Geophysical Research Letters

RESEARCH LETTER
10.1029/2020GL089286

Special Section:
The COVID-19 Pandemic: Linking Health, Society and Environment

Key Points:
- Urban vegetation can well explain the large spatial variability of the COVID-19 incidence and can slow down the spread of COVID-19
- Population density and the timing of government intervention on COVID-19 are strongly associated with the spread of COVID-19
- There is no evidence that warm weather would curb the spread of COVID-19

Supporting Information:
- Supporting Information S1

Correspondence to:
S. Pan,
panshuf@auburn.edu

Citation:
You, Y., & Pan, S. (2020). Urban vegetation slows down the spread of coronavirus disease (COVID-19) in the United States. *Geophysical Research Letters*, *47*, e2020GL089286. https://doi.org/10.1029/2020GL089286

Received 10 JUN 2020
Accepted 31 AUG 2020
Accepted article online 9 SEP 2020

Urban Vegetation Slows Down the Spread of Coronavirus Disease (COVID-19) in the United States

Yongfa You[1] and Shufen Pan[1]

[1]International Center for Climate and Global Change Research, School of Forestry and Wildlife Sciences, Auburn University, Auburn, AL, USA

Abstract Coronavirus Disease 2019 (COVID-19) is spreading around the world, and the United States has become the epicenter of the global pandemic. However, little is known about the causes behind the large spatial variability of the COVID-19 incidence. Here we use path analysis model to quantify the influence of four potential factors (urban vegetation, population density, air temperature, and baseline infection) in shaping the highly heterogeneous transmission patterns of COVID-19 across the United States. Our results show that urban vegetation can slow down the spread of COVID-19, and each 1% increase in the percentage of urban vegetation will lead to a 2.6% decrease in cumulative COVID-19 cases. Additionally, the mediating role of urban vegetation suggests that urban vegetation could reduce increases in cumulative COVID-19 cases induced by population density and baseline infection. Our findings highlight the importance of urban vegetation in strengthening urban resilience to public health emergencies.

Plain Language Summary Quantitative analysis of the causes behind the large spatial variability of the incidence of COVID-19 in the United States is lacking, which seriously hinders our progress in curbing the COVID-19 transmission. Here we used an innovative method to analyze the role of four important factors (urban vegetation, population density, air temperature, and baseline infection) in shaping the highly heterogeneous transmission patterns of COVID-19 in the conterminous United States. Our results show that urban vegetation can well explain the large spatial variability of the COVID-19 incidence and plays an important role in slowing down the spread of COVID-19. Population density and the timing of government intervention on COVID-19 are also strongly associated with its spread, whereas the impact of temperature is limited. Our study highlights the importance of urban vegetation as a resilient infrastructure, especially in times of crisis. Increasing the proportion of urban vegetation coverage needs to be i ncorporated into future urban planning to strengthen the resilience of cities to public health emergencies.

1. Introduction

Coronavirus Disease 2019 (COVID-19), a highly contagious respiratory virus, has spread to more than 200 countries and territories (Chen et al., 2020; Lu et al., 2020; Roser et al., 2020). As of 24 May 2020, there were over 5.41 million confirmed COVID-19 cases and 340,000 COVID-19 deaths worldwide (Dong et al., 2020). In the United States, the first confirmed case of COVID-19 was reported on 20 January 2020 and continued to spread rapidly, making the United States the epicenter of the global pandemic (Bashir et al., 2020; Holshue et al., 2020). By 24 May 2020, the cumulative number of COVID-19 cases in the United States has exceeded 1.63 million, with more than 96,000 deaths. However, the number of confirmed COVID-19 cases in different counties varies greatly, ranging from zero to tens of thousands, and the causes behind the large spatial variation in the transmission patterns of COVID-19 remain unclear. Therefore, there is an urgent need to investigate the potential factors that play a critical role in shaping the transmission patterns of COVID-19, which will be very helpful in controlling the speed and severity of COVID-19 transmission and making optimal decisions to cope with future public health emergencies.

Previous studies have indicated that the patterns of pandemic outbreaks and transmission are largely shaped by physical and human geographical features (Cauchemez et al., 2011; Dalziel et al., 2018; Dudas et al., 2017; Pybus et al., 2015; Yu et al., 2019). Urban vegetation, an important geographical factor associated with pandemic diseases (Liu et al., 2019), could serve as an ideal resilient place for people to maintain physical and mental health while practicing social distancing (Samuelsson et al., 2020). The health benefits of exposure to urban green space are well explained by numerous studies (Becker et al., 2019; James et al., 2015; Maas et al., 2006; Tsai et al., 2019). Consequently, it is not unreasonable to hypothesize urban vegetation may also play a critical role in shaping the transmission patterns of COVID-19. Specifically, urban vegetation could potentially influence the spread of COVID-19 in several ways, including improving air quality (Janhäll, 2015), maintaining psychological well-being (Hartig & Kahn, 2016), and keeping social distancing (Samuelsson et al., 2020). However, the exact role of urban vegetation in shaping the transmission patterns of COVID-19 has not been quantified yet. Many other studies have also investigated the associations between the spread of COVID-19 and common geographical factors such as air temperature, humidity, population density, and air quality (Bashir et al., 2020; Kamel Boulos & Geraghty, 2020; Ma et al., 2020; Wu et al., 2020; Xie & Zhu, 2020); however, most of them only correlate individual drivers with COVID-19 cases in insolation and fail to consider the complexity of interactions among these drivers. Furthermore, the quantitative analysis of how these factors directly and indirectly shape the transmission patterns of COVID-19 is still rare until now, which seriously hinders our in-depth understanding of the transmission mechanism of COVID-19. Therefore, adopting more comprehensive quantitative methods to reveal the complex interactions between COVID-19 transmission and potential influencing factors is very much needed.

Here, we used path analysis model (PAM) to explore how multiple geographical factors (urban vegetation, population density, air temperature, and baseline infection) have affected the magnitude and large spatial variation of the COVID-19 confirmed cases across U.S. counties. Cumulative confirmed cases during the early stage of the COVID-19 outbreak from the first COVID-19 case to the date that U.S. President Donald Trump declared the COVID-19 pandemic a national emergency (hereinafter referred to as the baseline infection) was also incorporated into the PAM to investigate the impact of the timing of the implementation of interventions on the spread of COVID-19. The direct and indirect effects of each factor on the transmission of COVID-19 were quantified by PAM. Our results highlight the important role of urban vegetation in shaping the transmission patterns of COVID-19 in the United States.

2. Materials and Methods

2.1. Data Sets

2.1.1. Confirmed Cases of COVID-19

According to the daily confirmed cases of COVID-19 in the United States released by USAFacts (https://usafacts.org/) (USAFacts, 2020), we found that the cumulative number of confirmed cases in the United States was relatively small before early March and increased sharply around mid-March (Figure S1 in the supporting information). Meanwhile, President Donald Trump declared the COVID-19 pandemic a national emergency on 13 March 2020 (White House, 2020). Therefore, we chose 13 March 2020 as the breakpoint and divided the study period into two stages for analysis (Figures S2a and S2e). Specifically, we used the data from 20 January to 13 March as the first stage (hereinafter referred to as the baseline infection), which can be used to study the impact of the timing of the implementation of interventions on the spread of COVID-19. Meanwhile, the data from 14 March to 24 May were used as the second stage, which is referred to as the cumulative COVID-19 cases. In addition, to truly reveal the relationship between each factor and the transmission patterns of COVID-19, we selected counties with a cumulative number of confirmed cases greater than 100 between 14 March and 24 May for analysis. After screening, a total of 989 counties were included.

2.1.2. Urban Vegetation Cover Data

The National Land Cover Database (NLCD) 2016 with a spatial resolution of 30 m (Homer et al., 2004, 2015) was used to extract urban vegetation to investigate its role in shaping the transmission patterns of COVID-19 (Figure S2b). The category of urban vegetation was obtained by aggregating open spaces and low-intensity development urban areas in the NLCD using Google Earth Engine, adopting the urban vegetation definition (i.e., developed areas with less than 50% impervious cover) proposed by Becker et al. (2019). The percentage of urban vegetation on impervious surfaces in each county was obtained by counting the number of pixels of urban vegetation and dividing by the number of pixels of impervious surfaces within that county.

2.1.3. Population Density and Temperature Data

Population density data in each county were collected from the Census Bureau of the United States (Figure S2c). Daily temperature data with a spatial resolution of 4 km from 20 January to 24 May was extracted from the PRISM Spatial Climate Datasets, which was produced by the PRISM Climate Group at

Oregon State University (http://prism.oregonstate.edu). In this study, we calculated the county-level average temperature from 20 January to 24 May for analysis (Figure S2d).

2.2. Quantitative Effects of Different Factors on COVID-19 Transmission

Two statistical analysis methods were used to investigate the role of urban vegetation, population density, baseline infection, and temperature in shaping the transmission patterns of COVID-19. Specifically, we first conducted simple correlation analysis to investigate the associations between different factors and cumulative COVID-19 cases. Then PAM considered the interactions between factors was used to quantitatively analyze the direct and indirect effects of different factors on cumulative COVID-19 cases. Meanwhile, we also performed a controlled experiment to reveal the mediating role of urban vegetation in relationship to other factors and cumulative COVID-19 cases. That is, by adding or removing urban vegetation from PAM to investigate the changes in the impact of population density, baseline infection and temperature on the spread of COVID-19. The county-level statistical data were used as the analysis unit.

PAM is a multivariate quantitative statistical technique and belongs to the structural equation model. Compared to common statistical methods such as simple or multiple regressions, it is capable of quantifying the complex and dynamic relationships among multiple dependent and independent variables, and it allows to separate the direct and indirect effects of explanatory variable on response variable (Alwin & Hauser, 1975; Hoyle, 1995; You et al., 2020). A detailed description of PAM is provided in the supporting information (see Text S1), including the definition of relevant terms; the key steps in constructing PAM; the process of calculating standardized path coefficient; the method for calculating direct, indirect, and total effects; and significance test and goodness of fit test in PAM. Before performing PAM, a conceptual model needs to be established based on prior knowledge of the empirical relationships between variables. In this study, we developed a conceptual model by specifying the relationship between different factors and cumulative COVID-19 cases while considering the interactions between these factors. Specifically, our conceptual model assumes that population density, urban vegetation, and temperature not only directly affect cumulative COVID-19 cases but also indirectly affect cumulative COVID-19 cases through baseline infection as well as interactions between these factors. Meanwhile, because urban vegetation only accounts for a small part of the total area of the county, it has little effect on the county-level mean temperature, so we did not include associations between temperature and urban vegetation in PAM. The effect of the explanatory variable on response variable was quantified using standardized path coefficients. For example, the total effect of urban vegetation on cumulative COVID-19 cases was calculated as the sum of products of the standardized path coefficients along each pathway tracing from urban vegetation to cumulative COVID-19 cases. In addition, two model fit indices, namely, comparative fit index (CFI) and root mean square error of approximation (RMSEA), were used to assess the fit of PAM (Bentler, 1990; Steiger, 1990). In this study, PAM was conducted in R using the "lavaan" package (Rosseel, 2012), and all variables were standardized before analysis.

3. Results

3.1. Descriptive Analysis

To truly reveal the role of different geographical factors in shaping the transmission patterns of COVID-19 in the United States, we selected counties with a cumulative number of confirmed cases greater than 100 between 14 March and 24 May for analysis (see section 2.1.1). After screening, a total of 989 counties were included in this study (Figure 1a). Generally, counties distributed in the southeastern, northeastern, and southwestern regions of the United States have a relatively high cumulative number of confirmed cases, and the percentage of urban vegetation in these counties is relatively low (Figure 1b), suggesting that a low proportion of urban vegetation coverage would facilitate the spread of COVID-19. Furthermore, the spatial distribution of the ratio of cumulative COVID-19 cases to the percentage of urban vegetation also revealed a negative correlation between cumulative cases and urban vegetation (Figure 1c). In addition, the descriptive statistics of these factors in selected counties are provided in the supporting information (see Table S1), showing that the cumulative COVID-19 cases varied from 100 to 71,970, with a mean value of 1,588.41 people. Meanwhile, the mean value of the percentage of urban vegetation, population density, temperature, and baseline infection of these counties were 81.71%, 228.11 people/km^2, 10.11°C, and 2.11 people, respectively.

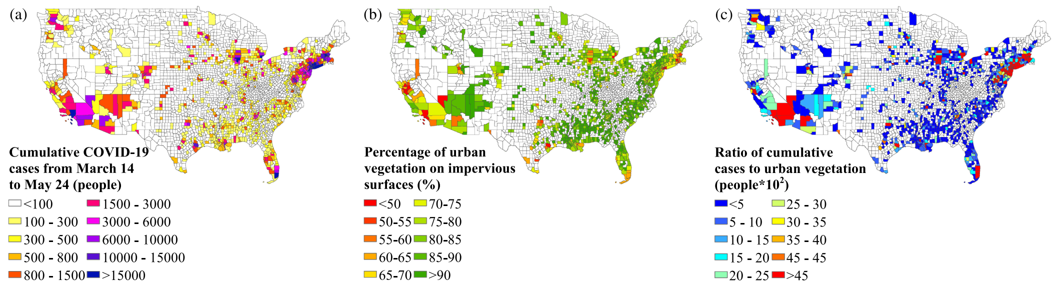

Figure 1. Spatial distributions of the county-level cumulative COVID-19 cases from 14 March to 24 May (a), the percentage of urban vegetation on impervious surfaces (b), and the ratio of the cumulative COVID-19 cases to the percentage of urban vegetation (c).

3.2. Exposure-Response Relationship

We conducted simple correlation analysis to investigate the associations between the cumulative COVID-19 cases and different forcing factors (see section 2.2). The exposure-response curves revealed that there was a strong negative linear relationship between the log cumulative COVID-19 cases and the percentage of urban vegetation ($p < 0.001$), with a slope of −0.029 (Figure 2a). Air temperature was also negatively and linearly correlated with the log cumulative COVID-19 cases, but the correlation was very weak (Figure 2b). Our analysis also showed that cumulative COVID-19 cases revealed a nonlinear relationship with population density (Figure 2c) as well as baseline infection (Figure 2d), with an inflection point (i.e., peak of cumulative cases) of 7,344 people/km^2 and 113 cases, respectively. In addition, we calculated the partial regression coefficient between urban vegetation and the cumulative COVID-19 cases by controlling the effects of the other three factors (i.e., population density, air temperature, and baseline infection). Results showed that the partial regression coefficient between urban vegetation and the cumulative COVID-19 cases is −0.026, suggesting that each 1% increase in the percentage of urban vegetation will lead to a 2.6% decrease in cumulative COVID-19 cases.

3.3. Path Analysis Results

Due to strong interactions between these factors, PAM was used to quantify the direct and indirect effects of each factor on the cumulative number of COVID-19 cases (see section 2.2). Since urban vegetation only occupies a small part of the total area of the county, it has little effect on the county-level mean air temperature, so we did not include the associations between air temperature and urban vegetation in PAM. The CFI of PAM was larger than 0.95, and the RMSEA was less than 0.1, suggesting that this model could explain the variance of cumulative COVID-19 cases well. As shown in Figure 3a, the percentage of urban vegetation showed a significantly negative correlation with cumulative COVID-19 cases, with a direct effect of −0.28, suggesting that an increase in the percentage of urban vegetation can slow the spread of COVID-19. Population density is also strongly associated with cumulative COVID-19 cases, with a direct effect of 0.37, indicating that a high population density tends to result in a high number of cumulative cases. Meanwhile, baseline infection showed a significantly positive correlation with cumulative cases, with a direct effect of 0.19, suggesting that early implementation of control measures can effectively curb the spread of COVID-19 (Tian et al., 2020). Furthermore, air temperature showed a negative correlation with cumulative COVID-19 cases, but the correlation is not statistically significant. Overall, the path coefficient between population density and cumulative COVID-19 cases is larger than that of the other three factors, indicating that population density has the greatest role in directly regulating the spread of COVID-19 among these factors. In addition to the direct effects, these factors can also influence cumulative cases through interactions (i.e., indirect effects). For example, urban vegetation can indirectly affect cumulative COVID-19 cases by directly affecting population density and baseline infection (indirect effect was quantified as −0.25).

On the other hand, a comparative experiment that does not include urban vegetation in PAM was also conducted to analyze the mediating role of urban vegetation in relationship to other factors and the transmission of COVID-19 (Figure 3b). After removing urban vegetation from PAM, both the direct and indirect effects of population density, baseline infection, and temperature on the cumulative COVID-19 cases increased, suggesting that urban vegetation also acts as an intermediate factor in regulating the spread of

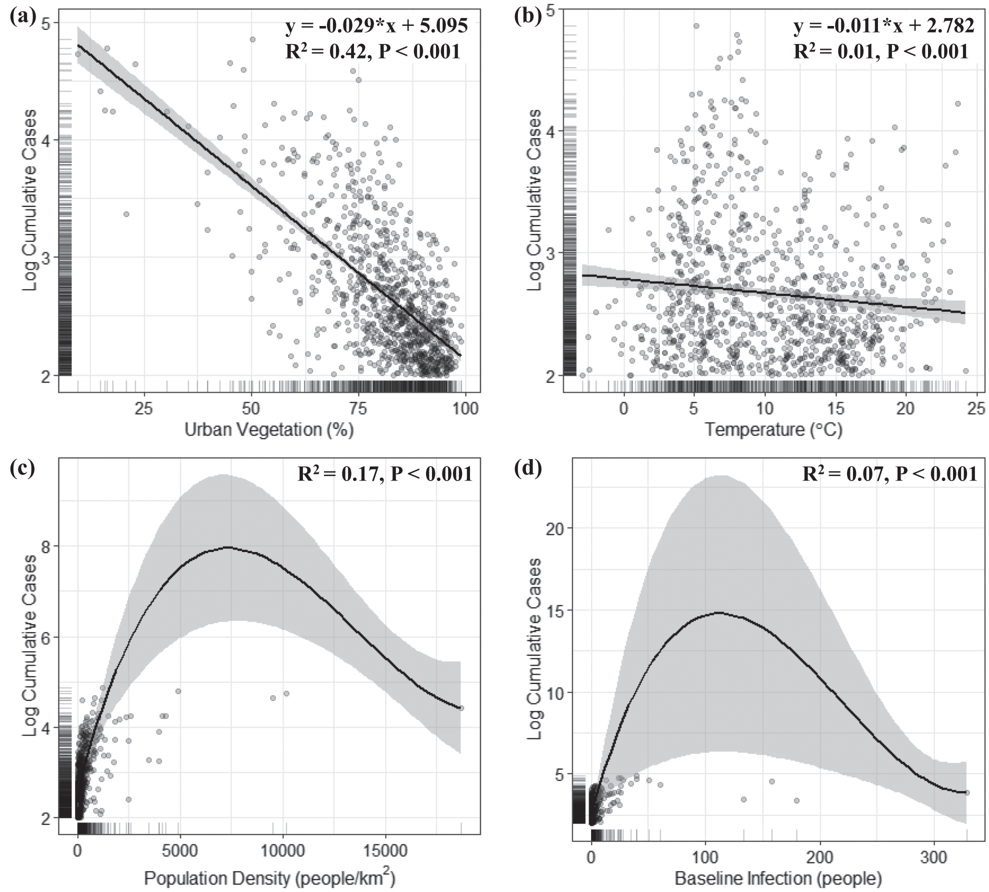

Figure 2. The exposure-response curves between the log cumulative COVID-19 cases (from 14 March 2020 to 24 May 2020) and the percentage of urban vegetation (a), air temperature (b), population density (c), and baseline infection (d). The *Y* axis is the log cumulative COVID-19 cases, and *X* axis is the corresponding forcing factor. Baseline infection denotes the cumulative number of confirmed COVID-19 cases between 20 January 2020 and 13 March 2020, representing the period from the first COVID-19 case to the date that President Donald Trump declared the COVID-19 pandemic a national emergency.

COVID-19 by weakening the associations between COVID-19 transmission and population density as well as baseline infection.

4. Discussion

The causes behind the large spatial variation in the transmission patterns of COVID-19 in the conterminous United States remain unclear. Here, we used PAM in which we considered the interactions among explanatory variables to examine the role of four factors (i.e., urban vegetation, population density, air temperature, and baseline infection) in shaping the transmission patterns of COVID-19 in the United States. Our results show that urban vegetation can well explain the large spatial heterogeneity of cumulative COVID-19 cases on a county level and there is a strong negative linear correlation between them. Population density and baseline infection were positively associated with cumulative COVID-19 cases, but these positive relationships could be weakened by the mediating role of urban vegetation. Although air temperature was negatively correlated with the cumulative cases, this relationship is statistically insignificant.

A recent study suggests that urban vegetation may play an important role during the COVID-19 pandemic, which provides an ideal resilient place for people to maintain well-being while continuing to social distance (Samuelsson et al., 2020). The importance of urban vegetation in times of crisis is also demonstrated in our study. Specifically, our quantitative analysis shows that urban vegetation plays a critical role in shaping the transmission patterns of COVID-19 and increasing the coverage of urban vegetation can slow down the

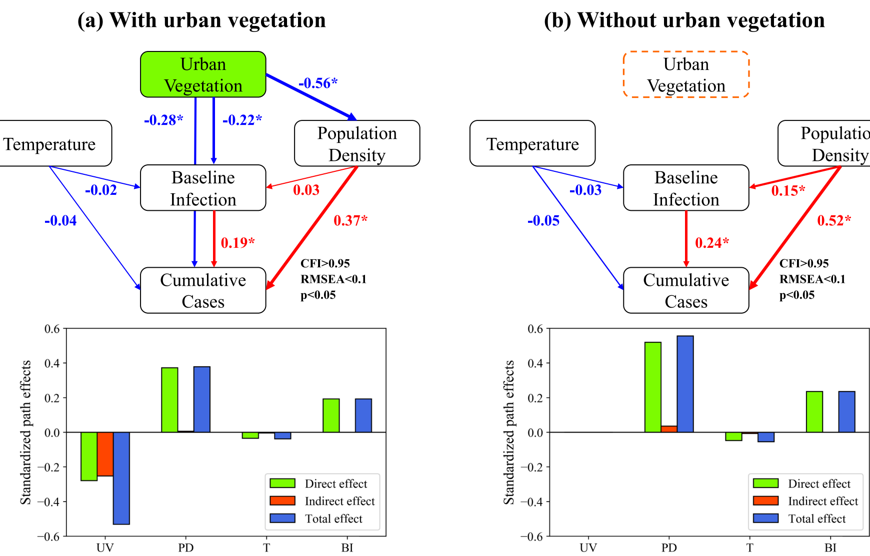

Figure 3. Path analysis results with urban vegetation (a) and without urban vegetation (b). Numbers adjacent to arrows in the path diagrams are standardized path coefficients indicating the magnitude of the influence between factors, and the significance level is indicated by * ($p < 0.05$). The width of arrows is proportional to the strength of standardized path coefficients, and the blue and red colors indicate positive and negative effects, respectively. The total effect of each factor on cumulative COVID-19 cases was calculated as the sum of the products of the standardized path coefficients along each pathway tracing from the corresponding factor to cumulative COVID-19 cases. CFI represents the comparative fit index, RMSEA represents the root mean square error of approximation, UV represents the percentage of urban vegetation, PD represents population density, T represents temperature, and BI represents baseline infection.

spread of COVID-19. In addition to directly preventing the spread of pandemics, urban vegetation is also closely associated with human well-being (Lee & Maheswaran, 2011; Tsai et al., 2019; Wolch et al., 2014), especially for people living in densely populated areas. Specifically, since avoiding close physical contact between people is the key to curb COVID-19 spreading (Tian et al., 2020; Wilder-Smith & Freedman, 2020), many countries have enacted unprecedented measures of social distancing such as banning public gatherings and "Shelter in Place" orders to prevent the spread of COVID-19. However, such large and sudden social isolation also has adverse effects on human health such as increased risks of suffering from depression, loneliness, and anxiety (Brooks et al., 2020; Usher et al., 2020). During such times of crisis, urban green space can provide a refuge for people to temporarily get rid of family confinement, reduce stress, and relax, thereby improving mental health (Hartig et al., 2014; Nutsford et al., 2013). Furthermore, urban vegetation is also closely related to air quality (Nowak et al., 2006), and some studies have shown that exposure to atmospheric pollutants (e.g., $PM_{2.5}$, PM_{10}, and NO_2) may contribute to the spread of COVID-19 and increase the death rate due to increased risk of respiratory and cardiovascular diseases (Bashir, Ma, Bilal, et al., 2020; Coccia, 2020; Fattorini & Regoli, 2020; Wu et al., 2020). Therefore, increasing the proportion of urban vegetation coverage should be considered in future urban planning, which is precisely important for human well-being and achieving sustainable development Goals 3 and 11 (i.e., good health and well-being, resilient, and sustainable cities).

The role of population density, baseline infection, and air temperature in shaping the transmission patterns of COVID-19 has also been analyzed in previous studies (Bashir, Ma, Komal, et al., 2020; Ma et al., 2020; Tian et al., 2020; Xie & Zhu, 2020), and our findings are consistent with these studies. The positive correlation between population density and cumulative COVID-19 cases suggests that strict social distancing is still needed to suppress the spread of COVID-19 (Dalton et al., 2020), and restarting the economy (e.g., reopening entertainment venues, gyms, and hair salons) too fast may cause a rebound of outbreaks of COVID-19. Furthermore, the positive correlation between baseline infection and cumulative COVID-19 cases also indicates that early intervention and quick response to the outbreaks of COVID-19 can effectively curb its spread (Pan et al., 2020; Tian et al., 2020). A retrospective analysis also indicated that if the U.S. government implemented the same control measures 1–2 weeks earlier than the actual date, 61.6% of the reported cases and

55.0% of the reported deaths could have been avoided as of 3 May 2020 (Pei et al., 2020). Furthermore, our study shows that there is a negative correlation between air temperature and cumulative COVID-19 cases, suggesting that high temperatures may be able to inhibit the activity of COVID-19 to some extent, consistent with previous epidemiological studies on other coronavirus-related diseases such as MERS-CoV and SARS-CoV (Casanova et al., 2010; Chan et al., 2011; Tan et al., 2005). However, it should be noted that such correlation in PAM is not statistically significant, suggesting that an increased air temperature may not slow down the spread of COVID-19. Therefore, the government and public should not expect an increased temperature to curb COVID-19 spread in the same way as the common flu.

There are some limitations in this study. First, the spatial resolution of the NLCD, 30 m × 30 m, is too coarse to accurately capture the presence of small vegetated areas (Becker et al., 2019; Wickham et al., 2013), and the NLCD used in this study is the land cover pattern in 2016 (the latest version to date), both of which will bring uncertainty to our results. Second, some other potential factors that may affect the spread of COVID-19, such as medical conditions, the government response to COVID-19, the cross-region dynamic transmission of COVID-19, and the social-economic situation, were not analyzed in this study. In addition, the United States did not start COVID-19 testing (widely testing among residents) until after President Trump declared it as a national emergency; therefore, the baseline infection number is in fact lower than what it should be, which could potentially affect various mathematical values. Future research needs to adopt a comprehensive framework in conjunction with multisource data to quantify the impact of potential factors on the spread of COVID-19.

5. Conclusions

To the best of our knowledge, this study is the first endeavor to quantitatively analyze the role of urban vegetation in shaping the transmission patterns of COVID-19 in the United States. Our results show that urban vegetation plays an important role in slowing down the spread of COVID-19 and each 1% increase in the percentage of urban vegetation will lead to a 2.6% decrease in cumulative COVID-19 cases. Population density and baseline infection will contribute to the initiation and acceleration of COVID-19 cases, but this promoting effect could be weakened by the mediating role of urban vegetation. Air temperature was negatively correlated with the incidence of COVID-19, but this correlation is not statistically significant. Our study highlights the importance of urban vegetation in strengthening urban resilience to public health emergencies and can provide valuable policy implications for the government to achieve sustainable development goals such as good health and well-being, resilient, and sustainable cities.

Data Availability Statement

The four data sources for supporting this analysis are publicly available: (1) confirmed cases of COVID-19: The daily confirmed cases of COVID-19 data are available from USAFacts (https://usafacts.org/); (2) urban vegetation cover data: The NLCD 2016 with a spatial resolution of 30 m are available from the Multi-Resolution Land Characteristics Consortium (https://www.mrlc.gov/); (3) population density: Population density data in each county were collected from the Census Bureau of the United States (https://www.census.gov); and (4) temperature data: Daily temperature data with a spatial resolution of 4 km from 20 January to 24 May was extracted from the PRISM Spatial Climate Datasets, which was produced by the PRISM Climate Group at Oregon State University (http://prism.oregonstate.edu). In addition, all data and codes supporting this analysis are archived in the International Center for Climate and Global Change Research at Auburn University (https://wp.auburn.edu/cgc/).

Acknowledgments

The authors are extremely grateful to Professor Hanqin Tian for providing insightful comments and suggestions, Kelly Pippin and Naiqing Pan for helpful discussion and review on this manuscript. This study is partially supported by the National Science Foundation grants (1903722 and 1922687).

References

Alwin, D. F., & Hauser, R. M. (1975). The decomposition of effects in path analysis. *American Sociological Review*, 37–47.

Bashir, M. F., Ma, B., Komal, B., Bashir, M. A., Tan, D., & Bashir, M. (2020). Correlation between climate indicators and COVID-19 pandemic in New York, USA. *Science of the Total Environment*.

Bashir, M. F., Ma, B. J., Bilal, Komal, B., Bashir, M. A., Farooq, T. H., et al. (2020). Correlation between environmental pollution indicators and COVID-19 pandemic: A brief study in Californian context. *Environmental Research*, *187*, 109652. http://www.sciencedirect.com/science/article/pii/S0013935120305454, https://doi.org/10.1016/j.envres.2020.109652

Becker, D. A., Browning, M. H. E. M., Kuo, M., & Van Den Eeden, S. K. (2019). Is green land cover associated with less health care spending? Promising findings from county-level Medicare spending in the continental United States. *Urban Forestry & Urban Greening*, *41*, 39–47. http://www.sciencedirect.com/science/article/pii/S161886671830534X

Bentler, P. M. (1990). Comparative fit indexes in structural models. *Psychological Bulletin*, *107*(2), 238–246. https://doi.org/10.1037/0033-2909.107.2.238

Brooks, S. K., Webster, R. K., Smith, L. E., Woodland, L., Wessely, S., Greenberg, N., & Rubin, G. J. (2020). The psychological impact of quarantine and how to reduce it: Rapid review of the evidence. *The Lancet*.

Casanova, L. M., Jeon, S., Rutala, W. A., Weber, D. J., & Sobsey, M. D. (2010). Effects of air temperature and relative humidity on coronavirus survival on surfaces. *Applied and Environmental Microbiology*, *76*(9), 2712–2717. https://doi.org/10.1128/AEM.02291-09

Cauchemez, S., Bhattarai, A., Marchbanks, T. L., Fagan, R. P., Ostroff, S., Ferguson, N. M., et al. (2011). Role of social networks in shaping disease transmission during a community outbreak of 2009 H1N1 pandemic influenza. *Proceedings of the National Academy of Sciences*, *108*(7), 2825–2830.

Chan, K. H., Peiris, J. S., Lam, S. Y., Poon, L. L. M., Yuen, K. Y., & Seto, W. H. (2011). The effects of temperature and relative humidity on the viability of the SARS coronavirus. *Advances in Virology*, *2011*.

Chen, H., Guo, J., Wang, C., Luo, F., Yu, X., Zhang, W., et al. (2020). Clinical characteristics and intrauterine vertical transmission potential of COVID-19 infection in nine pregnant women: A retrospective review of medical records. *The Lancet*, *395*(10226), 809–815. https://doi.org/10.1016/S0140-6736(20)30360-3

Coccia, M. (2020). How sustainable environments have reduced the diffusion of coronavirus disease 2019: The interaction between spread of COVID-19 infection, polluting industrialization, wind (renewable) energy. arXiv preprint arXiv:2005.08293.

Dalton, C. B., Corbett, S. J., & Katelaris, A. L. (2020). Pre-emptive low cost social distancing and enhanced hygiene implemented before local COVID-19 transmission could decrease the number and severity of cases. *The Medical Journal of Australia*, *212*(10), 1.

Dalziel, B. D., Kissler, S., Gog, J. R., Viboud, C., Bjørnstad, O. N., Metcalf, C. J. E., & Grenfell, B. T. (2018). Urbanization and humidity shape the intensity of influenza epidemics in US cities. *Science*, *362*(6410), 75–79. https://doi.org/10.1126/science.aat6030

Dong, E., Du, H., & Gardner, L. (2020). An interactive web-based dashboard to track COVID-19 in real time. *The Lancet infectious diseases*.

Dudas, G., Carvalho, L. M., Bedford, T., Tatem, A. J., Baele, G., Faria, N. R., et al. (2017). Virus genomes reveal factors that spread and sustained the Ebola epidemic. *Nature*, *544*(7650), 309–315. https://doi.org/10.1038/nature22040

Fattorini, D., & Regoli, F. (2020). Role of the chronic air pollution levels in the Covid-19 outbreak risk in Italy. *Environmental Pollution*, *264*, 114732. http://www.sciencedirect.com/science/article/pii/S0269749120332115

Hartig, T., & Kahn, P. H. (2016). Living in cities, naturally. *Science*, *352*(6288), 938.

Hartig, T., Mitchell, R., De Vries, S., & Frumkin, H. (2014). Nature and health. *Annual Review of Public Health*, *35*, 207–228. https://doi.org/10.1146/annurev-publhealth-032013-182443

Holshue, M. L., DeBolt, C., Lindquist, S., Lofy, K. H., Wiesman, J., Bruce, H., et al. (2020). First case of 2019 novel coronavirus in the United States. *New England Journal of Medicine*.

Homer, C., Dewitz, J., Yang, L., Jin, S., Danielson, P., Xian, G., et al. (2015). Completion of the 2011 National Land Cover Database for the conterminous United States—representing a decade of land cover change information. *Photogrammetric Engineering & Remote Sensing*, *81*(5), 345–354.

Homer, C., Huang, C., Yang, L., Wylie, B., & Coan, M. (2004). Development of a 2001 national land-cover database for the United States. *Photogrammetric Engineering & Remote Sensing*, *70*(7), 829–840.

Hoyle, R. H. (1995). The structural equation modeling approach: Basic concepts and fundamental issues. In *Structural equation modeling: Concepts, Issues, and applications* (pp. 1–15). Thousand Oaks, CA, US: Sage Publications, Inc.

James, P., Banay, R. F., Hart, J. E., & Laden, F. (2015). A review of the health benefits of greenness. *Current Epidemiology Reports*, *2*(2), 131–142. https://doi.org/10.1007/s40471-015-0043-7

Janhäll, S. (2015). Review on urban vegetation and particle air pollution—Deposition and dispersion. *Atmospheric Environment*, *105*, 130–137. http://www.sciencedirect.com/science/article/pii/S1352231015000758

Kamel Boulos, M. N., & Geraghty, E. M. (2020). Geographical tracking and mapping of coronavirus disease COVID-19/severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) epidemic and associated events around the world: How 21st century GIS technologies are supporting the global fight against outbreaks and epidemics. *International Journal of Health Geographics*, *19*(1). https://doi.org/10.1186/s12942-020-00202-8

Lee, A. C. K., & Maheswaran, R. (2011). The health benefits of urban green spaces: A review of the evidence. *Journal of Public Health*, *33*(2), 212–222. https://doi.org/10.1093/pubmed/fdq068

Liu, L., Zhong, Y., Ao, S., & Wu, H. (2019). Exploring the relevance of green space and epidemic diseases based on panel data in China from 2007 to 2016. *International Journal of Environmental Research and Public Health*, *16*(14), 2551.

Lu, H., Stratton, C. W., & Tang, Y. W. (2020). Outbreak of pneumonia of unknown etiology in Wuhan, China: The mystery and the miracle. *Journal of Medical Virology*, *92*(4), 401–402.

Ma, Y., Zhao, Y., Liu, J., He, X., Wang, B., Fu, S., et al. (2020). Effects of temperature variation and humidity on the death of COVID-19 in Wuhan China. *Science of the Total Environment*.

Maas, J., Verheij, R. A., Groenewegen, P. P., De Vries, S., & Spreeuwenberg, P. (2006). Green space, urbanity, and health: How strong is the relation? *Journal of Epidemiology & Community Health*, *60*(7), 587–592. https://doi.org/10.1136/jech.2005.043125

Nowak, D. J., Crane, D. E., & Stevens, J. C. (2006). Air pollution removal by urban trees and shrubs in the United States. *Urban Forestry & Urban Greening*, *4*(3–4), 115–123.

Nutsford, D., Pearson, A. L., & Kingham, S. (2013). An ecological study investigating the association between access to urban green space and mental health. *Public Health*, *127*(11), 1005–1011. https://doi.org/10.1016/j.puhe.2013.08.016

Pan, A., Liu, L., Wang, C., Guo, H., Hao, X., Wang, Q., et al. (2020). Association of Public Health Interventions With the Epidemiology of the COVID-19 Outbreak in Wuhan, China. *JAMA*, *323*(19), 1915. https://doi.org/10.1001/jama.2020.6130

Pei, S., Kandula, S., & Shaman, J. (2020). Differential effects of intervention timing on COVID-19 spread in the United States. medRxiv: The preprint server for health sciences, 2020.05.15.20103655. https://doi.org/10.1101/2020.05.15.20103655

Pybus, O. G., Tatem, A. J., & Lemey, P. (2015). Virus evolution and transmission in an ever more connected world. *Proceedings of the Royal Society B: Biological Sciences*, *282*(1821).

Roser, M., Ritchie, H., & Ortiz-Ospina, E. (2020). Coronavirus disease (COVID-19)–Statistics and research. Our World in data.

Rosseel, Y. (2012). Lavaan: An R package for structural equation modeling and more. Version 0.5–12 (BETA). *Journal of Statistical Software*, *48*(2), 1–36.

Samuelsson, K., Barthel, S., Colding, J., Macassa, G., & Giusti, M. (2020). Urban nature as a source of resilience during social distancing amidst the coronavirus pandemic. https://doi.org/10.31219/osf.io/3wx5a

Steiger, J. H. (1990). Structural model evaluation and modification: An interval estimation approach. *Multivariate Behavioral Research*, *25*(2), 173–180. https://doi.org/10.1207/s15327906mbr2502_4

Tan, J., Mu, L., Huang, J., Yu, S., Chen, B., & Yin, J. (2005). An initial investigation of the association between the SARS outbreak and weather: With the view of the environmental temperature and its variation. *Journal of Epidemiology & Community Health*, *59*(3), 186–192. https://doi.org/10.1136/jech.2004.020180

Tian, H., Liu, Y., Li, Y., Wu, C.-H., Chen, B., Kraemer, M. U. G., et al. (2020). An investigation of transmission control measures during the first 50 days of the COVID-19 epidemic in China. *Science*, *368*(6491), 638–642. https://doi.org/10.1126/science.abb6105

Tsai, W.-L., Leung, Y.-F., McHale, M. R., Floyd, M. F., & Reich, B. J. (2019). Relationships between urban green land cover and human health at different spatial resolutions. *Urban Ecosystem*, *22*(2), 315–324.

USAFacts (2020). Coronavirus locations: COVID-19 Map by County and State. https://usafacts.org/visualizations/coronavirus-covid-19-spread-map/

Usher, K., Bhullar, N., & Jackson, D. (2020). Life in the pandemic: Social isolation and mental health. *Journal of Clinical Nursing*, *29*(15–16), 2756–2757. https://doi.org/10.1111/jocn.15290

White House (2020). *Proclamation on declaring a national emergency concerning the novel coronavirus disease (COVID-19) outbreak*. https://www.whitehouse.gov/presidential-actions/proclamation-declaring-national-emergency-concerning-novel-coronavirus-disease-covid-19-outbreak/

Wickham, J. D., Stehman, S. V., Gass, L., Dewitz, J., Fry, J. A., & Wade, T. G. (2013). Accuracy assessment of NLCD 2006 land cover and impervious surface. *Remote Sensing of Environment*, *130*, 294–304. http://www.sciencedirect.com/science/article/pii/S0034425712004579

Wilder-Smith, A., & Freedman, D. O. (2020). Isolation, quarantine, social distancing and community containment: Pivotal role for old-style public health measures in the novel coronavirus (2019-nCoV) outbreak. *Journal of travel medicine*, *27*(2), taaa020.

Wolch, J. R., Byrne, J., & Newell, J. P. (2014). Urban green space, public health, and environmental justice: The challenge of making cities "just green enough". *Landscape and Urban Planning*, *125*, 234–244.

Wu, X., Nethery, R. C., Sabath, B. M., Braun, D., & Dominici, F. (2020). Exposure to air pollution and COVID-19 mortality in the United States. medRxiv: The preprint server for health sciences, 2020.04.05.20054502. https://doi.org/10.1101/2020.04.05.20054502

Xie, J., & Zhu, Y. (2020). Association between ambient temperature and COVID-19 infection in 122 cities from China. *Science of the Total Environment*.

You, Y., Wang, S., Pan, N., Ma, Y., & Liu, W. (2020). Growth stage-dependent responses of carbon fixation process of alpine grasslands to climate change over the Tibetan Plateau, China. *Agricultural and Forest Meteorology*, *291*, 108085. http://www.sciencedirect.com/science/article/pii/S0168192320301878

Yu, P., Hu, B., Shi, Z.-L., & Cui, J. (2019). Geographical structure of bat SARS-related coronaviruses. *Infection, Genetics and Evolution*, *69*, 224–229. http://www.sciencedirect.com/science/article/pii/S156713481830902X