	Number of COVID-19 deaths per 100,000	• Population density; Black non-Hispanic; Population aged 65+; Gini index of income inequality; Median home value; Unemployment rate; Without high school diploma; Population without insurance; SARS-CoV-2 testing rate; Diabetes;

Table 1
Continued

Study (1st author, year)	Country	Measure of green infrastructure	Temporal extent	Sample size	Measure of COVID-19 impact	Covariates
						Obesity; Stroke; Hypertension; Heart stroke; Smoker; Essential worker; Places of interest visits; Commute by walking; Physical inactivity; Mobility; Mobility index; Stay-at-hope orders; Public mask mandate; Bars closed and reopened; Restaurant closed and reopened; Crowded housing; Proximity to highway; Airport density; Railway density; Road density; $PM_{2.5}$; PM_{10}; NO_2; Maximum temperature; Humidity; Wind speed
Zhai et al. (2022)	United States of America	• Urban green spaces visitation	27 February 2020–27 May 2020	3,108	Effective COVID-19 reproduction number	• Age; Proportion of blacks; Poverty rate; Population density; Essential occupation rate; Trump share; Healthcare workers

3.3. Greenness and COVID-19 Mortalities

We found that an increase in greenness was strongly linked to a lower mortality rate ratio (MRR = 0.9272; 95% CI: 0.8788–0.9783; $t = -3.05$; $p = 0.009$) with a prediction interval of [0.7683–1.1189] (95% CI) (Figure 5). Furthermore, an estimated 0.0069 between-study heterogeneity variance (95% CI: 0.0032–0.0228) was observed

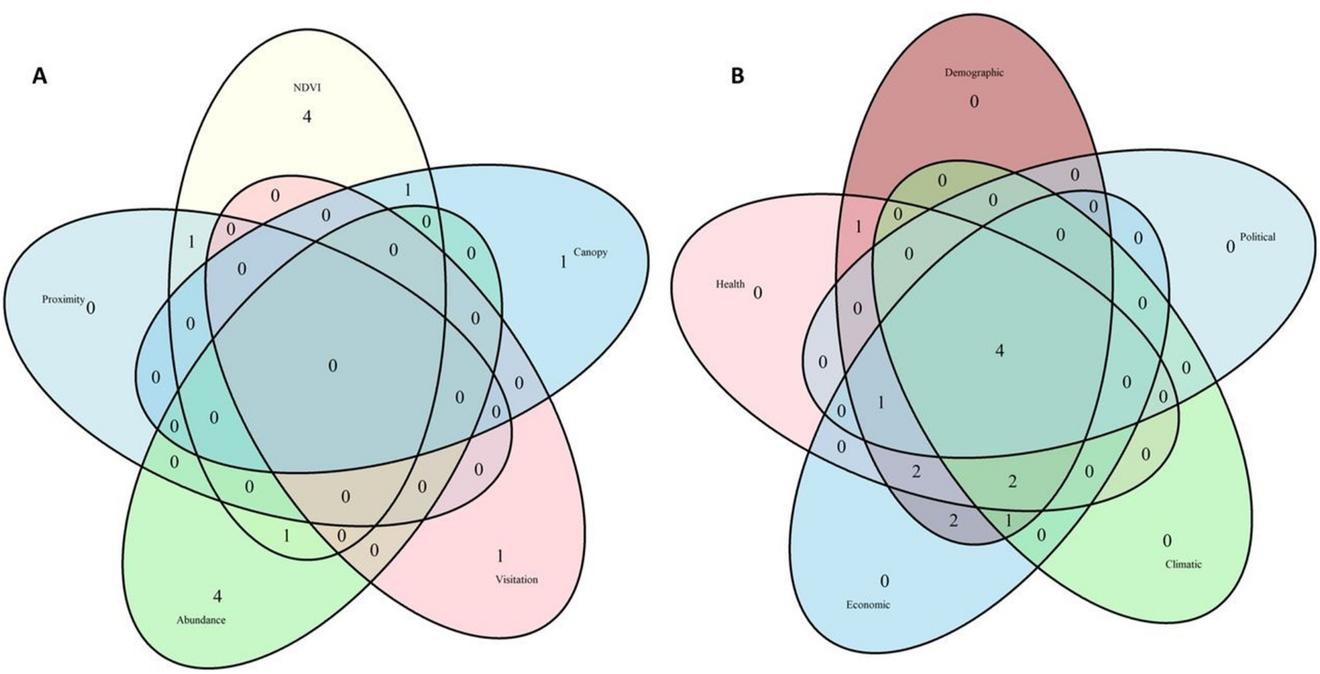

Figure 3. The illustration of the diversity of the use of (a) COVID-19 predictors and (b) covariates in the 13 studies that were included in the synthesis.

Study	ß	SE	Weight	ß IV, Random, 95% CI
Grigsby_toussaint	0.3100	0.2400	0.7%	0.31 [−0.16; 0.78]
Grigsby_toussaint	0.4600	0.2100	0.9%	0.46 [0.05; 0.87]
Grigsby_toussaint	0.0300	0.3200	0.5%	0.03 [−0.60; 0.66]
Grigsby_toussaint	−0.4300	0.1400	1.4%	−0.43 [−0.70; −0.16]
Grigsby_toussaint	−0.5000	0.1300	1.6%	−0.50 [−0.75; −0.25]
Grigsby_toussaint	−0.3500	0.1800	1.1%	−0.35 [−0.70; 0.00]
Jiang	−0.0590	0.0070	3.0%	−0.06 [−0.07; −0.05]
Jiang	0.0190	0.0090	3.0%	0.02 [0.00; 0.04]
Jiang	0.0170	0.0070	3.0%	0.02 [0.00; 0.03]
Jiang	−0.0220	0.0060	3.0%	−0.02 [−0.03; −0.01]
Jiang	0.0160	0.0080	3.0%	0.02 [0.00; 0.03]
Jiang	0.0580	0.0080	3.0%	0.06 [0.04; 0.07]
Jiang	−0.0580	0.0090	3.0%	−0.06 [−0.08; −0.04]
Jiang	−0.0870	0.0080	3.0%	−0.09 [−0.10; −0.07]
Johnson	0.1100	0.0110	3.0%	0.11 [−0.01; 0.03]
Johnson	0.0035	0.0110	3.0%	0.00 [−0.02; 0.02]
Johnson	−0.0570	0.0084	3.0%	−0.06 [−0.07; −0.04]
Johnson	0.0320	0.0110	3.0%	0.03 [0.01; 0.05]
Johnson	0.0240	0.0108	3.0%	0.02 [0.00; 0.04]
Lin	−1.1300	0.3291	0.4%	−1.13 [−1.78; −0.49]
Lin	−0.6900	0.3112	0.5%	−0.69 [−1.30; −0.08]
Lin	−0.8700	0.3699	0.4%	−0.87 [−1.59; −0.14]
Lin	−0.8000	0.3725	0.4%	−0.80 [−1.53; −0.07]
Lu	−0.3100	0.1250	1.6%	−0.31 [−0.56; −0.07]
Lu	−0.3100	0.1122	1.8%	−0.31 [−0.53; −0.09]
Lu	−0.3200	0.1250	1.6%	−0.32 [−0.56; −0.07]
Lu	−0.4200	0.1020	1.9%	−0.42 [−0.62; −0.22]
Lu	−0.1200	0.0918	2.1%	−0.12 [−0.30; 0.06]
Lu	0.0100	0.1225	1.6%	0.01 [−0.23; 0.25]
Lu	0.0100	0.0944	2.0%	0.01 [−0.18; 0.19]
Lu	−0.0900	0.1097	1.8%	−0.09 [−0.30; 0.13]
Peng	−0.0830	0.0130	3.0%	−0.08 [−0.11; −0.06]
Phogole	−0.2707	0.0588	2.5%	−0.27 [−0.39; −0.16]
Phogole	−0.2665	0.0651	2.4%	−0.27 [−0.39; −0.14]
Phogole	−0.0158	0.0473	2.7%	−0.02 [−0.11; 0.08]
Phogole	−0.2707	0.0588	2.5%	−0.27 [−0.39; −0.16]
Phogole	0.1397	0.0473	2.7%	0.14 [0.05; 0.23]
Phogole	−0.3410	0.0605	2.5%	−0.34 [−0.46; −0.22]
Spotswood	−0.0600	0.0200	2.9%	−0.06 [−0.10; −0.02]
Spotswood	−0.0200	0.0300	2.9%	−0.02 [−0.08; 0.04]
Zhai	0.0040	0.0020	3.0%	0.00 [0.00; 0.01]
Zhai	0.0050	0.0020	3.0%	0.00 [0.00; 0.01]
Zhai	0.0060	0.0020	3.0%	0.01 [0.00; 0.01]
Zhai	0.0060	0.0020	3.0%	0.01 [0.00; 0.01]
Zhai	0.0070	0.0020	3.0%	0.01 [0.00; 0.01]
Total (95% CI)			**100.0%**	**−0.08 [−0.14; −0.03]**
Prediction interval				**[−0.36; 0.20]**

Heterogeneity: $Tau^2 = 0.0184$; $Chi^2 = 749.60$, df = 44 ($P < 0.01$); $I^2 = 94\%$

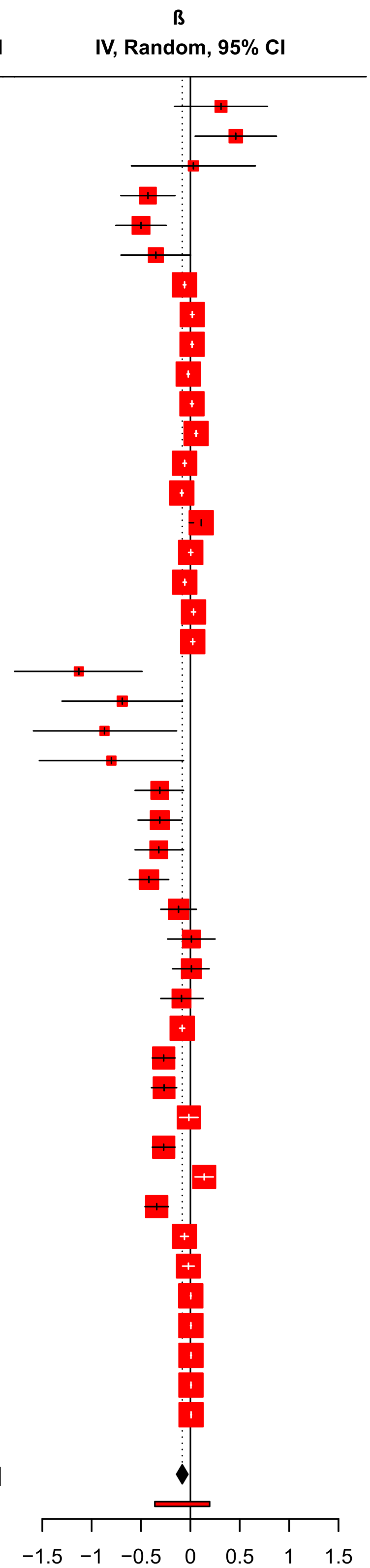

Figure 4. A forest plot depicting the relationship between COVID-19 infection and green spaces.

Table 2
Stratified Analyses of the Pooled Estimate of COVID-19 Infections and Green Infrastructure

Stratified analysis	Number of results	Pooled estimate [95% CI]	Subgroup difference X^2, df (p-value)
Study year	45	−0.08 [−0.14; −0.03]	8.24, df = 2 ($p = 0.02$)
2,021	15	−0.07 [−0.15; 0.01]	
2,022	20	−0.02 [−0.06; 0.02]	
2,023	10	−0.32 [−0.57; −0.07]	
Sample size	45	−0.08 [−0.14; −0.03]	0.01, df = 1 ($p = 0.91$)
Small ($n < 2{,}000$)	19	−0.09 [−0.16; −0.02]	
Large ($n \geq 2{,}000$)	26	−0.08 [−0.18; 0.02]	
Predictor	45	−0.08 [−0.14; −0.03]	129.68, df = 4 ($p < 0.01$)
Abundance	25	−0.06 [−0.12; −0.00]	
NDVI/EVI	11	−0.24 [−0.55; 0.07]	
Canopy	3	−0.44 [−0.62; −0.27]	
Visitation	5	0.01 [0.00; 0.01]	
Proximity	1	−0.02 [−0.08; 0.04]	
Covariates: demographic	45	−0.08 [−0.14; −0.03]	NA
With demographic covariates	45	−0.08 [−0.14; −0.03]	
Without demographic covariates	0		
Covariates: health	45	−0.08 [−0.14; −0.03]	1.35, df = 1 ($p = 0.25$)
With health covariates	37	−0.06 [−0.11; 0.00]	
Without health covariates	8	−0.13 [−0.28; 0.01]	
Covariates: economic	45	−0.08 [−0.14; −0.03]	NA
With economic covariates	45	−0.08 [−0.14; −0.03]	
Without economic covariates	0		
Covariates: climatic	45	−0.08 [−0.14; −0.03]	0.35, df = 1 ($p = 0.56$)
With climatic covariates	19	−0.12 [−0.27; 0.03]	
Without climatic covariates	26	−0.08 [−0.14; −0.02]	
Covariates: political	45	−0.08 [−0.14; −0.03]	8.27, df = 1 ($p < 0.01$)
With political covariates	14	−0.01 [−0.04; 0.01]	
Without political covariates	31	−0.15 [−0.24; −0.05]	

with an I^2 value of 92% (95% CI: 88.3%–94.5%). We also found that year of publication ($X^2 = 19.10$; $p < 0.01$), sample size ($X^2 = 7.92$; $p < 0.01$), choice of predictors ($X^2 = 14.92$; $p < 0.01$), and use of health ($X^2 = 7.92$; $p < 0.01$) and political covariates ($X^2 = 22.75$; $p < 0.01$) strongly impact the degree of heterogeneity (see Table 3 and Figures S7–S13 in Supporting Information S1).

3.4. Publication Bias

The existence of publication bias was investigated using the Funnel approach and Orwin fail-safe number. The presence of funnel plot symmetry (Figure 6a) indicated a lack of publication bias for studies that investigate the effect of greenness on COVID-19 infections (Fail-safe N: 45). Publication bias was, however, observed for studies that test the relationships between greenness and COVID-19 mortalities (Figure 6b; Fail-safe N: 14).

4. Discussion

Our meta-analysis provides evidence that an increase in abundance or exposure to greenness is associated with a significant reduction in COVID-19 infection rates and death cases (Jiang et al., 2022; Klompmaker et al., 2021; Sikarwar et al., 2023). However, we found high heterogeneity between the studies that were included in the meta-

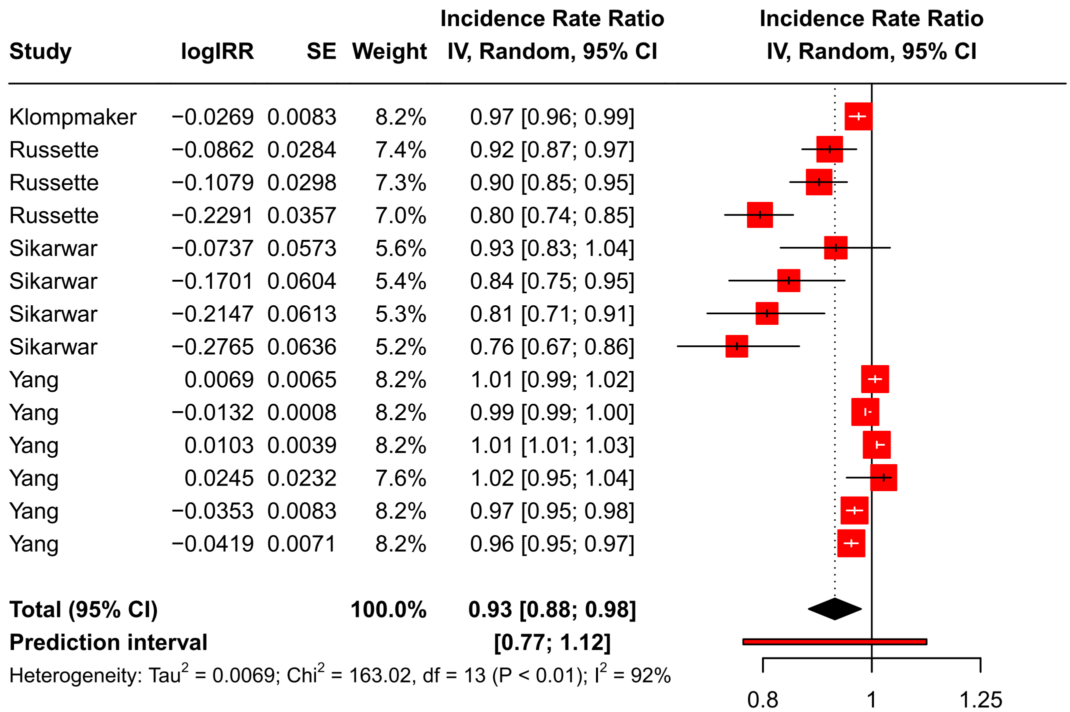

Figure 5. A forest plot depicting the relationship between COVID-19 mortality and green spaces.

analysis. Subgroup analyses revealed that heterogeneity in studies on COVID-19 infections and mortality is strongly predicted by the studies' years of publication, choices of predictors (e.g., metrics of greenness), and inclusion of political covariates. Additionally, sample size and consideration of health covariates strongly affect the heterogeneity of studies on COVID-19 mortalities.

The sensitivity of effect size to year of publication can be attributed to the availability of data to adequately model the impact of COVID-19. The spread of COVID-19 and increased global testing for COVID-19 infection have accelerated over time, thus allowing successive studies to have an increasingly larger data pool to analyze (OWD, 2023; Singh et al., 2021). This may also impact the sample sizes that are adopted in each study. As more regions produce more data on COVID-19 infections and mortality, their eligibility to be included in studies investigating the correlations between COVID-19 and greenness may enhance study designs. In our subgroup analysis, we found that studies that used smaller sample sizes (n < 2,000) are likely to report larger effect sizes compared to studies with larger sample sizes. Given the importance of selecting an appropriate sample size, the need to define an appropriate sample size to investigate the health benefits of green infrastructure remains critical.

The diversity of greenness metrics, ranging from street trees to large forests, presents a unique challenge while measuring their impacts. Commonly, studies that cover large study areas use vegetation indices such as NDVI or EVI which are retrieved from satellite imagery (Brochu et al., 2022; Fong et al., 2018; Grigsby-Toussaint & Shin, 2022). Since the health benefits of greenness are usually felt closer to the greenness (Dennis et al., 2020; Ngom et al., 2016), several studies consider local greenness such as household gardens (Chalmin-Pui et al., 2021), street trees (Marselle et al., 2020; Wolf et al., 2020), and local parks (Orstad et al., 2020; Weber et al., 2023) in their analysis. However, this approach is only feasible when focusing on smaller areas. In some cases, subjective measures of greenness were used (Lehberger et al., 2021; Yessoufou et al., 2020). Our findings in the present study suggest that the choice of greenness metrics adopted in different studies affects its effect size. The use of NDVI, EVI or vegetation canopy size produces large effects of greenness against COVID-19 infections and mortalities. In contrast, studies that use proximity or visitation patterns are likely to report marginal effects.

All studies in our meta-analysis have included demographic covariates, and 92% of studies included economic covariates. While modeling the effects of greenness, the inclusion of demographic variables such as population density and age structure, as well as economic indicators such as gross domestic product and household income level as covariates have been largely adopted (Klompmaker et al., 2021; Peng et al., 2022; Russette et al., 2021;

Table 3
Stratified Analyses of Pooled Mortality Rate Ratio of COVID-19 Deaths

Stratified analysis	Number of results	Pooled mortality rate ratio [95% CI]	Subgroup difference X^2, df (p-value)
Year of publication	14	0.93 [0.88; 0.98]	19.10, df = 2 ($p < 0.01$)
2021	4	0.90 [0.78; 1.03]	
2022	6	0.99 [0.96; 1.02]	
2023	4	0.83 [0.73; 0.96]	
Sample size	14	0.93 [0.88; 0.98]	7.92, df = 1 ($p < 0.01$)
Small ($n < 2{,}000$)	4	0.83 [0.73; 0.96]	
Large ($n \geq 2{,}000$)	10	0.96 [0.91; 1.01]	
Predictor	14	0.93 [0.88; 0.98]	14.92, df = 2 ($p < 0.01$)
Canopy	3	0.87 [0.72; 1.05]	
NDVI/EVI	5	0.87 [0.76; 0.99]	
Abundance	6	0.99 [0.96; 1.02]	
Covariates: demographic	14	0.93 [0.88; 0.98]	NA
With demographic covariates	14	0.93 [0.88; 0.98]	
Without demographic covariates	0		
Covariates: health	14	0.93 [0.88; 0.98]	7.92, df = 1 ($p < 0.01$)
With health covariates	10	0.96 [0.91; 1.01]	
Without health covariates	4	0.83 [0.73; 0.96]	
Covariates: economic	14	0.93 [0.88; 0.98]	2.60, df = 1 ($p = 0.11$)
With economic covariates	11	0.95 [0.89; 1.01]	
Without economic covariates	3	0.87 [0.72; 1.05]	
Covariates: climatic	14	0.93 [0.88; 0.98]	2.60, df = 1 ($p = 0.11$)
With climatic covariates	11	0.95 [0.89; 1.01]	
Without climatic covariates	3	0.87 [0.72; 1.05]	
Covariates: political	14	0.93 [0.88; 0.98]	22.75, df = 1 ($p < 0.01$)
With political covariates	7	0.85 [0.80; 0.92]	
Without political covariates	7	0.99 [0.97; 1.01]	

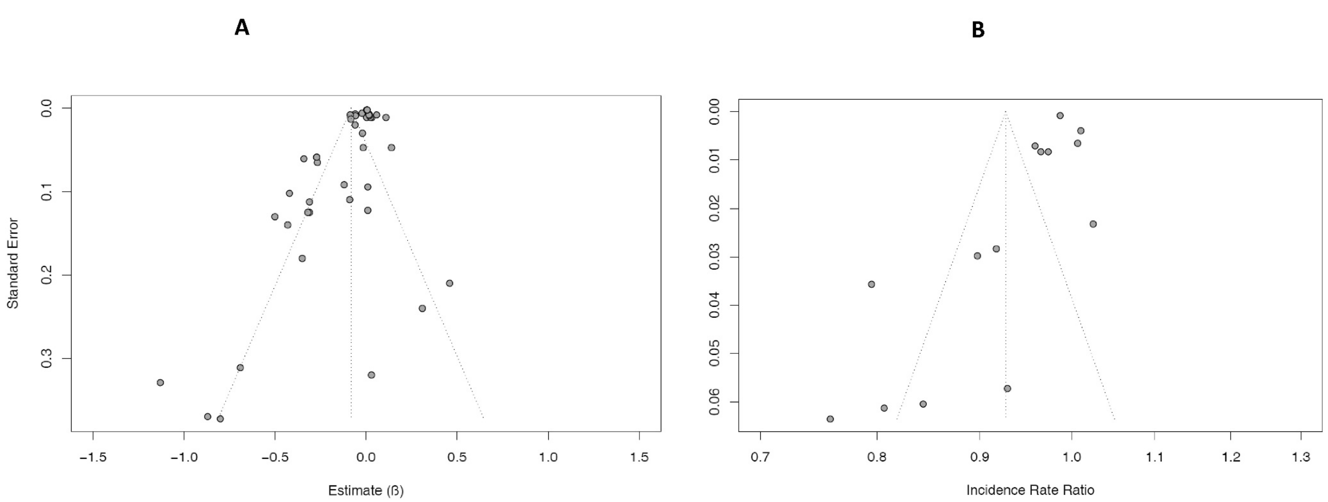

Figure 6. Illustrations of the results of the Funnel plot test for publication bias in studies on (a) COVID-19 infection and (b) COVID-19 mortality.

Spotswood et al., 2021). Furthermore, the use of health covariates was featured in several studies (Jiang et al., 2022; Lin et al., 2023; Yang et al., 2022). However, consideration of political covariates in the modeling of greenness benefits to human wellbeing in the context of COVID-19 is only starting to emerge (Yang et al., 2022; Zhai et al., 2022). Political factors such as the promulgation of mobility restrictions (Haug et al., 2020; Huang et al., 2021) and face-masks mandates (Aravindakshan et al., 2022) have been shown to be significant predictors of COVID-19 impacts, although their inclusion in studies linking greenness to COVID-19 infection and severity remains limited. We found that the use of political covariates significantly affects the effect size. The inclusion of political covariables resulted in a greater effect size in studies of COVID-19 mortality and a smaller effect size in studies of COVID-19 infections. This may suggest that existing policies are more effective in reducing COVID-19 fatalities than curbing the spread of infections.

5. Conclusions

Overall, when meta-analyzing studies from Africa, Asia, Europe, and USA, we found strong support for the beneficial effects of greenness on humans in the face of COVID-19 infection and severity, suggesting that positive correlations reported in some studies between greenness versus infection and mortality rates (Huang et al., 2021; Pan et al., 2021) might simply imply that the greenness metrics used in those studies (e.g., green space density or accessibility to greenspaces) may not fully capture important facets of greenness. This calls for a need to homogenize greenness metrics in studies to come. There is also a need for homogenization of COVID-19 severity metrics since we could not include hospitalization rate in the present study as a measure of COVID-19 severity because very limited studies have investigated hospitalization rate. Lastly, our results showed a high degree of between-study heterogeneity which can be explained by year of publication, sample size, and choice of predictor variables and covariates. However, evidence from existing studies shows that green infrastructure moderates the impacts of COVID-19 by reducing the prevalence of infections and associated mortalities.

Nevertheless, our findings have some far-reaching implications for the establishment and management of green infrastructure. In several countries, including the US, poor communities are less green than their rich counterparts (Spotswood et al., 2021; Venter et al., 2020), and it is poor communities that bear the highest burden of COVID-19 infection and severity—the pandemic injustice (McPhearson et al., 2020). In such context, clarifying that greenness shows significant negative correlations with COVID-19 infection rates and severity implies that greenspaces must be acknowledged as critical infrastructure that has substantial broader public health values, and as such, deserve enough funding from governments worldwide, especially in the developing world.

Although this study provides key insights into the benefits of greenspaces against COVID-19, there is a notable limitation that exists. Given the recency of the topic, there is a limited number of studies on this topic which resulted in the small number of studies that were included in this meta-analysis. As this topic receives more scholarly attention, the number of studies on this subject is expected to increase with strong coverage of different geographical contexts.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

Data is available at Phogole and Yessoufou (2024).

Acknowledgments

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