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Examining the association between urban green space and viral transmission of COVID-19 during the early outbreak

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A B S T R A C T

Even though exposure to urban green spaces (UGS) has physical and mental health benefits during COVID-19, whether visiting UGS will exacerbate viral transmission and what types of counties would be more impacted remain to be answered. In this research, we adopted mobile phone data to measure the county-level UGS visitation across the United States. We developed a Bayesian model to estimate the effective production number of the pandemic. To consider the spatial dependency, we applied the geographically weighted panel regression to estimate the association between UGS visitation and viral transmission. We found that visitations to UGS may be positively correlated with the viral spread in Florida, Idaho, New Mexico, Texas, New York, Ohio, and Pennsylvania. Especially noteworthy is that the spread of COVID-19 in the majority of counties is not associated with green space visitation. Further, we found that when people visit UGS, there may be a positive association between median age and viral transmission in New Mexico, Colorado, and Missouri; a positive association between concentration of blacks and viral transmission in North Dakota, Minnesota, Wisconsin, Michigan, and Florida; and a positive association between poverty rate and viral transmission in Iowa, Missouri, Colorado, New Mexico, and the Northeast United States.

1. Introduction

The COVID-19 pandemic has caused unprecedented impacts across the world, which not only damages the public health system, but also slows economic growth (Zhai, Liu, & Peng, 2020; Zhai & Peng, 2020). Due to the spiking growth of COVID-19 cases and deaths, the situation in the United States (US) has become extremely dreadful (Zhai & Yue, 2022). Many countries have resorted to containment measures to slow viral transmission and curb the increasing number of cumulative infections. Such actions include restrictive use of public spaces, schools, recreation centers, and non-essential businesses and forcing people to stay at home (Gostin & Wiley, 2020), which are non-pharmaceutical approaches to curtail human contact, thereby reducing viral transmission (Musselwhite, Avineri, & Susilo, 2020). Moreover, the social distancing order was issued by many governments considering that direct physical contact is the most important risk factor (Freeman & Eykelbosch, 2020). For instance, if people need to do essential outdoor activities such as grocery shopping or physical exercise, they are required to keep their distance at least six feet apart (Chu et al., 2020).

In the meantime, containment actions also have disrupted every aspect of people’s lives, especially for the mental and physical well-being of individuals, because staying away from the natural environment may lead to depression (Caria et al., 2020; Thompson et al., 2012). Therefore, during COVID-19, urban green spaces (UGS) become essentially important because UGS can reduce mental exhaustion (Beyer et al., 2014; Freeman & Eykelbosch, 2020), increase social support and social cohesion (Beyer et al., 2014; Grahn & Stigsdotter, 2010; Maas, Van Dillen, Verheij, & Groenewegen, 2009; Ugolini et al., 2020), enhance the sense of community (Pretty, Andrews, & Collett, 1994), and transfer the stress and low spirit into optimistic (Roe et al., 2013). As places for outdoor physical exercise, UGS can also be beneficial to people’s physical function, such as cardiovascular health, obesity, hypertension, and diabetes (Slater, Christiana, & Gustat, 2020), which are risky complications derived from the coronavirus. Therefore, opportunities for city dwellers to receive mental and physical health benefits from UGS may become even more important during such a destructive pandemic.

However, visiting UGS inevitably exposes people to the virus and
In a time of extreme stress associated with the uncertain health and well-being of individuals, getting rid of an effective resource for stress relief could generate unexpected health problems and drive other undesirable behaviors (Freeman & Eykelbosh, 2020). Moreover, if people cannot access UGS and other public spaces, they may go to other less desirable options (e.g., sidewalks and pavements) that are not primarily designed to encourage social distancing when occupancy is high (Freeman & Eykelbosh, 2020). Besides, the existing literature has found that access to UGS is determined by people’s socioeconomic status (Yu, Zhu, & He, 2020), race (Gobster, 2002), age (Hillman, Adam, & Whitelegg, 1990), and health condition (Kronenberg et al., 2020), etc., meaning that the impacts of UGS on community viral transmission can be unequal.

The uncertainty presents a unique challenge to policymakers to ensure UGS is accessible, safe, and well-maintained, while also meeting the evolving needs of residents based on their experience, and the perceived access and importance during COVID-19. People who actively comply with social distancing are also hesitant on visiting UGS because whether UGS are held accountable for the spread of COVID-19 or not is inconclusive. However, answering this question is not only necessary but also urgent. Even though the existing studies have hypothesized that the sufficient provision of large open green space could reduce the risk of virus transmission in a community (Slater et al., 2020), most of them lack empirical evidence. Therefore, in this research, we aim to answer two research questions.

1. Whether UGS visitations would increase the spread of COVID-19? Where are these counties?
2. What types of counties are more vulnerable to COVID-19 in terms of visiting UGS?

The rest of this paper proceeds as follows. We first reviewed the existing literature. Then, we introduced the method and data used in this paper. Next, we presented the results and findings. Following the findings, we proposed policy suggestions and discussed the limitations. Finally, we concluded the research.

2. Literature review

2.1. Urban green spaces and viral transmission during COVID-19

UGS has been widely demonstrated to be relatively safe compared to indoor spaces because UGS can allow for more physical distancing, which is beneficial to containing COVID-19 (Van Doremalen et al., 2020). For instance, Nishiura et al. (2020) investigated the transmission pattern of COVID-19 and found that the likelihood of a primary case transmitting COVID-19 in an indoor space was 18.7 times greater compared to outdoor space. Leclerc et al. (2020) analyzed 201 global transmission clusters of COVID-19 and found only 21 of them were indoor environments.

However, the infection risk still exists in UGS. One of the main concerns for UGS visitors is whether the coronavirus can be transmitted through the exhalations of strangers in the green space. Especially, visiting UGS means that people may encounter asymptomatic patients and be exposed to the virus. Moreover, aerosol transmission raises concerns that the 2-m “safe distance” may not be enough because Bourouiba (2020) found that human sneezes could propel aerosols up to 8 m by an infected patient. Blocken et al. (2020) found that turbulence created during physical exercises in the park, such as biking, running, and walking, can entrain droplets, leading them to stay suspended longer and thus also expanding the safe radius.

Even though people practice physical distancing and do not gather in the UGS, there are other possibilities of being infected by the virus. First, the coronavirus can live on surfaces and be shed into the toilets by infected individuals (Chen et al., 2020; Ong et al., 2020), thereby using public washrooms in UGS is also risky. Also, restroom taps, door handles, and other facilities in UGS are the main transmission medium (Cai et al., 2020).

Especially, individuals are used to exercising in UGS without wearing a mask, sharing public restrooms, fitness equipment, and walking dogs, which increases the risk of people being exposed to the virus. Second, viral transmission can be through dogs, increasing the likelihood of human-animal transmission (Goumenou, Spandidos, & Tsatsakis, 2020). Thus, during COVID-19, UGS could still be high-risk places where contact and connection occur in a more open, democratic, inclusive, and yet unpredictable way (Low and Smart, 2020).

To this end, policymakers are falling into a dilemma in terms of opening UGS during the pandemic. To the best of our knowledge, the existing literature has neither examined whether visiting UGS would exacerbate the community-level viral spread or not. Furthermore, little is known about where are riskier, necessitating further exploration in this research.

2.2. Urban green spaces and unequal impacts during COVID-19

UGS, as a form of public assets, are expected to be distributed equally (Boone, Buckley, Grove, & Sister, 2009; Rigolon, 2016). However, the existing studies in environmental justice suggest that green space is not equally accessed due to socioeconomic disparities (Kronenberg et al., 2020; Ekkel & de Vries, 2017; Dai, 2011), leading to unequal impacts of UGS on the viral transmission during the pandemic. Specifically, age is a determining factor that is associated with people’s access to UGS, thereby indirectly impacting viral transmission. The elderly people have less access to UGS because of the inconvenience of mobility and need to be taken care of. Gated UGS for preventing anti-social activity unintentionally meant that disabled elderly could not access pushchair spaces by themselves. Knowles and Hanson (2018) found that the stay-at-home order confined older people to stay in indoor spaces, with fewer chances to go outside and visit UGS. In addition, Chiu and Tucker (2020) found a similar finding that during COVID-19, neighborhoods with more older people have a high proportion of stay-at-home residents. Likewise, Dasgupta, Jonsson Funk, Lazard, White, and Marshall (2020) found that counties, with high compliance with social distancing during the pandemic, had 8.2% fewer youth and 7.4% more elderly. Children also have less access to UGS considering that many nature parks lack infrastructure such as maternity rooms and it is inconvenient to change the diapers and clothes, especially when a child in winter had multiple layers of clothing on (Cronin-de-Chavez, Islam, & McEachan, 2019). Children who also rely on adults for mobility often prefer green spaces closer to their homes in the first place (Hillman et al., 1990).

Low-income individuals lack access to high-quality UGS, especially in newly constructed low-socioeconomic communities (Yu et al., 2020), and they are more likely to visit small and congested green spaces. However, small green spaces are not suitable for physical exercise because they are risky for viral transmission (Rigolon, 2016). Zhai et al. (2020) also observed that residents in low-income counties have fewer visitations to UGS than those in high-income counties in the US during the early outbreak of COVID-19. Low-income communities may also have difficulties in practicing social distancing because they exhibit lower education levels and less trust in science (Chiu & Tucker, 2020). This is empirically evidenced by mobile phone data showing reduced compliance in poor communities (Wright, Sonin, Driscoll, & Wilson, 2020).
The behaviors of ethnic minorities during the pandemic are inconclusive, making it difficult to predict the impacts on viral transmission in UGS. Most of the ethnic minorities have lower socioeconomic status with less wage (Pager & Shepherd, 2008), less car ownership (Boone et al., 2009; Wolch, Wilson, & Fehrenbach, 2005), and longer working time (He & Baker, 2005), which make them difficult to access UGS in longer distances. Also, ethnic minorities are more likely to face discrimination by visitors, police, and staff in urban parks (Gobster, 2002). By a survey in New York City, Lopez et al. (2020) found that UGS use was lower for Hispanic respondents, and the importance of UGS for health was perceived as lower for black respondents during COVID-19. It is generally more difficult to sustain social norms, such as practicing social distancing, in ethnically diverse communities (Algan, Hémet, & Laitin, 2016). However, Egorov et al. (2020) argued that ethnic diversity would, in turn, increase socially beneficial behavior based on evidence in Russia and the US amid the COVID-19 outbreak. Further, Dasgupta et al. (2020) found that counties with a better performance in social distancing had more ethnic minorities. Additionally, Chiou and Tucker (2020) discovered that residents in neighborhoods with a higher proportion of blacks have a higher chance to comply with the social distancing order during the pandemic.

Overall, we found that the disadvantaged population may be selected towards heterogeneous social distancing behaviors during the pandemic. In addition, the communities with varying social characteristics may have unequal impacts on viral transmission when people visit UGS, which is extremely important for policymakers in terms of understanding what types of communities should be more cautious about opening UGS. However, the unequal impacts are still understudied during COVID-19.

3. Method and data

3.1. Study area and data

We employ the contiguous US as the study area, which includes 3108 counties. We collected the data from multiple sources, ranging from February 27th, 2020 to May 27th, 2020. First, we retrieved daily confirmed positive cases from the New York Times data repository to measure the spread of COVID-19 itself at the county level (New York Times, 2020a), regarding that the county is the finest unit where daily new confirmed cases are reported.

Second, to explore the uneven viral spread in counties with various socio-economic and political variables, we adopted the 2018 American Community Survey (ACS) data to construct estimates of the poverty rate, the percent of blacks, the median age, the percent of healthcare workers, and population density of counties. The Department of Homeland Security’s Cybersecurity and Infrastructure Security Agency (CISA) released an “Essential Critical Infrastructure Workforce” advisory list of occupations necessary to the “continuity of functions critical to public health and safety” in March 2020 (LMI Institute, 2020). We matched industry and subindustry codes in the ACS to the 6-digit Standard Occupation Codes (indexed by the US Bureau of Labor Statistics) in the CISA advisory list to identify essential workers in each of the sampled urban census tracts. We also collected 2020 election results to infer the Trump share of each county (New York Times, 2020b).

Third, we retrieved individuals’ UGS visitation data from SafeGraph (2020), which can be referred to in Supplementary Video A. Specifically, the SafeGraph data features the number of visitations to Points of Interest (POI) across 60 million places using 45 million mobile phone devices in the U.S. To define UGS, we particularly considered 90,013 POIs for nature parks and botanical gardens in the urban area. Note that the home location is determined based on the most frequent nighttime location of each device over six weeks. That is, we can estimate where people live and which POI they have visited during the given period. Thereafter, we can quantify the visitation to UGS for each county.

Supplementary video related to this article can be found at https://doi.org/10.1016/j.apgeog.2022.102768

3.2. Measuring the county-level spread of COVID-19

The daily number of newly confirmed cases, commonly used as a primary measure for the spread of COVID-19 by many governments and researchers, is imperfect due to reporting delays and unavailability of testing (Chiou & Tucker, 2020). The basic reproduction number \( R_0 \) is traditionally employed to represent the spread of an infectious disease (Zhai, Liu, Fu, & Peng, 2021). \( R_0 \) represents the number of secondary infections caused by an infected person, assuming that the disease first takes place in a completely susceptible population. However, not all contacts are susceptible to infection in the real world and the transmission can be reduced with interventions and containment actions. Therefore, it is important to estimate temporal variations of the viral transmission, which can be accomplished using the effective reproduction number \( R_e \) (Nishiura & Chowell, 2009). When \( R_e > 1 \), the pandemic spreads through the entire population. When \( R_e < 1 \), the pandemic would be gradually under control. In short, the lower the value of \( R_e \), the more manageable the situation is. Therefore, \( R_e \) is considered a better measure for the transmissibility of infectious diseases when containment interventions have occurred.

New COVID-19 cases are reported daily. We can then calculate \( R_e \) based on daily data. Specifically, the value of \( R_e \) today is determined by the value of \( R_{e,1} \) (yesterday’s value) and every previous value of \( R_{e,m} \) (the value of \( m \) days ago) for that matter. To model the process, we adopted the Bayesian approach developed by Bettencourt and Ribeiro (2008) to estimate real-time \( R_e \) based on the new case count that is reported each day using the following equation:

\[
P(R_e | k) = \frac{P(R_e) \cdot \mathcal{L}(k | R_e)}{P(k)}
\]

where \( P(R_e | k) \) presents the distribution of \( R_e \) given that we have seen \( k \) new cases; \( P(R_e) \) represents the prior probability of \( R_e \); \( \mathcal{L}(k | R_e) \) represents the likelihood of \( R_e \) given that we have seen \( k \) new cases. \( P(k) \) can be omitted, as it mainly serves as normalization:

\[
P(R_e | k) \propto \prod_{i=0}^{t} \mathcal{L}(k | R_e)
\]

To make Equation (2) iterative, we can estimate the value of \( R_e \) at day \( t \) with \( k_t \) new cases.

\[
P(R_e | k_t) \propto P(R_e) \cdot \prod_{i=0}^{t} \mathcal{L}(k_t | R_e)
\]

With a uniform prior \( P(R_e) \), the formula can be reduced to:

\[
P(R_e | k_t) \propto \prod_{i=0}^{t} \mathcal{L}(k_t | R_e)
\]

Therefore, the problem here is to estimate the likelihood function that says how likely the value of \( R_e \) is given an observed number of new cases \( k \). Following Syriostom (2020), we applied the Poisson distribution to model the probability of seeing \( k \) new cases given an average arrival rate of \( \lambda \) new cases per day. The representation is as follows:

\[
\mathcal{L}(k | R_e) = \frac{\lambda^k e^{-\lambda}}{k!}
\]

Based on the demonstration in Bettencourt and Ribeiro (2008), there is a connection between \( R_e \) and \( \lambda \):

\[
\lambda = k e^{\gamma (R_e - 1)}
\]

where \( \gamma \) is the reciprocal of the serial interval, which is approximately four days for COVID-19 according to Du et al. (2020). By assuming \( \theta = \gamma (R_e - 1) \), which observes a random walk, we can solve the value of \( R_e \) by \( R_e = \theta + 1 \).

To accomplish the Bayesian approach using the real-world COVID-19
data, an inevitable bias is that the laboratory-confirmed infection date is unlikely to be the date of infection. Hence, prior to estimating \( R_t \), we first need to translate positive test counts to the dates where they may occur. Specifically, we adopted the onset dates and confirmed dates of patients documented by Xu et al. (2020) to infer the probability distribution and cumulative distribution function of delayed days, respectively (Fig. 1a). Given the probability distribution function, we can distribute case counts back in time. To accomplish this, we reversed the series again to obtain the onset curve. Further, we adjusted the onset curve based on the cumulative distribution function to avoid underestimating the onset cases (Fig. 1b). For example, one week ago, there were 100 onset cases while not all of these cases would be reported over the course of this week. If the portion of the reported case was 60%, then the current count of onset on that day only represents 60% of the total, meaning that the total is 167% (100/60) higher. We apply this correction to estimate what actual onset cases could possibly be. Therefore, to precisely estimate the likelihood of \( R_t \), we used the onset cases. That is, \( I \) of Poisson in Eq. (5) and Eq. (6) is the expected onset cases on that day.

Fig. 2 and Supplementary Video B illustrates the spatial distribution of effective production number over time. Since most states enacted the stay-at-home orders and people started actively practicing social distancing across the nation in April, it is clear that the viral spread has been greatly reduced. Particularly, by the middle of April, many counties along the East Coast and West Coast were under control since the reproduction number was less than 1. Thereafter, for three weeks running, the distribution of \( R_t \) remained relatively stable compared to the distribution of novel outbreaks in the early stage. However, the reproduction number in many Western states, such as Utah and New Mexico, has bounced back since early May. Additionally, COVID-19 regression analysis. We adopted the Global Moran’I test to examine the spatial autocorrelation of our variables (Moran, 1950), with a positive z-score indicating that the variable is spatially clustered. Table 1 shows the test results for all our regression variables, that are exhibiting spatial non-stationarity (p < 0.01), thereby suggesting that considering spatial dependency in our regression analysis is not only necessary but also essential.

The conventional panel regression estimation of spatial data might yield biased results, because the regression residuals from spatial data are often spatially autocorrelated, violating the statistical assumption of independently distributed errors (Yu, 2010). Geographically weighted regression (GWR) has been widely used to address this issue by adopting each data point and its neighboring observations to estimate local regression coefficients (Brunsdon, Fotheringham, & Charlton, 1996). However, the conventional GWR model can only be applied to a cross-sectional dataset, and it cannot consider the temporal dimension of a panel dataset, like ours, in its model.

Therefore, in a first attempt, Yu (2010) developed the geographically weighted panel regression (GWPR) to explore the spatially varying effects, which is indeed a combined GWR and a panel model. Here, we adopted the GWPR framework with a fixed-effect model to investigate the local effects of stay-at-home behaviors, stay-at-home orders, and socioeconomic and demographic characteristics on the viral transmission at the county level. We applied the adaptive kernel function to obtain the optimal bandwidth size by minimizing the corrected Akaike Information Criterion. See Yu (2010) for detailed information about the GWPR model and its estimation. In our study, we consider bandwidths and spatial weights as time-invariant because our dataset is a relatively short panel.

We explore the effects of UGS visitation and additional effects of social variables on viral transmission using the following GWPR model:

\[
R_{u(v,t)} = a_{1(u,v)} \times \text{VisitUGS}_{u(v,t)} + a_{2(u,v)} \times \text{VisitUGS}_{u(v,t)} \times \text{PopDensity}_{u(v,t)} + a_{3(u,v)} \times \text{VisitUGS}_{u(v,t)} \times \text{Essential}_{u(v,t)} + a_{4(u,v)} \times \text{VisitUGS}_{u(v,t)} \times \text{HealthCare}_{u(v,t)} + \gamma_{u(v,t)} + \delta_{u(v,t)} + \epsilon_{u(v,t)}
\]

continues to expand into Midwestern counties, such as counties in Nevada and Montana. This is especially alarming as the White House has pushed for an even faster reopening of the US economy in early May.

Supplementary video related to this article can be found at https://doi.org/10.1016/j.apgeog.2022.102768

3.3. Geographically weighted panel regression

Regarding that our data include location information, it is essential to test the spatial non-stationarity of the studied variables for our spatial

![Onset vs. Confirmed Dates - COVID19](image1.png)

**Fig. 1.** (a) Onset and confirmed dates of patients; (b) An example showing the confirmed, onset, and adjusted onset cases over the days.
\[ \delta_{(u,v)}^t \text{represents a vector of week-level fixed effects at the location } (u,v); \]
\[ \epsilon_{(u,v)}^t \text{represents the error term at the location } (u,v) \text{ on week } t. \]
Note that we aggregated the data into weekly steps since the model is extremely computationally intensive.

It is well noted that multicollinearity can generate bias and inflate standard errors for the regression analysis, irrespective of the global model or the local model (Wheeler & Tiefelsdorf, 2005). To avoid this issue, we performed a Pearson product-moment correlation coefficient test among our initially selected socioeconomic and demographic variables. For the geographically weighted regression, the variables with coefficients that are greater than 0.7 were excluded (Wheeler & Tiefelsdorf, 2005). Table 2 shows that all our variables should be included in the regression models.

We also performed the OLS model to examine the fixed-effects regression without consideration of spatial dependence (Table 3). The mean values of coefficients generated from the GWPR model are consistent with that of the OLS model. It shows that visiting UGS may slightly increase the viral spread because the coefficient is significant, while the effect is negligible. While we found some of the interaction terms are not significant (e.g., median age and population

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**Table 1**

Descriptive statistics and Moran’s I test results of the study variables.

| Variable                      | Min  | Max   | Mean | SD  | Moran’s I index |
|-------------------------------|------|-------|------|-----|-----------------|
| **UGS visitation**            | 0    | 0.32  | 0.14 | 0.18| 0.334***        |
| **Variables of interest**     |      |       |      |     |                 |
| Median Age                    | 21.7 | 67.0  | 41.3 | 5.3 | 0.302***        |
| Percent of blacks             | 0    | 0.87  | 0.10 | 0.15| 0.778***        |
| Poverty rate                  | 0    | 0.79  | 0.15 | 0.10| 0.545***        |
| **Control variables**         |      |       |      |     |                 |
| Population density (people per square mile) | 0.80 | 720741 | 310 | 1947 | 0.323*** |
| Essential occupation rate     | 0.21 | 0.72  | 0.45 | 0.20| 0.242***        |
| Trump share                   | 0.10 | 0.87  | 0.41 | 0.16| 0.532***        |
| Percent of healthcare workers | 0.12 | 9.48  | 2.63 | 0.80| 0.216***        |

Note: \( P < 0.01 \) ***; \( P < 0.05 \) **; \( P < 0.1 \) *.

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Fig. 2. County-level effective production number across the United States.
To this end, we mainly present the time lag from 1 day to 7 days, to examine whether the temporal hysteresis in the infection data. To this end, we performed the sensitivity analysis, with a distribution pattern remains similar. Due to the space limit, we did not variable of interest for different time lags and found that the spatial (Table 3). We also mapped the coefficients and significance of each appendix) are consistent with results when the time lag is not considered.

In addition, there may be a temporal hysteresis in the response of viral transmission to UGS visitation. However, the real-world time lag is difficult to estimate since we did not have individual UGS visitor’s infection data. To this end, we performed the sensitivity analysis, with a time lag from 1 day to 7 days, to examine whether the temporal hysteresis would significantly impact the results (Eq. (A1) in the appendix). Our results show that the overall results (Table A1-Table A4 in the appendix) are consistent with results when the time lag is not considered (Table 3). We also mapped the coefficients and significance of each variable of interest for different time lags and found that the spatial distribution pattern remains similar. Due to the space limit, we did not put the maps in the appendix. To this end, we mainly present the findings that assume there is no time lag.

4. Results

4.1. Overall impacts of green space visitation on the viral spread

Fig. 3 indicates the impacts of UGS visitation on viral transmission across 2018 counties that have data. Overall, the coefficients of 48% of counties (970 counties) are negative and the coefficients in the remaining counties are positive (1138 counties). Clearly, in Fig. 3B, UGS visitations in most counties (67%) across the country do not exhibit statistically significant effects on viral transmission. That is, the opening of UGS for those counties may not significantly increase infection cases.

The coefficients of UGS visitation are positively associated with the reproduction number in some counties of Florida, Idaho, New Mexico, New York, Ohio, and Pennsylvania, thereby indicating that there might be a positive association between UGS visitation and the spread of COVID-19 in these regions (Fig. 3A). It could be partially explained by the different UGS closure policies of the local county. For example, in Florida, not all Florida State Parks were announced to be closed during the early outbreak, even though all Florida State Parks have changed day-use visitation hours to 8 a.m. to 5 p.m. Another example is that Governor Andrew Cuomo announced that New York would close down all urban parks and playgrounds in response to the pandemic till April 1, 2020. For counties that are more accessible to those opened parks, the viral transmission could be higher. The result facilitates some local policies that restrict the use of UGS to slow down viral transmission (Hasson et al., 2020).

However, for the majority of counties in Minnesota, Oregon, Colorado, Utah, and Wyoming, statistically significant coefficients imply that there might be a negative association between UGS visitation and viral transmission. It could be explained by the decreasing indoor activities and gathering activities due to more outdoor activities. For example,
some of these states, such as Colorado and Utah, issued the statewide policy of limiting personal gatherings to no more than 10 people in the early phase of COVID-19 so that people have more outdoor activities, which indeed contributes to the mitigation of viral transmission. The result aligns with the findings from Chu et al. (2020) that the risk of COVID-19 infection in the UGS is very low if people wear masks and keep 6-feet of social distance and do not talk with non-family members for a long time.

4.2. A summary of impacts moderated by control variables

For those control variables, our results also reveal some interesting findings. First, as shown in Fig. 4A and Fig. 4B, the population density could be positively associated with the viral spread in some Western counties in Texas, New Mexico, Arkansas, Mississippi, etc., while the associations are negative in North Dakota, Minnesota, Kentucky, etc. That is to say, population density sometimes may exacerbate the viral transmission because people are more likely to have contact with others in the same community. For example, in Texas, Harris, Travis, Hays, and Williamson counties, where big cities such as Houston and Austin are located, all exhibit positive associations with the viral transmission. However, counties with a higher population density could also be large counties with better healthcare resources and people are more likely to comply with social distancing. It is not surprising that the essential occupation rate is positively associated with the viral spread in many parts of the US (e.g., California, New York, Ohio, Kentucky) because those essential workers are highly possible to be exposed to the virus.

The existing studies have found that counties with more Trump supporters are less likely to practice social distancing, thereby resulting in higher infection rates (Gollwitzer et al., 2020). Our research again confirms these findings such that there are clear positive associations between Trump share and viral spread in Washington, California, New Mexico, Colorado, etc. Overall, the effects of healthcare workers exhibit negative associations with the viral spread because more healthcare workers represent that the community has a better capacity to take care of infected patients, thereby mitigating the spread of the virus, even though it may not reduce the infection rate everywhere.

4.3. Impacts moderated by age

Fig. 5 indicates the impacts of UGS visitations on viral transmission moderated by age. Overall, the coefficients of 43% of counties (868 counties) are negative and the coefficients in the remaining counties (1150 counties) are positive.
The coefficients are both positive and statistically significant in Florida, Colorado, and Missouri (Figs. 5A and 4B), indicating that there may be a positive association between the higher median age and the spread of COVID-19 when people visit UGS. It can be because the elderly people are more likely to choose nearby but overcrowded green spaces, whereas younger people can visit farther but bigger UGS where infection risk is lower. For example, warm weather and the low cost of living make Florida an ideal haven for retirement; but the uneven access to UGS in Florida has been a long-standing issue (Coutts, Horner, & Chapin, 2010). Meanwhile, the elderly, who are the most susceptible group to COVID-19, are more likely to be infected when they are exposed to the virus in public space (National Academies of Sciences Engineering and Medicine, 2020).

On the contrary, we also observe that higher median age could have a negative association with the viral spread in Washington, Pennsylvania, and Idaho. This can be explained that, in these regions, more high-education elderly trust science and pay more attention to social distancing in UGS during the pandemic (Chiou & Tucker, 2020). Meanwhile, the elderly, who are the most susceptible group to COVID-19, are more likely to be infected when they are exposed to the virus in public space (National Academies of Sciences Engineering and Medicine, 2020).

4.4. Impacts moderated by blacks

Fig. 6A and B shows the impacts of UGS visitations on viral transmission moderated by the proportion of blacks. In this case, the coefficients of 32% of counties (646 counties) are negative and the coefficients in the remaining 1372 counties are positive. The coefficients of the proportion of black are positively and significantly associated with the reproduction number in Georgia, Tennessee, Kentucky, Ohio, Louisiana, and California, meaning that there may be a positive association between viral transmission and a high concentration of blacks. For example, Georgia has the 4th largest Black population in the United States and they are more likely to be more distrustful of medical experts than other demographic groups, an example of how trust can be lost (Dougherty, Lindquist, & Bradbury, 2006). The finding aligns with Algan et al. (2016) that the ethnic minority groups are less likely to comply with the social norms, thus increasing the infection rate.

However, for some counties in North Dakota, Minnesota, Wisconsin, and Florida, the coefficient estimates statistically indicate otherwise. It could be because many ethnic minorities have less access to UGS due to unfair treatment and the lack of consideration of different cultural behaviors (Apparicio, Seguin, Landry, & Gagnon, 2012; Germann-Chiari & Seeland, 2004). For example, the ethnic minorities in Florida have been...
found to have insufficient mobility resources to access the UGS (Coutts et al., 2010). Therefore, for counties with a high proportion of blacks in Florida, the reproduction number can be relatively lower because the minority people may not visit UGS very often during the pandemic. Also, Egorov et al. (2020) have reported that, in some cases, the ethnic minority could be inclined to voluntarily adhere to socially beneficial norms during the pandemic, when they are aware of the co-existence of both public and private benefits from social distancing behaviors. Likewise, Zhai, Fu, Liu, and Peng (2021) found that some ethnic segregation neighborhoods in Greater Lakes Region, such as Minnesota and Wisconsin, could benefit from the segregation from dominant white groups, who are under higher infection risk in some cases.

4.5. Impacts moderated by poverty

Fig. 7A and B shows the impacts of UGS visitations on viral transmission moderated by the poverty rate. The coefficients of 34% of counties (686 counties) are negative and the coefficients in the remaining 1332 counties are positive. In Iowa, Missouri, Colorado, New Mexico, and the northeast region, the coefficient of poverty rate is statistically significant and positive, meaning that poverty may have a positive association with the reproduction number when people visit UGS. The results are consistent with previous studies that low-income counties are more likely to have smaller green spaces, which could lead to a higher spread of COVID-19 (Rigolon, 2016). Moreover, poverty has been demonstrated as a factor of low compliance with social distancing (Wright et al., 2020), regarding that low-income people are more likely not to trust science (Chiou & Tucker, 2020). Specifically, 13.2% of Missourians live below the federal poverty line and New Mexico (18.5%) ranks third in the poverty rate across the country. Hence, it is not surprising that more low-income people from these two states may be vulnerable to the virus in UGS.

However, for counties in South Carolina, Alabama, and Florida, the coefficients are negative. It is most likely that the majority of low-income people in these regions may not visit UGS at all during the pandemic. On one hand, low-income people themselves have no access to green space because public transit was not available in the early outbreak of COVID-19 (Wilbur et al., 2020). For example, some cities in South Carolina (e.g., Charleston) scaled back public transit services to protect health and safety in the early outbreak of COVID-19, making those low-income individuals have less access to UGS since not many of them can afford private cars. On the other hand, many UGS in these states have also been closed due to safety concerns. For instance, South Carolina state parks remained closed from early March to April 30 as part of the state’s response to the pandemic. To this end, even though the state has a high proportion of low-income people, they cannot gather either in indoor spaces or UGS.

5. Discussion

5.1. Urban green space management for pandemic

According to our study, we found that proper policy and bold action about UGS management should be considered to slow the spread of COVID-19 and protect disadvantaged populations. We have concluded the following policy implications from the study.

First, although the coefficients of most of the counties are non-significant, we still should place emphasis on those areas. One of the possible reasons for the non-significance is that the impacts of green space visitation within those non-significant counties exhibit contradictory effects on the viral transmission considering the diversity in American society. That is to say, the positive effects and negative effects could co-exist in one county, necessitating local level analysis in future studies. In addition, we found that there is considerable overlap for counties with non-significant results. For example, most of the counties in Nebraska, Kansas, Arizona, Wyoming, South Dakota, etc., remain non-significant for all the three variables of interest. It could be because the viral transmission expanded into these states not until May 2020. Thus, the UGS visitations in those states may not take effect in the viral transmission in the early outbreak. However, we still suggest that more attention should be paid to these areas in terms of better UGS management during the pandemic.

Second, regarding the health benefits, we suggest that UGS should not be all closed during the pandemic because, in the majority of counties, the visitations to UGS do not significantly increase the viral transmission except in Florida, Idaho, New Mexico, New York, Ohio, and Pennsylvania. We can remain some large green spaces open and issue entering rules to require visitors to follow the safety guidelines and instructions, such as wearing masks and maintaining physical distancing. In addition, when the number of visitors reaches the limit, we should notice visitors or directly restrict the visitation, which can avoid gathering and mitigate the viral spread. For example, Beijing has developed a real-time monitoring system to show the crowded index in each public park for all visitors, which could lead citizens to avoid gathering in a certain park. The parks can also provide disinfectants that can effectively protect people who are engaged in activities in the urban park.

Third, our results show that social characteristics can, to some extent, exert heterogeneous impacts on viral transmission when people
visit UGS. In counties with a higher proportion of vulnerable people, policymakers could carefully consider the implementation of more stringent requirements for UGS entry. The government could distribute an emergency health protection funding package to all green spaces to provide free face coverings and build test stations. In addition, the green space can set up special activity areas and provide exclusive services for vulnerable populations and implement more stringent health checks at the entrance (Fu & Zhai, 2021; Slater et al., 2020).

Fourth, the local government should ensure people have equal opportunities of accessing UGS across the city. In some low-income areas which lack green space, the officials could close some roads and free up more space for people to do outside activities, such as the “Stay Healthy Street” developed by the Washington Department of Transportation, which is a pilot program to allow for socially distanced transportation, recreation, and socialization. It is well-acknowledged that economically disadvantaged people are more likely to live in overcrowded accommodation with limited UGS nearby. The public transit agency could add some strictly disinfected buses or dedicated shuttles between the areas of high density. It could also provide free face coverings and build test stations. In addition, the green space of public transportation corridors or allowing free access to informal green spaces for disadvantaged neighborhoods.

5.2. Limitation

Even though our findings shed light on the management of UGS amid COVID-19, this research has the following limitations. First, the model for measuring the effective reproduction number can be improved with a variable, i.e., the viral transmission term. Although the COVID-19 pandemic can be regarded as an impetus for more social distancing, there is little evidence to substantiate our findings. Second, this research is descriptive. Although we carried out the analysis with consideration of time lag, we do not have an exogenous variation to substantiate the findings.

Table A1: Sensitivity analysis of lagged days

| Variable                  | Coefficients | SE     | Min    | Max    | Mean    |
|---------------------------|--------------|--------|--------|--------|---------|
| VisitUGS                  | 0.005**      | 0.002  | −0.011 | 0.019  | 0.004   |
| VisitUGS × Median age     | 0.012        | 0.009  | −0.022 | 0.042  | 0.015   |
| VisitUGS × Proportion of blacks | 0.011***      | 0.003  | −0.026 | 0.037  | 0.016   |
| VisitUGS × Poverty rate   | 0.021***      | 0.004  | −0.017 | 0.042  | 0.019   |

In summary, to answer our research questions, we applied the geographically weighted panel regression model in this research by combining the mobile phone data, confirmed infection data, and ACS data. For the first question, we found that visitations to UGS only increase viral spread in a small proportion of counties in Florida, Idaho, New Mexico, New York, Ohio, and Pennsylvania. That is, visiting UGS in the majority of counties would not exacerbate viral transmission. To answer the second question, we examined the impacts moderated by social factors. The results show that the impacts of the median age, the proportion of blacks, and the poverty rate are spatially heterogeneous, with either positive or negative coefficients. Especially, the high median age can increase the viral transmission in New Mexico, Colorado, and Missouri; the high concentration of blacks can increase the spread in North Dakota, Minnesota, Wisconsin, Michigan, and Florida; the high poverty rate can spread up the transmission in Iowa, Missouri, Colorado, New Mexico, and the northeast US. Therefore, the impacts of social factors are closely related to local policy and sociodemographic characteristics. We suggest that the local government should ensure people have equal opportunities of accessing UGS across the county. The coronavirus pandemic can reshape the values that people have for UGS, and thereby push local governments by social and political actions to reasonably propose the UGS policy during the crisis because no one-size-fits-all policy exists.

Appendix 1. Sensitivity analysis of lagged days

To perform the analysis with consideration of time lag, we revised formula (7) to formula (A1) by adding the time lag parameter in the dependent variable, i.e., the viral transmission term.

\[
R_{(a,x,t+1)} = \alpha_1(\alpha_x) \text{VisitUGS}_{(a,x,t)} + \alpha_2(\alpha_x) \text{VisitUGS}_{(a,x,t)} \times \text{Age}_{(a,x)} + \alpha_3(\alpha_x) \text{VisitUGS}_{(a,x,t)} \times \text{Black}_{(a,x)} + \alpha_4(\alpha_x) \text{VisitUGS}_{(a,x,t)} \times \text{Poverty}_{(a,x)} + \alpha_5(\alpha_x) \text{VisitUGS}_{(a,x,t)} \\
\times \text{PopDensity}_{(a,x,t)} + \alpha_6(\alpha_x) \text{VisitUGS}_{(a,x,t)} \times \text{Essential}_{(a,x)} + \alpha_7(\alpha_x) \text{VisitUGS}_{(a,x,t)} \times \text{Trumpl}_{(a,x)} + \alpha_8(\alpha_x) \text{VisitUGS}_{(a,x,t)} \times \text{Healthcare}_{(a,x)} + \gamma_{(\alpha_x)} + \delta_{(\alpha_x,t)} + \epsilon_{(\alpha,x,t)}
\]

where \( l \) in \( R_{(a,x,t+1)} \) represents the pre-defined time lag; other variables and parameters remain the same meaning as formula (7).

Table A1: Summary of regression results using OLS and GWPR [Time lag = 1 day]

| Variable                  | OLS       | GWPR     |
|---------------------------|-----------|----------|
| VisitUGS                  | Coefficients | SE | Min | Max | Mean |
| VisitUGS × Median age     | 0.012     | 0.009    | −0.022 | 0.042 | 0.015 |
| VisitUGS × Proportion of blacks | 0.011***      | 0.003    | −0.026 | 0.037 | 0.016 |
| VisitUGS × Poverty rate   | 0.021***      | 0.004    | −0.017 | 0.042 | 0.019 |

(continued on next page)
### Table A1 (continued)

| Variable                        | OLS       | GWPR      |
|---------------------------------|-----------|-----------|
| \( \text{VisitUGS} \times \text{Population density} \) | -0.010    | 0.008     |
| \( \text{VisitUGS} \times \text{Essential occupation rate} \) | 0.012***  | 0.002     |
| \( \text{VisitUGS} \times \text{Trump share} \) | 0.011**   | 0.005     |
| \( \text{VisitUGS} \times \text{Healthcare workers} \) | -0.019*** | 0.004     |
| County fixed-effects            | Yes       | Yes       |
| R squared                       | 0.54      | 0.54      | 0.58 | 0.54 |

Note: \( P < 0.01 \) ‘***’; \( P < 0.05 \) ‘**’; \( P < 0.1 \) ‘*’.

### Table A2
Summary of regression results using OLS and GWPR [Time lag = 3 days]

| Variable                        | OLS       | GWPR      |
|---------------------------------|-----------|-----------|
| \( \text{VisitUGS} \times \text{Population density} \) | -0.010    | 0.008     |
| \( \text{VisitUGS} \times \text{Essential occupation rate} \) | 0.012***  | 0.002     |
| \( \text{VisitUGS} \times \text{Trump share} \) | 0.011**   | 0.005     |
| \( \text{VisitUGS} \times \text{Healthcare workers} \) | -0.019*** | 0.004     |
| County fixed-effects            | Yes       | Yes       |
| R squared                       | 0.54      | 0.54      | 0.58 | 0.54 |

Note: \( P < 0.01 \) ‘***’; \( P < 0.05 \) ‘**’; \( P < 0.1 \) ‘*’.

### Table A3
Summary of regression results using OLS and GWPR [Time lag = 5 days]

| Variable                        | OLS       | GWPR      |
|---------------------------------|-----------|-----------|
| \( \text{VisitUGS} \times \text{Population density} \) | -0.010    | 0.008     |
| \( \text{VisitUGS} \times \text{Essential occupation rate} \) | 0.012***  | 0.002     |
| \( \text{VisitUGS} \times \text{Trump share} \) | 0.011**   | 0.005     |
| \( \text{VisitUGS} \times \text{Healthcare workers} \) | -0.019*** | 0.004     |
| County fixed-effects            | Yes       | Yes       |
| R squared                       | 0.54      | 0.54      | 0.58 | 0.54 |

Note: \( P < 0.01 \) ‘***’; \( P < 0.05 \) ‘**’; \( P < 0.1 \) ‘*’.

### Table A4
Summary of regression results using OLS and GWPR [Time lag = 7 days]

| Variable                        | OLS       | GWPR      |
|---------------------------------|-----------|-----------|
| \( \text{VisitUGS} \times \text{Population density} \) | -0.010    | 0.008     |
| \( \text{VisitUGS} \times \text{Essential occupation rate} \) | 0.012***  | 0.002     |
| \( \text{VisitUGS} \times \text{Trump share} \) | 0.011**   | 0.003     |
| \( \text{VisitUGS} \times \text{Healthcare workers} \) | -0.019*** | 0.004     |
| County fixed-effects            | Yes       | Yes       |
| R squared                       | 0.54      | 0.54      | 0.58 | 0.54 |

Note: \( P < 0.01 \) ‘***’; \( P < 0.05 \) ‘**’; \( P < 0.1 \) ‘*’.

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