Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.
COVID-19, green space exposure, and mask mandates

Diana S. Grigsby-Toussaint *, Jong Cheol Shin

Department of Behavioral and Social Sciences, Brown University School of Public Health, Providence, Rhode Island, United States of America
Department of Epidemiology, Brown University School of Public Health, Providence, Rhode Island, United States of America

HIGHLIGHTS

• Counties with mask mandates and greater tree canopy had lower COVID-19 incidence.
• Mask mandates are an important policy tool for preventing the spread of COVID-19.
• Access to greenspace and exposure to air pollution may influence COVID-19 risk.

GRAPHICAL ABSTRACT

ABSTRACT

Introduction: Mask-wearing and social distancing are critical prevention measures that have been implemented to stem the spread of COVID-19. The degree to which these measures are adhered to in the US, however, may be influenced by access to outdoor resources such as green space, as well as mask mandates that may vary by state.

Purpose: To examine the association between the presence or absence of statewide mask mandates and green space exposure with COVID-19 cumulative incidence in the US.

Methods: In October 2020, COVID-19 case data for each US county was downloaded from USA Facts, in addition to statewide mask mandates from a database maintained by the American Association of Retired Persons. The Normalized Difference Vegetation Index from the US Geological Survey (USGS), was used as a measure of greenspace, while the 2016 National Land Cover Database was used to assess tree canopy exposure as an alternative measure of greenspace. We performed generalized linear regression to evaluate associations with COVID-19 incidence, adjusting for potential confounders such as other environmental factors (i.e., air pollution and climate) and socio-economic factors derived from the CDC social vulnerability index. In addition, we also performed spatial regression analyses to account for spatial autocorrelation across counties.

Results: Counties with mandatory mask-wearing policies had a lower cumulative incidence of COVID-19 (B = −0.299, SE = 0.038). Among environmental factors, precipitation (B = 0.005, SE = 0.001) and PM 2.5 (B = 0.072, SE = 0.012) were associated with a higher incidence of COVID-19, while tree canopy (B = −0.501, SE = 0.129) was associated with a lower risk of COVID-19. COVID-19 incidence was higher in counties with socially vulnerable populations regarding socioeconomic status, minority status, and housing and transportation.

Keywords: Greenspace
COVID-19
Mask mandates

* Corresponding author at: Department of Behavioral and Social Sciences, Department of Epidemiology, Brown University School of Public Health, 121 S Main Street, Providence, RI 02912, United States of America.
E-mail addresses: diana.grigsby-toussaint@brown.edu (D.S. Grigsby-Toussaint), jong_cheol_shin@brown.edu (J.C. Shin).

http://dx.doi.org/10.1016/j.scitotenv.2022.155302
Received 18 July 2021; Received in revised form 11 April 2022; Accepted 11 April 2022
Available online 18 April 2022
0048-9697/© 2022 Elsevier B.V. All rights reserved.
1. Introduction

The COVID-19 pandemic remains a pivotal public health issue, with more than 488 million cases and 6.1 million deaths reported as of March 31, 2022 (Johns Hopkins University, 2020). In the US, the pandemic continues, with 80.1 million cases reported to date, along with almost a million deaths (Johns Hopkins University, 2020). Regional variations have been observed in COVID-19 prevalence both globally and in the US (Johns Hopkins University, 2020), which may be due to differences in the implementation of measures to mitigate the spread of the severe acute respiratory coronavirus 2 (SARS-CoV-2), which causes COVID-19. As SARS-CoV2 spreads due to close contact and droplet transmission influenced by socio-environmental factors (Centers for Disease Control, 2020a), several studies have attempted to identify which social or environmental factors are key targets for effective interventions.

Concerning social factors, socio-economic status has emerged as a major influence on COVID-19 risk. Patel et al. (2020) found that low socio-economic status as proxied by household income is associated with a higher risk of COVID-19 hospitalizations (Patel et al., 2020). This finding may be due to limited occupational options that may force individuals to continue to work in close proximity with others, thus increasing the risk for transmission. Moreover, socially vulnerable communities with characteristics such as limited English proficiency, high unemployment, or limited transportation options have also been shown to have a disproportionately higher prevalence of COVID-19 compared to less socially vulnerable communities (Karaye and Horney, 2020; Khazanchi et al., 2020).

In addition to socio-economic factors, environmental factors have also been shown to affect COVID-19 risk (You et al., 2020). Several studies have found an association between high levels of particulate matter (e.g., PM 2.5 and PM 10) exposure and increased COVID-19 prevalence (Zoran et al., 2020) and mortality (Shoari et al., 2020). Other environmental factors such as precipitation, wind speed, and temperature may also increase or attenuate the spread of COVID-19 (Esram and Jalili, 2020; Shi et al., 2020; Menebo, 2020). For example, high wind speed has been associated with a lower risk of COVID-19 because it reduces the permanence of particles in polluted air (Shi et al., 2020).

Another less well explored environmental factor for COVID-19 risk is exposure to green space. Green space exposure is considered important in the context of COVID-19 as it helps to purify air (De Ridder et al., 2004), thus improving air quality and potentially reducing transmission risk due to particulate matter (Vienneau et al., 2017). Furthermore, tree canopy provides a more comfortable outdoor activity environment via cooling pedestrian areas, green views, and natural soundscapes. Moreover, green space exposure has also been shown to provide emotional and mental health benefits (Black and Richards, 2020), including attainment of sufficient sleep (Shin et al., 2020a). Hubbard et al. found that individuals with greater access to green space experienced better mental and physical health during the COVID-19 pandemic (Hubbard et al., 2021). In this sense, individuals tend to increase the use of green space as a way to seek refuge from the stressors of COVID-19 (Venter et al., 2020; Kleinschroth and Kowari, 2020). Notwithstanding these positive attributes, increased engagement with green space may also increase COVID-19 risk due to potential increased exposure to others (Freeman and Eykelbosh, 2020; Heo et al., 2021).

In addition to socio-environmental factors, several public health policies have been critical for preventing the spread of COVID-19 (Hernández-Padilla et al., 2020). Specifically, mask-wearing has emerged as one of the most effective prevention strategies implemented by governments and other health authorities (Chu et al., 2020). Mask mandates are considered particularly important for outdoor activities (Freeman and Eykelbosh, 2020), as they allow one to enjoy the benefits of outdoor activities while reducing the risk of droplet transmission during physical and social contact. Although several studies of the influence of socio-environmental factors on COVID-19 risk have been undertaken, few have simultaneously accounted for the role of public health policies.

Consequently, the purpose of this study is to examine whether an association exists between green space exposure and COVID-19 incidence within the context of various socio-environmental factors and mask mandate policies. Building on our previous work to conceptualize geographic units that best capture greenspace exposure, we created measures of community activity spaces (Shin et al., 2020b). This method can address challenges with variations in the shapes of geographic units that may also influence measures of greenspace, such as zoning policies. Briefly, instead of using larger county units to estimate exposure to green space, we constructed smaller units of activity spaces for each county to account for areas that people are more likely to traverse each day, that is, we weight environmental exposures more heavily where people live and work (Shin et al., 2020b). In this way, we believe we were able to better capture areas where people actually live and work, and thus, better measure their potential greenspace exposure. We hypothesize that higher levels of exposure to green space will be associated with a lower incidence of COVID-19, even after accounting for social vulnerability and mask mandates.

2. Methods

2.1. Study design

A cross-sectional study using secondary data sources was performed.

2.2. Data sources and measures

A summary of all of the publicly available data sources and descriptions of the measures are available in Appendix A.

2.3. COVID-19 cases and cumulative incidence

County-level COVID-19 cases from 3108 contiguous counties in the US as of October 1, 2020, were obtained from USA Facts (2021) (Appendix A). Five-year population estimates from the American Community Survey (2013–2018) were used with the COVID-19 case data to calculate COVID-19 cumulative incidence across counties.

2.4. Mask mandates

State-level data on mandatory mask mandates was obtained on October 1, 2020, from the American Association of Retired Persons (AARP) (Markowitz, 2020). The AARP database was used to create a dichotomous measure, indicating whether counties did or did not have mandatory mask mandates.

2.5. Socio-demographic factors

The Social Vulnerability Index (SVI) dataset from the Centers for Disease Control and Prevention (CDC) was used to derive the county-level social vulnerability with respect to socio-demographic and economic factors. The index was assembled by four themes which are based on 15 variables describing the following population characteristics: Theme 1, Socioeconomic status (4) – below poverty, unemployed, income, no high school diploma; Theme 2, Household composition and disability (4) – aged 65 or older, aged 17 or younger, civilian with a disability, single-
parent households; Theme 3. Minority status and language (2) – minority, speaks English “less than well”; and Theme 4. Housing & transportation (5) – multi-unit structures, mobile homes, crowding, no vehicle, group quarters (Centers for Disease Control, 2020b).

2.6. County status – urban vs. rural

County status (urban or rural) was identified using the National Center for Health Statistics (NCHS) Urban-Rural Scheme (Ingram and Sheila, 2013). The scheme has six classifications based on the number of inhabitants (i.e., large central metro, large fringe metropolitan, medium metropolitan, small metropolitan, micropolitan, and non-core). Of these, micropolitan and non-core, which are defined as non-metropolitan, were selected as rural counties (Ingram and Sheila, 2013). We expect that rural counties are less dense, so they will experience lower COVID-19 incidence.

2.7. Green space measures

eMODIS Remote Sensing Phenology Products, which are produced by the U.S. Geological Survey (USGS), were used to extract the Normalized Difference Vegetation Index (NDVI) for green space exposure measurement (USGS, 2019). NDVI is a ratio between the near-infrared reflectance and visible-red reflectance to estimate the density of greenness in vegetation coverage. Through the use of multi-temporal NDVI images as of 2018, the study used the maximum NDVI, which reflects the highest exposure to green space over the course of a year. The 2016 National Land Cover database (Jin et al., 2019) was used to create a measure of green space exposure based on tree coverage. Tree canopy, which is highly related to other green space measurements such as NDVI, is a good indicator that is also associated with urban greening policies (Kondo et al., 2020). The potential range of values for green space (i.e., NDVI and tree coverage) is between 0 and 100%, with higher percentages indicating a higher density of trees or greenness.

2.8. Air pollution and climate

Air pollution data was derived from the COVID-19 PM 2.5 project at Harvard University (Wu et al., 2020). The original PM 2.5 predictions dataset contains a 1 km grid resolution from the Atmospheric Composition Analysis Group at Dalhousie University (Van Donkelaar et al., 2019). Historical daily PM 2.5 exposure was estimated using the average of the zip code level measurement between 2000 and 2016, which was aggregated at the county level. Other climate information such as temperature, precipitation, and wind speed were derived from the WorldClim V2 dataset, which was developed by the Sustainable Intensification Innovation Lab of Kansas State University (Fick and Hijmans, 2017). This dataset includes average climate information for a 30-year (1970–2000) time window with a 1 km resolution image, including the summer (Fick and Hijmans, 2017).

2.9. Community activity space

To fully capture spaces that people utilize on a daily basis, we created “community activity spaces” for environmental variables such as precipitation. The community activity spaces allowed us to exclude areas of limited accessibility such as bodies of water or farmland using raster data (Shin et al., 2020b). The COVID-19 cumulative incidence data as well as the SVI data, however, were all collected at the county level.

2.10. Analysis

The primary unit of analysis for the study was the county. Unlike social vulnerability and COVID-19 related factors, spatial analysis was performed to examine accessibility to environmental resources and to account for spatial autocorrelation at the county level. Therefore, environmental exposure was calculated within the community activity space in each county and then aggregated to provide the average score (Shin et al., 2020b). All spatial analysis used ArcGIS version 10.8.1 (ArcGIS Desktop [program], 2018) to create maps showing the distribution of environmental factors and to calculate the COVID-19 cases, policy status, and environmental attributes of each county.

Descriptive statistics and correlation analysis among the variables were conducted using the JMP statistical analysis package (JMP® [program], 1989–2020). Generalized linear regressions were performed using R Studio version 1.2.1 (RStudio: Integrated Development for R [program], 2020) to examine the influence of mask mandates, socio-economic factors, and environmental factors on COVID-19 incidence adjudicated by the minimum AIC and BIC measures. GeoDa version 1.14.0 (Anselin et al., 2010) was used to perform two types of spatial regression analysis (i.e., spatial lag model and spatial error model). The residuals of the regressions were analyzed using the Global Moran’s I regarding spatial autocorrelation, and the Akaike Information Criterion (AIC) and Log likelihood were used to compare and select the final models.

3. Results

Of the 3108 counties included in the analysis, 2117 counties (68.1%) had mask mandates. Table 1 shows the socioeconomic and environmental characteristics of the study area by mask mandate policy. The median county COVID-19 incidence (i.e., positive cases per 1000) was significantly lower (p < 0.001) in mask mandate counties (Median = 1.11) compared to non-mask mandate counties (Median = 1.61). Compared to counties with a mask mandate, counties without a mask mandate had more diverse populations (p < 0.001), worse air pollution, less precipitation/average temperature/wind speed and higher tree canopy (P < 0.001) (Fig. 1).

The spatial variation of COVID-19 cumulative incidence and the environmental variables are presented in Fig. 1. Counties with a higher incidence of COVID-19 were concentrated in the Southeastern US states, such as Alabama, Kentucky, Florida, Georgia, Louisiana, Mississippi, South Carolina, and Tennessee, as well as some counties in the Southwest and Southern New England.

The correlation analysis (Fig. 2) illustrates the patterns and associations between selected variables. COVID-19 incidence was positively significant for all social vulnerability sub-indexes and environmental factors, except

| Variables | Total (n = 3108) | Mask mandate (n = 2117) | No mask mandate (n = 991) |
|-----------|-----------------|-------------------------|--------------------------|
| Rural (n, %) | 1948 (62.68) | 1278 (60.37) | 670 (67.61) |
| COVID-19 cases (n) | 6,338,229 | 4,496,434 | 1,841,795 |
| Population (n) | 326,092,106 | 250,978,250 | 75,113,856 |
| COVID-19 incidence (per 1000) | 19.437 | 17.916 | 24.520 |

SVI: Social Vulnerability Index, NDVI: Normalized Difference Vegetation Index, PM: particulate matter.

- Average in summer (June to August).
- Measurement based on the community activity space in each county.
wind speed \( r = -0.207, p < 0.001 \) and mask mandates \( r = -0.152, p < 0.001 \). Positive correlations were observed within the social vulnerability sub-indexes, with socioeconomic status being highly correlated to other index themes \( r \) for SVI theme 2 = 0.619, \( p < 0.001 \); \( r \) for SVI theme 4 = 0.544, \( p < 0.001 \). Although NDVI and tree canopy are both indicators of aspects of green space, their correlation to other variables was not the same (Fig. 2).

Table 2 contains multivariate regression analysis for the hierarchical models which show the influence of environmental exposure and mandatory mask mandates on COVID-19 incidence. Although Model six had the lowest AIC and Log likelihood values, Model five is selected as the preferred model with respect to spatial autocorrelation (Moran’s \( I = 0.009, p > 0.05 \)). Within models adjusted for social vulnerability and environmental exposures, places with mandatory mask mandates had a statistically significant lower risk of COVID-19 incidence compared to those without regulation (\( B = -0.299, SE = 0.038 \)). In model five, precipitation (\( B = 0.004, SE = 0.001 \)), county status (\( B = 0.115, SE = 0.040 \)), and PM 2.5 (\( B = 0.072, SE = 0.012 \)) were associated with the higher risk of COVID-19 incidence;

---

**Fig. 1.** COVID-19 related factors and environmental factors in the US a) states with mandatory mask mandates and environmental exposure as defined by community activity space, b) COVID-19 cumulative incidence, c) average temperature in summer, d) precipitation in summer, e) wind speed in summer, and f) tree canopy.

---
while tree canopy (B = −0.399, SE = 0.16) was associated with a lower risk of COVID-19 incidence. For the social vulnerability index, socioeconomic status (B = 0.834, SE = 0.101), minority status (B = 1.130, SE = 0.077), and housing and transportation (B = 0.455, SE = 0.075) had a higher association with COVID-19 incidence, while housing composition and disability (B = −0.433, SE = 0.077) showed a lower risk.

Fig. 3 illustrates the residuals of two spatial models based on the green space data sources (i.e., NDVI and the NLCD tree canopy). Although residuals were not dramatically clustered on the maps, there are several counties in the Midwest and South with higher COVID-19 incidence compared to the model estimation. Notably, there were few over-estimated areas (i.e., dark green) within all models after considering potential spatial autocorrelation. Although the figures for all four models look similar, the tree canopy GLM model and spatial lag models showed fewer over- or under-estimated locations compared to the NDVI model or the spatial error model.

4. Discussion

We found that environmental, social, and public policy factors influence the geographic variation observed in COVID-19 incidence in the US. Specifically, COVID-19 incidence for each county increased 8 per 1000 people for each μg/m³ of PM 2.5 level and decreased 40 per 1000 people for a 1% increase of tree canopy. Also, COVID-19 incidence decreased 45 per 1000 people in states with mandatory mask-wearing policies. These findings are consistent with recent studies on exposure to air pollution and increased risk for COVID-19, as well as the protective effect of greenspace exposure on COVID-19 risk (Klompmaker et al., 2021). Clearly, for a condition such as COVID-19 that impacts the lungs, inhaling polluted air with hazardous particles such as PM 2.5 makes survival with COVID-19 more challenging, and may explain higher rates of incidence and mortality (Zoran et al., 2020; Wu et al., 2020). Tree canopy has been shown to have positive impacts on health based on economic analyses in the US (Kondo et al., 2020), and has some of the strongest evidence in the literature of showing an association with positive health outcomes (Kondo et al., 2020; Astell-Burt and Feng, 2020). We also used a unique measure of community activity space (Shin et al., 2020b) to better capture potential exposure to green space in a county. By using the Normalized Difference Vegetation Index (NDVI) to measure exposure to greenness, Klompmaker and colleagues also found that the association between greenspace and COVID-19 incidence was stronger in states with stay-at-home orders (Klompmaker et al., 2021).

These results support the previous health policy recommendation that potential access to recreational green space and its usage can help to reduce the spread of COVID-19 (Klompmaker et al., 2021). However, You et al. also found that the higher public greenspace density increased COVID-19 morbidity during the early stages of the COVID-19 pandemic in Wuhan, China, which they attributed to an increased opportunity for physical contact with others (You et al., 2020). That finding suggests that exposure to green space and its accessibility should occur under proper public health guidelines and control. As such, we examined the impact of mask mandates, and found that mandatory mask-wearing policies were associated with a significantly lower risk of COVID-19 incidence at the county-level, while accounting for exposure to tree canopy and a variety of potential confounding variables.

The significantly positive association between COVID-19 incidence and social vulnerability aligns with other patterns of health disparities in the US. We also found that social status and residential conditions are highly associated with COVID-19 risk. Higher COVID-19 morbidity or mortality was
Table 2
Regression analysis to examine the influence of mask mandate policies, social vulnerability, and environmental factors on COVID-19 cumulative incidence in the US, October 1st, 2020.

| NDVI          | GLM | Spatial lag model | Spatial error model | Tree canopy | GLM | Spatial lag model | Spatial error model |
|---------------|-----|-------------------|---------------------|-------------|-----|-------------------|---------------------|
|               | Model 1 | Model 2        | Model 3            | Model 4 | Model 5 | Model 6          |                     |
| B (SE)        | p-Value | B (SE)        | p-Value            | B (SE) | p-Value | B (SE)          | p-Value              |
| Constant      | -2.11 (0.3)*** | -1.63 (0.27)**   | -1.9 (0.47)**      | -1.54 (0.21)*** | -0.86 (0.2)*** | -1.63 (0.36)*** |                     |
| Mask mandate (ref. no) | -0.51 (0.04)*** | -0.31 (0.04)*** | -0.44 (0.07)*** | -0.5 (0.04)*** | -0.3 (0.04)*** | -0.43 (0.07)*** |                     |
| SVI theme 1 = socioeconomic status | 1 (0.1)*** | 0.8 (0.1)*** | 0.99 (0.11)*** | 1.04 (0.11)*** | 0.83 (0.1)*** | 1.01 (0.11)*** |                     |
| SVI theme 2 = household composition & disability | -0.47 (0.09)*** | -0.41 (0.08)*** | -0.42 (0.08)*** | -0.49 (0.09)*** | -0.43 (0.08)*** | -0.43 (0.08)*** |                     |
| SVI theme 3 = minority status & language | 1.65 (0.09)*** | 1.16 (0.08)*** | 1.42 (0.1)*** | 1.63 (0.08)*** | 1.13 (0.08)*** | 1.42 (0.09)*** |                     |
| Rural (ref. urban) | 0.18 (0.04)*** | 0.12 (0.04)*** | 0.07 (0.04) | 0.18 (0.04)*** | 0.11 (0.04)*** | 0.07 (0.04) |                     |
| Population density (people/hectare) | 0 (0) | 0 (0) | -0.01 (0) | 0 (0) | 0 (0) | -0.01 (0) |                     |
| Precipitation (mm)** | 0.01 (0)*** | 0 (0)*** | 0.01 (0)*** | 0.01 (0)*** | 0 (0)*** | 0.01 (0)*** |                     |
| Average temperature (°C)** | 0.06 (0.01)*** | 0.01 (0.01) | 0.06 (0.01)*** | 0.05 (0.01)*** | 0 (0.01) | 0.05 (0.01)*** |                     |
| Wind Speed (m/s)** | -0.05 (0.03) | 0.04 (0.03) | -0.04 (0.05) | -0.12 (0.04)** | -0.05 (0.03) | -0.09 (0.05) |                     |
| PM 2.5 (μg/m³) | 0.12 (0.01)*** | 0.07 (0.01)*** | 0.12 (0.02)*** | 0.12 (0.01)*** | 0.07 (0.01)*** | 0.11 (0.02)*** |                     |
| NDVI          | 0.31 (0.24) | 0.46 (0.21)*** | 0.03 (0.32) | -0.43 (0.14)*** | -0.5 (0.13)*** | -0.35 (0.18) |                     |
| Tree canopy (%) | -4477.69 | -4199.3 | -4173.18 | -4473.91 | -4193.8 | -4171.34 |                     |
|ρ (spatial lag parameter) | 0.49 (0.02)*** | 0.49 (0.02)*** | 0.56 (0.02)*** | 0.56 (0.02)*** |                     |                     |
|λ (spatial error parameter) | 8983.38 | 8426.61 | 8372.36 | 8975.82 | 8415.6 | 8368.68 |                     |
|Log likelihood | <0.01 | <0.029** |                     |                     | 0.009 | <0.029** |                     |

SVI: Social Vulnerability Index, NDVI: Normalized Difference Vegetation Index, PM: particulate matter.

* Average in summer.
* p < 0.05;
** p < 0.01;
*** p < 0.001.

Fig. 3. Maps of regression residuals from the spatial lag model and spatial error model.
reported in minority groups (Grisby-Toussaint et al., 2021; Williamson et al., 2020), and individuals with economically vulnerable factors such as living below the poverty level, or among those limited to a high school education (You et al., 2020). Vulnerability in housing and transportation showed a positive association with COVID-19 incidence, likely due to more frequent interaction with people in indoor settings. Specifically, the findings supported the evidence of higher COVID-19 risk in people who live in insecure housing such as multi-unit structures, mobile homes, and group quarters (Rosenberg et al., 2020; Team V and Manderson, 2020). Unlike other subscales, the second social vulnerability index, household composition and disability, had a negative association with COVID-19 incidence. Conditions such as disability and age may tend to restrict mobility (Rosso et al., 2013; Skär and Tamms, 2002) due to limited opportunities for social interactions, thereby explaining the potential for lower transmission rates (Nouvellet et al., 2021; Kraemer et al., 2020).

5. Conclusion

Our findings indicate that both green space exposure and mandatory mask mandates are associated with a lower risk for COVID-19. Furthermore, both the social environment (e.g., mobility, residence status, ease of physical and social contact, high population density) and natural environment (e.g., air quality, wind speed, and greenspace) influence COVID-19 transmission. As such, future public health policies and practices should consider environmental factors that may mitigate the spread of COVID-19 in order to reduce the burden of this disease and perhaps others into the future.

Credit authorship contribution statement

Diana Grigsby-Toussaint conceptualized the study, oversaw the data analysis, and wrote the manuscript. Jong Cheol Shin performed the data analysis and co-wrote the manuscript.

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.

Acknowledgements

This work was partially supported by grant 1P20GM139743-01 from the National Institute of General Medical Sciences, National Institutes of Health.

Appendix A. Data sources

| Variable | Conceptual theme | Details | Data sources |
|----------|------------------|---------|--------------|
| COVID-19 cumulative incidence (cases per 100K) | Outcome variable | Total cases per total population of each county | USA Facts (https://usafacts.org/visualizations/coronavirus-covid-19-spread-map/)
| Mask mandate (yes/no) | Health policy | Statewide order of face mask mandate | AARP (https://www.aarp.org/health/healthy-living/inf-2020/states-mask-mandates-coronavirus.html)
| Normalized Difference Vegetation Index (NDVI) (%) | Environment | Maximum NDVI in an annual time series | USGS-2019 eMODIS Remote Sensing Phenology Products (https://earthexplorer.usgs.gov)
| Tree canopy (%) | Environment | Total percentage of tree cover layer | USGS-MRLC NLCD 2016 UPS Tree canopy cover (https://www.mrlc.gov/data/nlcd-2016-uds-tree-canopy-cover-conus)
| PM 2.5 (μg/m³) | Environment | Average exposure to fine particulate matter | COVID-19 PM2.5 project of Harvard University (https://projects.iq.harvard.edu/covid-pm)
| Precipitation (mm) | Environment | Average of precipitation during the summer (June-August) | Worldclim V2 dataset (https://www.worldclim.org/)
| Average temperature (°C) | Environment | Average of temperature during the summer (June-August) | Worldclim V2 dataset (https://www.worldclim.org/)
| Wind speed (m/s) | Environment | Average of wind speed during the summer (June-August) | Worldclim V2 dataset (https://www.worldclim.org/)
| County status (rural/urban) | Population | County characteristics of a metropolis | NCHS - Urban-Rural Scheme (https://www.cdc.gov/nchs/data_access/urban_rural.htm)
| Population density | Population | Number of residences per hectare | 2018 ACS
| Socioeconomic status | Social vulnerability | Combination of Poverty, Income, Unemployment, High school diploma | CDC – SVI (https://www.atsdr.cdc.gov/placeandhealth/svi/index.html)
| Household composition & disability | Social vulnerability | Combination of aged 65+, age 17+, disability, and single parent | CDC – SVI
| Minority status & language | Social vulnerability | Combination of Minority and Language proficiency | CDC – SVI
| Housing & transportation | Social vulnerability | Combination of Multi-Unit Structures Mobile Homes | CDC – SVI
| Crowding No Vehicle Group Quarters | Social vulnerability | | 

AARP: American Association of Retired Persons, ACS: American Community Survey, CDC: Centers for Disease Control and Prevention, MRLC: Multi-Resolution Land Characteristics, NCHS: National Center for Health Statistics, NDVI: Normalized Difference Vegetation Index, NLCD: National Land Cover Database, PM: Particulate Matter, SVI: Social vulnerability Index.

References

Amelin, L., Sybiri, L, Kho, Y., 2010. GeoSin: an introduction to spatial data analysis. Handbook of Applied Spatial Analysis. Springer, pp. 73-89.
ArcGIS Desktop [program]. 10.8.1 Version. Environmental Systems Research Institute, Inc., Redlands, CA.
Astell-Burt, T., Feng, X., 2020. Urban green space, tree canopy and prevention of cardiometabolic diseases: a multilevel longitudinal study of 46 786 Australians. Int. J. Epidemiol. 49 (3), 926–933.
Black, J.K., Richard, M., 2020. Eco-gentrification and who benefits from urban green amenities: NYC’s high line. Landsc. Urban Plan. 204, 101390. https://doi.org/10.1016/j.landurbplan.2020.101390.
Centers for Disease Control, 2020. CDC scientific brief: SARS-CoV-2 and potential airborne transmission. Secondary CDC scientific brief: SARS-CoV-2 and potential airborne transmission. https://www.cdc.gov/coronavirus/2019-ncov/ncov-more/scientific-brief-sars-cov-2.html.
Centers for Disease Control, 2020. CDC SVI 2018 Documentation. 24.
Chu, D.K., Ali, E.A., Duda, S., et al., 2020. Physical distancing, face masks, and eye protection to prevent person-to-person transmission of SARS-CoV-2 and COVID-19: a systematic review and meta-analysis. Lancet 395 (10242), 1973–1987. https://doi.org/10.1016/S0140-6736(20)31142-9.
De Ridder, K., Adamec, V., Bañuelos, A., et al., 2004. An integrated methodology to assess the influence COVID-19 transmission. As such, future public health policies and practices should consider environmental factors that may mitigate the spread of COVID-19 in order to reduce the burden of this disease and perhaps others into the future.
Credit authorship contribution statement
Diana Grigsby-Toussaint conceptualized the study, oversaw the data analysis, and wrote the manuscript. Jong Cheol Shin performed the data analysis and co-wrote the manuscript.
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.
Acknowledgements
This work was partially supported by grant 1P20GM139743-01 from the National Institute of General Medical Sciences, National Institutes of Health.

Appendix A. Data sources

| Variable | Conceptual theme | Details | Data sources |
|----------|------------------|---------|--------------|
| COVID-19 cumulative incidence (cases per 100K) | Outcome variable | Total cases per total population of each county. | USA Facts (https://usafacts.org/visualizations/coronavirus-covid-19-spread-map/)
| Mask mandate (yes/no) | Health policy | Statewide order of face mask mandate | AARP (https://www.aarp.org/health/healthy-living/inf-2020/states-mask-mandates-coronavirus.html)
| Normalized Difference Vegetation Index (NDVI) (%) | Environment | Maximum NDVI in an annual time series | USGS-2019 eMODIS Remote Sensing Phenology Products (https://earthexplorer.usgs.gov)
| Tree canopy (%) | Environment | Total percentage of tree cover layer | USGS-MRLC NLCD 2016 UPS Tree canopy cover (https://www.mrlc.gov/data/nlcd-2016-uds-tree-canopy-cover-conus)
| PM 2.5 (μg/m³) | Environment | Average exposure to fine particulate matter | COVID-19 PM2.5 project of Harvard University (https://projects.iq.harvard.edu/covid-pm)
| Precipitation (mm) | Environment | Average of precipitation during the summer (June-August) | Worldclim V2 dataset (https://www.worldclim.org/)
| Average temperature (°C) | Environment | Average of temperature during the summer (June-August) | Worldclim V2 dataset (https://www.worldclim.org/)
| Wind speed (m/s) | Environment | Average of wind speed during the summer (June-August) | Worldclim V2 dataset (https://www.worldclim.org/)
| County status (rural/urban) | Population | County characteristics of a metropolis | NCHS - Urban-Rural Scheme (https://www.cdc.gov/nchs/data_access/urban_rural.htm)
| Population density | Population | Number of residences per hectare | 2018 ACS
| Socioeconomic status | Social vulnerability | Combination of Poverty, Income, Unemployment, High school diploma | CDC – SVI (https://www.atsdr.cdc.gov/placeandhealth/svi/index.html)
| Household composition & disability | Social vulnerability | Combination of aged 65+, age 17+, disability, and single parent | CDC – SVI
| Minority status & language | Social vulnerability | Combination of Minority and Language proficiency | CDC – SVI
| Housing & transportation | Social vulnerability | Combination of Multi-Unit Structures Mobile Homes | CDC – SVI
| Crowding No Vehicle Group Quarters | Social vulnerability | | 

AARP: American Association of Retired Persons, ACS: American Community Survey, CDC: Centers for Disease Control and Prevention, MRLC: Multi-Resolution Land Characteristics, NCHS: National Center for Health Statistics, NDVI: Normalized Difference Vegetation Index, NLCD: National Land Cover Database, PM: Particulate Matter, SVI: Social vulnerability Index.

References

Ametlin, L., Sybiri, L, Kho, Y., 2010. GeoSin: an introduction to spatial data analysis. Handbook of Applied Spatial Analysis. Springer, pp. 73-89.
ArcGIS Desktop [program]. 10.8.1 Version. Environmental Systems Research Institute, Inc., Redlands, CA.
Astell-Burt, T., Feng, X., 2020. Urban green space, tree canopy and prevention of cardiometabolic diseases: a multilevel longitudinal study of 46 786 Australians. Int. J. Epidemiol. 49 (3), 926–933.
Black, J.K., Richard, M., 2020. Eco-gentrification and who benefits from urban green amenities: NYC’s high line. Landsc. Urban Plan. 204, 101390. https://doi.org/10.1016/j.landurbplan.2020.101390.
Centers for Disease Control, 2020. CDC scientific brief: SARS-CoV-2 and potential airborne transmission. Secondary CDC scientific brief: SARS-CoV-2 and potential airborne transmission. https://www.cdc.gov/coronavirus/2019-ncov/ncov-more/scientific-brief-sars-cov-2.html.
Centers for Disease Control, 2020. CDC SVI 2018 Documentation. 24.
