GeoHealth

RESEARCH ARTICLE

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**Key Points:**

- We investigated human mobility patterns to parks under COVID-19 pandemic and wildfire season in western and central United States
- We found a general trend of avoidance to the parks with fewer visits and dwell time in the places with high COVID-19 cases
- With special demand of physical activities in pandemic, people travel further and spend longer time at the parks away from the wildfires

**Supporting Information:**

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

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# Human Mobility to Parks Under the COVID-19 Pandemic and Wildfire Seasons in the Western and Central United States

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**Abstract** In 2020, people's health suffered a great crisis under the dual effects of the COVID-19 pandemic and the extensive, severe wildfires in the western and central United States. Parks, including city, national, and cultural parks, offer a unique opportunity for people to maintain their recreation behaviors following the social distancing protocols during the pandemic. However, massive forest wildfires in western and central US, producing harmful toxic gases and smoke, pose significant threats to human health and affect their recreation behaviors and mobility to parks. In this study, we employed the geographically and temporally weighted regression (GTWR) Models to investigate how COVID-19 and wildfires jointly shaped human mobility to parks, regarding the number of visits per capita, dwell time, and travel distance to parks, during June - September 2020. We detected strong correlations between visitations and COVID-19 incidence in southern Montana, western Wyoming, Colorado, and Utah before August. However, the pattern was weakened over time, indicating the decreasing trend of the degree of concern regarding the pandemic. Moreover, more park visits and lower dwell time were found in parks further away from wildfires and less air pollution in Washington, Oregon, California, Colorado, and New Mexico, during the wildfire season, suggesting the potential avoidance of wildfires when visiting parks. This study provides important insights on people's responses in recreation and social behaviors when facing multiple severe crises that impact their health and wellbeing, which could support the preparation and mitigation of the health impacts from future pandemics and natural hazards.

**Plain Language Summary** This study investigates the variations of human mobility patterns to parks in space and time during the COVID-19 pandemic and wildfire seasons in 2020 across the western and central United States. We estimate how the COVID-19 outbreaks, wildfire occurrence, and wildfire-induced air pollutions affect the number of visits per capita to the parks, the minimum dwell time people spent at parks, and the travel distances to parks. People tended to travel closer to parks and spent less time at parks where there were more COVID-19 cases reported likely due to the infection protection behavior and risk altitude. However, the pattern was weakened over time due to the decrease in the concerns of the pandemic. Also, during the major wildfire season (August–September), more people traveled further to visit the parks away from the wildfires and stayed longer there. This study explored patterns in physical activity and human mobility to parks under multiple crises that pose threats to human health and wellbeing, which might provide some insights in the preparation for future pandemics and natural hazards.

## 1. Introduction

The year 2020 saw the confluence of two major crises, that is, the COVID-19 pandemic and the extensive, severe wildfires in August–September, impacting people's health and wellbeing in western and central United States. The Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2), commonly known as COVID-19, was initially detected in Wuhan, China, and has widely spread across the globe (Zhu et al., 2020). On

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January 30, 2020, the World Health Organization (WHO) declared the outbreak as a public health emergency of international concern, due to its rapid and hazardous spread and the need for a coordinated response among countries worldwide (World Health Organization, 2020). In the United States (US), there were about 20 million confirmed cases and 344,227 deaths as of December 31, 2020. Given that there was no effective vaccines and treatment available for SARS-CoV-2, non-pharmaceutical interventions (NPIs) have been used as the key weapon against the COVID-19 pandemic. Multiple NPI strategies and policies have been conducted across the US since February 2, 2020 (NAFSA, 2021), including travel bans, lockdowns, school/business closures, movement restrictions, and social distancing policies (Perra, 2021).

Similar to other infectious disease systems, COVID-19 transmission and host behaviors are often intertwined (Perra, 2021; A. Yang et al., 2021). On one hand, contact heterogeneity and movements of the host population play critical roles in facilitating disease transmission (Mbunge, 2020); on the other hand, the outbreak severity might trigger some infection prevention behaviors of the host and induce the changes to their movements and daily activities (Weston et al., 2018). In the COVID-19 pandemic, due to the risk attitudes and the NPIs, like social distancing and gathering restrictions, human daily activities and mobility have changed significantly worldwide (Chan et al., 2020; Woods et al., 2020). Particularly, several studies have suggested that the usage of public parks and open spaces were impacted by the COVID-19 pandemics and its NPI policies (Gelman et al., 2014; Shoari et al., 2020; Volenec et al., 2021; Xie et al., 2020).

Human mobility to parks can be driven by the COVID-19 pandemic in different ways. Recent studies pointed out that some places with strict NPI policies or having people with risk-averse attitudes might result in the overall increase in social confinement which led to reductions in human mobility (Chan et al., 2020). However, others have suggested that people have substantially used parks as a substitute for indoor fitness and recreation, leading to an increasing trend of visitations to open spaces and public parks during the COVID-19 pandemic (Geng et al., 2021; Volenec et al., 2021). Public parks and open spaces serve an important societal function as recreation spaces for diverse communities of people to support community cohesion, city sustainability, and human physical and mental health (Bedimo-Rung et al., 2005; Ulrich & Addoms, 1981). Under the COVID-19 pandemic, quarantine/self-isolation, potential health issues, limited outdoor and social activities, and other pandemic-driven stressors all yielded negative impacts on human health and wellbeing (Geng et al., 2021). Accessibility to parks and open green spaces becomes particularly essential since (a) those places often allow people to conduct their recreation behaviors following the social distancing protocols to avoid the risks (Volenec et al., 2021), and (b) recreation behaviors and physical activities can mitigate the pandemic stress and benefit the overall health condition (Xie et al., 2020).

Besides the COVID-19 pandemic, another crisis that complicates people's recreation behavior and mobility to the parks was the massive, severe wildfires and the wildfire-induced air pollution in the western and central US. Global climate change promotes the conditions on which the potential and severity of the wildfires depend, including the increases in the frequency and intensity of heat waves and drought (Jones et al., 2010; Xu et al., 2020). Until October 2020, over 44,714 wildfires were occurring in the western and central US, associated with over 7.8 million acres of burned areas (Insurance Information Institute, 2020). Uncontrolled wildfires can impact human recreation behaviors and activities, although the available evidence of the impact of wildfires on recreation demand is ambiguous (Nobel et al., 2020). The wildfire-induced smoke often consists of highly elevated concentrations of fine particulate matter, carbon monoxide, nitrogen oxides, and volatile organic compounds, which pose major impacts to animal and human health (Tao et al., 2020; D. Yang et al., 2021). Previous studies demonstrated a significant association between wildfire smoke exposure and risk of respiratory illness in humans (DeFlorio-Barker et al., 2019; Hänninen et al., 2009; Moore et al., 2006). The wildfire-induced air pollution can even be transported over a long range (e.g., over 1,000 km) and cause the illness and death of humans there (Kollanus et al., 2016). However, some other studies also found that wildfires can increase visitations to parks close to wildfires due to people's curiosity of the wildfire events and their impacts (Sánchez et al., 2016). Thus, wildfires can drive human mobility in different directions, which might complicate human's recreation behaviors during the pandemic.

Patterns of human visitation to parks and open space is highly related to the spatial proximity to the parks, which is known as the theory of "distance decay": Distance can have negative impacts on visitations to parks and tourism destinations (Xiao, Zhang, et al., 2021; J. Zhang et al., 1999). However, given dual effects of COVID-19 pandemic and wildfires in 2020 summer to early fall, the spatial patterns of people's mobility to parks might change and can be different from the mobility patterns affected by a single crisis. Previous studies have focused on the human mobility to parks during the COVID-19 pandemics or under wildfire seasons separately (Kim & Jakus, 2019; Kupfer et al., 2021). However, the estimation of the compound effects and their interplay on human mobility to parks remain unknown. Understanding people's social and recreation behaviors under multiple severe crises might help provide insights in preparing and mitigating future threats to people's health and wellbeing.

Both space and time are fundamental in human activities and physical or ecological processes. geographical and temporal weighted regression (GTWR) considers both spatial and temporal nonstationarity simultaneously which is one of the common spatiotemporal models that has been employed in many domains, including economy, environmental science, public health and others (He et al., 2021; Huang et al., 2010; W. Zhang et al., 2021). Unlike the global spatiotemporal models which assume the processes being examined to be constant over space and time, GTWR is the local model which is developed to account for local effects in both space and time (Fotheringham et al., 2015). A weighting matrix integrating both spatial and temporal information is incorporated in the models.

In this study, we investigated the spatial and temporal patterns of human's mobility to public parks and open spaces in the western and central US, where COVID-19 and wildfire co-occurred in June–September 2020. Specifically, we employed the GTWR models to examine how different factors, including the COVID-19 outbreaks, wildfires, air quality, and drought, drove the following three metrics that describe human recreation and mobility at public parks: (a) the number of visits per capita, (b) the median of minimum dwell time they spent at the park, and (c) the median travel distance to parks.

## 2. Materials and Methods

### 2.1. Study Area and Human Mobility Data to Parks

The study area covers 12 states in the western and central US (Figure 1). We accessed the human mobility patterns to the parks from the SafeGraph data set (https://www.safegraph.com/). This data set provided an aggregated and anonymized foot traffic patterns at over 4.5 million businesses and consumer point-of-interest (POI) across the US based on mobile phone records. Here, we collected the monthly aggregated human mobility patterns to parks from SafeGraph in June–September 2020. The six-digit North American Industry Classification System (NAICS) codes "712130" and "712190" (https://www.naics.com/search/) which identify as park POIs were used to filter for the park-related location from the SafeGraph Data set. A total of 42,211 park-related POI locations were selected based on the study area. To investigate the people's mobility pattern to parks, we use three metrics that attached to the park-related location to describe human mobility and usage of public parks, including (a) the number of visits to POIs, (b) median distance to park traveled by visitors, and (b) median minimum dwell time that people spent at POIs. Due to the increasing concern and interests in human movements and social behaviors during the pandemic, those three metrics from SafeGraph have been increasingly used to describe human mobility patterns recently, including the stay-at-home behaviors and daily activities to restaurants/bars, groceries, healthcare facilities, and parks (e.g., Atkinson et al., 2020; Jiao et al., 2021; Juhász & Hochmair, 2020). We aggregated the park-related POIs with those three metrics to the county level into each month of June -September using SpatialJoin Tools ArcGIS 10.8 (ESRI Inc.). We standardized the number of visits to parks in each county into the unit of number of visits per capita.

### 2.2. Environmental Variables

We included nine potential variables to consider the effects of the COVID-19 pandemic, wildfires, and wildfire-induced air pollution on human mobility and recreation behaviors at public parks. These variables were accessed and processed from multiple sources (see details in Table 1). For the COVID-19 pandemic situations, we accessed the county-level outbreak and death data in each month of June–September from USAFacts (https://usafacts.org/) and standardized them into the incidence and death rates, respectively (case number per total population). For the wildfire effects, we considered wildfire events, toxic gases, and smoke levels. The wildland fire location data set was accessed from National Interagency Fire Center. We screened any wildfire events that occurred and lasted for at least a week within each of June–September and

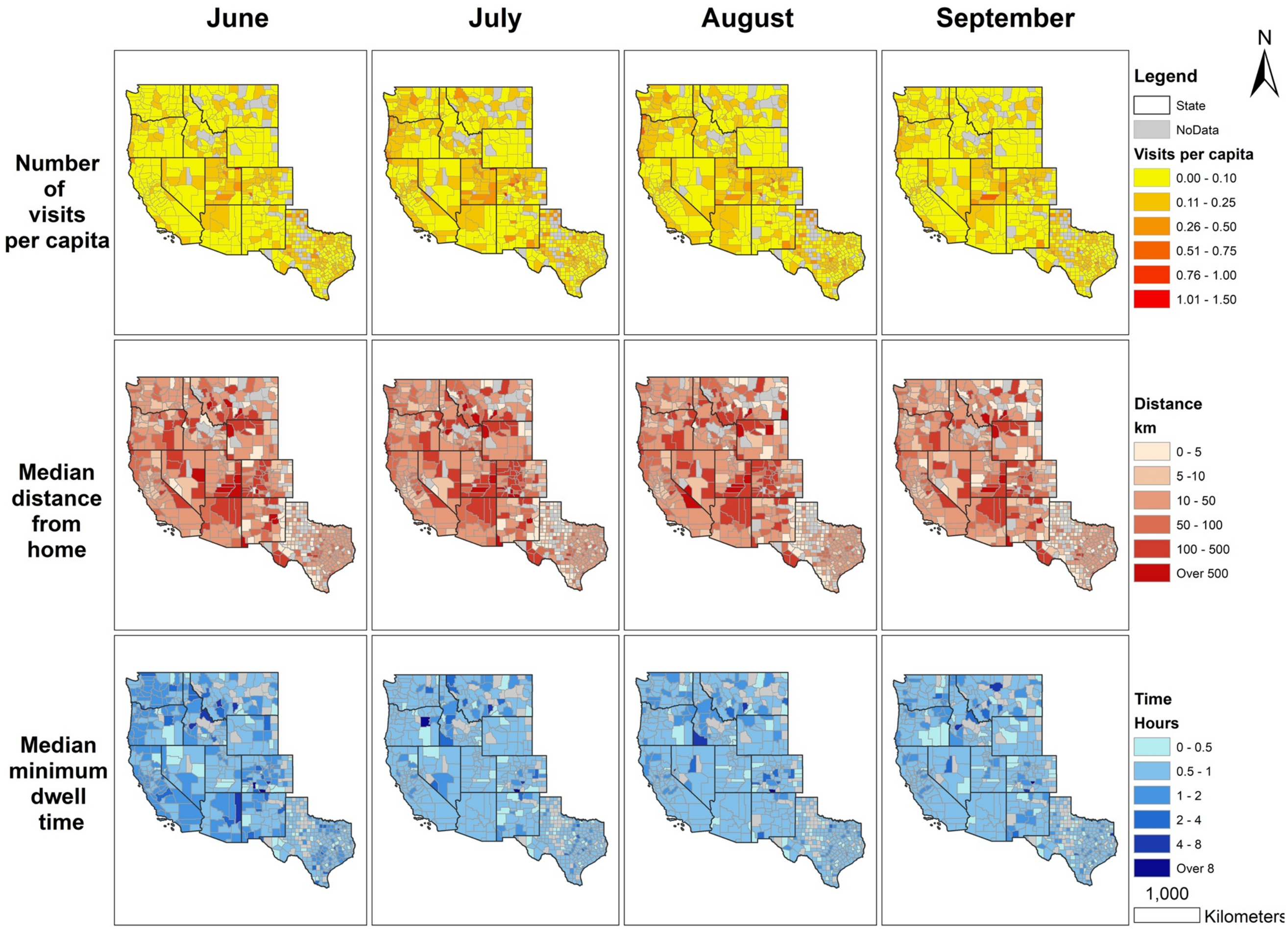


**Figure 1.** Study area and monthly distribution of the number of visits per capita, median distance to park, and median minimum dwell time.

computed the Euclidean distance to the closest wildfire events (Fire distance) and the density of wildfires (Fire density) over the study area using ArcMap 10.8. Smoke observations were downloaded from Hazard Mapping System Fire and Smoke Product at NOAA. Given that the smoke was measured every 5 min, we extracted the daily maximum and minimum smoke values and then aggregated them to monthly scale. The toxic gases were directly accessed from the data sources.

Additionally, we also considered some other potential factors (16 variables) that might impact human mobility to parks, including the land cover types, climatic conditions, population, and park types and numbers (see all of them in Table 1). For the land cover variables, we reclassified the 2016 map of USGS National Land Cover Database (NLCD) into the following five classes to account for the major land cover types in the study area: forest (original class # 41–43), agricultural (original class #81, 82), grass (original class #51, 52, 71–74), urban and barren land (original class #21–24, 31), and water (original class #11, 12). We incorporated two variables to estimate the effects of park sizes and recreation levels on the mobility patterns (Powers et al., 2020; Xiao, Lee, & Larson, 2021), including a vector representing the number of state parks (State Parks) in each county and a dummy variable indicating the presence of national parks (National Park). Climatic measurements accessed from "climateR" R-package were included to consider the influence of weather and climate on recreation and park visitation, as well as the potential seasonality in human mobility (Smith, 1993). All the variables were aggregated to the county level in each month of June–September.

**Table 1**
*Descriptions and Data Sources of the Covariates*

| Factors | Covariates (names) | Descriptions | Sources |
|---|---|---|---|
| COVID-19 outbreaks | Confirmed cases (COVID case) | The reported positive COVID-19 cases in each month | USAFacts |
| | Death cases (COVID death) | The reported COVID-19 deaths in each month | |
| Wildfires effects | Carbon monoxide (CO) | Monthly average CO concentration | Sentinel-5P TROPOMI |
| | Sulfur dioxide ($SO_2$) | Monthly average $SO_2$ concentration | |
| | Nitrogen dioxide ($NO_2$) | Monthly average $NO_2$ concentration | |
| | Distance to fire (fire distance) | Euclidean distance to the closest wildfire that occurred in each month (m) | National Interagency Fire Center |
| | Fire density (fire density) | Density of the wildfire event distributions in each month | |
| | Minimum smoke (smoke minimum) | Monthly average of daily minimum smoke values | NOAA Hazard Mapping System Fire and Smoke Product |
| | Maximum smoke (smoke maximum) | Monthly average of daily maximum smoke values | |
| Climatic Variables | Precipitation | Monthly average of daily precipitation (mm) | Gridded Meteorological Data set extracted from the "climateR" R-package |
| | Maximum humidity | Monthly average of daily maximum relative humidity (%) | |
| | Minimum humidity | Monthly average of daily minimum relative humidity (%) | |
| | Wind | Monthly average of daily wind speed (m/s) | |
| | Vapor pressure deficit (VPD) | Monthly average of daily vapor pressure deficit (kPa) | |
| | Temperature (temperature average) | Monthly average of daily temperature × 10 (°C) | |
| Land cover types | Agriculture, forest, grass, urban, water | percentage of agricultural, forest, grass, urban, and water areas (%) | 2016 USGS National Land Cover Database |
| Topography | Elevation | Elevation (m) | GTOP030 |
| Population | Number of populations (population) | The number of total populations in each county | USAFacts |
| Park | Number of all parks (number of park) | The number of all parks in each county | SafeGraph |
| | National park | A dummy variable indicate whether a county with national park or not | |
| | Number of state parks (state parks) | The number of total state parks in each county | |

### 2.3. The GTWR Models

This study employed the GTWR models to explore the effects of different factors on the spatial and temporal patterns of three metrics that describe the human mobility to public parks at a monthly scale for each county. A monthly scale was selected to consider the potential inter-month seasonality in human mobility, COVID-19 situations and wildfire conditions. Human mobility and travels to parks often vary over time and space, which violate the assumption of statistical independence of the observations in some global statistical approaches. The GTWR models considering the local spatial and temporal heteroscedasticity simultaneously can provide the spatiotemporal estimation of effects of covariates and can capture the space-time patterns of human mobility to parks (He et al., 2021; Huang et al., 2010). See following model specification:

$$Y_i = \beta_0\left(\mu_i, v_i, t_i\right) + \sum_k \beta_k\left(\mu_i, v_i, t_i\right) X_{\mathrm{ik}} + \varepsilon_i \quad (1)$$

where $Y_i$ is the dependent variable of the $i$th record of data, which represents the number of visits per capita, the median of minimum dwell time at parks, or the travel distance to park. $X_{\mathrm{ik}}$ are the matrices of the independent variables at the $i$th record of data. $\mu_i$, $v_i$, and $t_i$ represent the spatial and temporal information of the $i$th record of data, i.e., $(\mu_i, v_i)$ gives the coordinates and $t_i$ shows the time. $\beta_0\ (\mu_i, v_i, t_i)$ is the intercept for the

$i$th record, while $\beta_k$ ($\mu_i$, $v_i$, $t_i$) represents the coefficient for the $k$th independent variable. The coefficients $\beta_k$ ($\mu_i$, $v_i$, $t_i$) can be estimated using the Weighted Least Square as follows:

$$\hat{\beta}_k\left(u_i, v_i, t_i\right) = \left[X^{\mathrm{T}} W\left(u_i, v_i, t_i\right) X\right]^{-1} X^{\mathrm{T}} W\left(u_i, v_i, t_i\right) Y \tag{2}$$

where $W(u_i, v_i, t_i) = \mathrm{diag}(\alpha_{i1}, \alpha_{i2}, ..., \alpha_{\mathrm{in}})$ and $n$ is the number of observations. $\alpha_{ij}$ ($1 \le j \le n$) is space-time distance decay function of ($\mu_i$, $v_i$, $t_i$) corresponding to the weight that is adopted to calibrate a weighted regression adjacent to the $i$th record of data. Various of the space-time distance decay functions can be used including Gaussian, exponential, and bi-square distributions. Here, we employed a Gaussian distance function:

$$W_{ij}^{\mathrm{ST}} = \exp\left[\left(\frac{d_{ij}^{\mathrm{st}}}{h^{\mathrm{st}}}\right)^2\right] \tag{3}$$

where $d_{ij}^{\mathrm{st}}$ represents a spatiotemporal distance between the $i$th and $j$th record of data. $h^{\mathrm{st}}$ is a spatiotemporal bandwidth, the optimal of which can be computed based on the corrected Akaike information criterion (AICc) (Huang et al., 2010; Hurvich et al., 1998).

Before building the GTWR models, we first screened all the 25 potential variables for the multicollinearity. For any variables with the Pearson's correlations greater than 0.5 (see the correlation of the covariates in Figure S1 in the Supporting Information S1), we selected one of them to be incorporated into the models based on the information criterion (AICc). We also standardized the dependent and independent variables to directly compare the coefficients in the later GTWR models. We investigated the effects of COVID-19 outbreaks and wildfires on visits per capita, the median of minimum dwell time at the park, and the travel distance to park separately with three different sets of GTWR models. For each set of GTWR models, we generated all additive possible combination of covariates. All the GTWR models were conducted using the GTWR AddIn in ArcMap 10.8 (Huang et al., 2010). The model performance and predictive accuracy were evaluated based on AICc and global $R^2$, respectively. For model selection, the ΔAICc for each model were computed as the differences in the AICc values between the lowest AICc and each following model. Any candidate model with ΔAICc < 2 was accounted for as the competing model that informationally indistinguishable (Anderson & Burnham, 2004). The number of covariates incorporated in the competing models and their global $R^2$ were also considered in model selection procedures.

### 2.4. Mean Difference Test

We performed a mean difference test to statistically estimate the differences in the local impacts between wildfires and COVID-19 pandemics (Liu et al., 2021). We employed the Welch's t test in R version 3.4.0 (R Core Team, 2019) to examine the differences of sample mean between the coefficients of wildfire related variables (wildfire distance or wildfire density) and COVID-19 incidence rate (COVID case) estimated from the top-selected models to describe the spatiotemporal patterns of county-level visits per capita, minimum dwell time they spent at the park, and travel distance to park.

## 3. Result

### 3.1. Results for the Number of Visits per Capita

Model 1.1 shown in Table 2 is the top-selected model with the lowest AICc value and a predictive accuracy of a global $R^2$ as 0.412. We selected this model to describe the effects of different factors including COVID-19 outbreaks, wildfire, drought, and air quality on the pattern of the number of visits per capita for each county in the western and central US during June–September 2020.

We found that the county-level number of visits per capita in several states of the study areas (e.g., Washington, Oregon, Idaho, Nevada, and northwestern Texas) have the positive correlations with the COVID-19 incidence rate before the major wildfire season (Figure 2a). However, negative correlations have been dominant in central Montana, western Wyoming, Colorado, and Utah before the wildfire season in June–July.

**Table 2**
*Model Performance and Predictive Accuracy for the 10 Top Candidate GTWR Models to Estimate the Effects on the Number of Visits to Parks per Capita*

| No. | Model structure | K | ΔAICc | Global $R^2$ |
|---|---|---|---|---|
| 1.1 | COVID case + minimum humidity + wind + fire distance + smk minimum + water + agriculture + grass + CO + $NO_2$ + $SO_2$ + number of park + national park + state parks | 14 | 0 | 0.412 |
| 1.2 | COVID case + temperature average + minimum humidity + wind + fire density + smoke maximum + water + agriculture + forest + $NO_2$ + $SO_2$ + number of park + national park + state parks | 14 | 9.14 | 0.402 |
| 1.3 | COVID case + maximum humidity + wind + fire distance + smoke maximum + water + agriculture + forest + $NO_2$ + $SO_2$ + number of park + national park + state parks | 13 | 13.69 | 0.399 |
| 1.4 | COVID case + temperature average + precipitation + wind + fire distance + smoke minimum + urban + water + forest + CO + $NO_2$ + $SO_2$ + national park + state parks | 14 | 20.11 | 0.402 |
| 1.5 | COVID case + vapor pressure deficit + maximum humidity + wind + fire distance + smoke maximum + water + agriculture + grass + population + national park + state parks | 12 | 28.71 | 0.381 |
| 1.6 | COVID death + temperature average + precipitation + wind + fire distance + smoke minimum + urban + water + forest + CO + $NO_2$ + $SO_2$ + national park + state parks | 14 | 59.71 | 0.38 |
| 1.7 | COVID case + minimum humidity + wind + fire distance + smoke maximum + water + agriculture + grass + $NO_2$ + $SO_2$ + number of park + national park + state parks | 13 | 85.11 | 0.315 |
| 1.8 | COVID case + minimum humidity + wind + fire distance + smoke minimum + water + agriculture + grass + CO + $NO_2$ + $SO_2$ + number of park | 12 | 178.71 | 0.342 |
| 1.9 | COVID case + minimum humidity + wind + fire distance + elevation + smoke minimum + water + agriculture + grass + CO + $NO_2$ + $SO_2$ + number of park | 13 | 196.71 | 0.3 |
| 1.10 | COVID case + precipitation + vapor pressure deficit + wind + fire density + smoke maximum + water + agriculture + grass + population + state parks | 11 | 198.71 | 0.31 |

*Note*. We reported the number of covariates included in the candidate models (K), the difference of the Akaike information criterion (AICc) between the candidate model and the top-selected model (ΔAICc), and the global $R^2$.

There were more human visitations to parks detected further to the wildfires in Washington, Oregon, northern California, Montana, New Mexico, and Arizona (Figure 2b). Some states like Wyoming and Colorado show the negative correlations between the number of visits per capita and distance to wildfire before the major wildfire season, however, the trend switch to the opposite after August. A larger number of visits per capita was found in the counties with the larger daily minimum smoke level in the western study area. However, the trends were flipped over in August–September (Figure 2c). Additionally, most counties in the study area showed the negative relationships between the number of visits per capita and toxic gases except some parts in Texas, Washington, and Oregon (Figures 2d–2f).

### 3.2. Results for the Median of Minimum Dwell Time

Similarly, we selected Model 2.1 (Table 3) with the lower AIC value with the predictive power (global $R^2$) of 0.19 as the best model to describe the spatiotemporal pattern of the median minimum dwell time at parks for each county in the study area. For the effects of COVID-19 outbreaks, we found people spent less time in the counties with more positive cases, except Arizona and Utah in June–July and Washington and eastern Montana/Wyoming in August–September (Figure 3a). For the effects of monthly average of minimum smoke, we found the number of counties with positive correlations on the median of minimum dwell time increased from June–September (Figure 3b). For the effects of wildfires, we found people spent more time at parks with higher wildfire density in most counties of the study area (e.g., in Washington, Oregon, Colorado, and New Mexico) in June and July (Figure 3d). However, people avoided the wildfires with the negative correlation between dwell time and wildfire density in most areas in August and September except some parts of California, Colorado, and New Mexico.

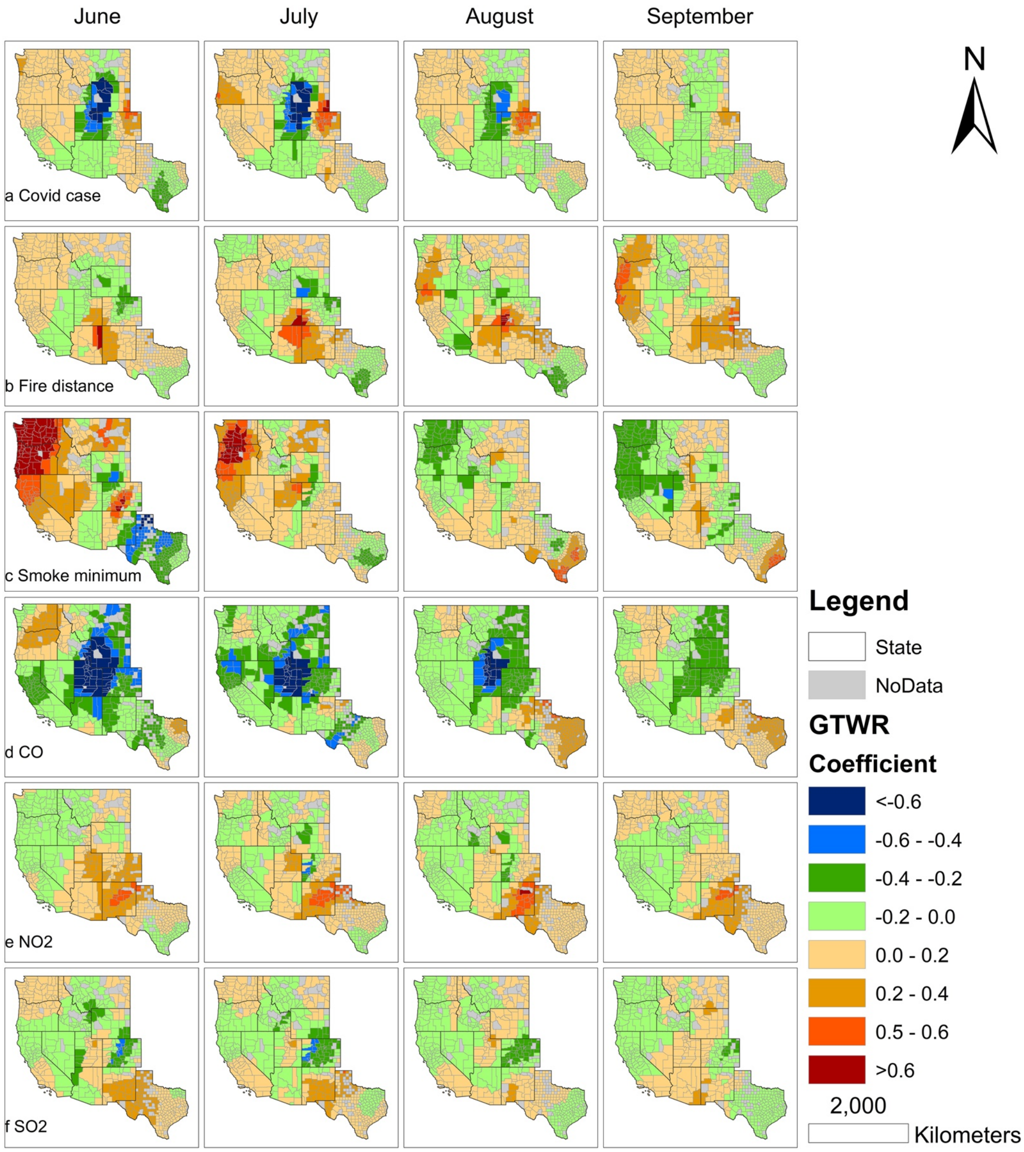


**Figure 2.** Spatiotemporal impacts of (a) COVID cases, (b) fire distance, (c) smoke minimum, (d) CO, (e) $NO_2$, and (f) $SO_2$ derived from the top-selected geographically and temporally weighted regression model on the pattern of the number of visits per population in each county of the western and central US during June–September 2020.

### 3.3. Results for the Travel Distance to Parks

With two competing models (Models 3.1 and 3.2 in Table 4) that are informationally indistinguishable ($\Delta AICc < 2$), we selected Model 3.1 as the top model to describe how different factors affected the travel distance to park, given that both competing models have the same number of variables incorporated and Model 3.1 has a better predictive accuracy of 0.405. We found people traveled a longer distance to parks in some counties with higher COVID-19 positive cases of Montana, Wyoming, Colorado, and New Mexico. However, this pattern diminished gradually from June–September (Figure 4a). For the wildfire effects, we found the travel distance to park is positively correlated with distance to wildfire in western Wyoming, Utah, and New Mexico in June–July (Figure 4c). In August and September, this pattern extended to other parts of the study area, except for the western Montana, Idaho, and Texas. For the effects of the monthly average of maximum smoke, the number of counties with positive correlations decreased significantly from June–September (Figure 4c). People traveled further to the parks with less $NO_2$ level except in Washington and Montana in June–July and to parks with less $SO_2$ level except in northern California, Nevada, and Texas

**Table 3**
*Model Performance and Predictive Accuracy for the 10 Top Candidate GTWR Models to Estimate the Effects on the Median of the Minimum Dwell Time Spent at Parks*

| No. | Model structure | K | ΔAICc | Global $R^2$ |
|---|---|---|---|---|
| 2.1 | COVID case + precipitation + vapor pressure deficit + wind + fire density + elevation + smoke minimum + water + agriculture + grass + number of park + national park | 12 | 0 | 0.19 |
| 2.2 | COVID case + minimum humidity + wind + fire density + elevation + smoke minimum + water + agriculture + grass + number of park | 10 | 7.19 | 0.176 |
| 2.3 | COVID case + precipitation + vapor pressure deficit + wind + elevation + smoke minimum + water + agriculture + grass + number of park + national park | 11 | 13.19 | 0.161 |
| 2.4 | COVID case + precipitation + minimum humidity + wind + elevation + smoke minimum + water + agriculture + grass + number of park + national park + state parks | 12 | 19.44 | 0.164 |
| 2.5 | COVID case + precipitation + vapor pressure deficit+ +wind + fire density + elevation + smoke minimum + water + agriculture + grass + number of park + state parks | 12 | 19.92 | 0.183 |
| 2.6 | COVID case + precipitation + vapor pressure deficit + wind + fire density + elevation + smoke minimum + water + agriculture + grass + number of park + national park + state parks | 13 | 20.59 | 0.185 |
| 2.7 | COVID case + temperature average + precipitation + wind + fire distance + smoke minimum + water + agriculture + grass + CO + $NO_2$ + $SO_2$ + population + national park + state parks | 15 | 59.03 | 0.137 |
| 2.8 | COVID case + precipitation + vapor pressure deficit + wind + fire density + smoke minimum + water + agriculture + grass + CO + $NO_2$ + $SO_2$ + population | 13 | 64.73 | 0.142 |
| 2.9 | COVID case + temperature average + minimum humidity wind + fire density + smoke minimum + agriculture + water + grass + number of park + national park + state parks | 12 | 68.33 | 0.1559 |
| 2.10 | COVID case + precipitation + vapor pressure deficit + wind + fire density + smoke minimum + water + agriculture + grass + population + national park + state parks | 12 | 70.05 | 0.131 |

*Note*. We reported the number of covariates included in the candidate models ($K$), the difference of the Akaike information criterion (AICc) between the candidate model and the top-selected model (ΔAICc), and the global $R^2$.

in August–September (Figures 4d and 4e). The effects of other factors such as the number of state parks, climatic variables, and land cover types for the number of visits per capita, median of minimum dwell time at the park, and travel distance to park were given in Figures S2, S3, and S4 in the Supporting Information S1, respectively.

### 3.4. Results for the Mean Difference Test

We found the local impacts of COVID-19 incidence and wildfire situation in all three top-selected models that were used to estimate spatiotemporal trends of visits per capita, minimum dwell time, and travel distances from home to parks were statistically different between each other (Table 5). This indicates the both factors impacted humen mobility to parks differently.

## 4. Discussion

The pandemic has imposed constraints on people's social behavior, mobility, and daily activities globally (Nouvellet et al., 2021; Van Bavel et al., 2020). Parks and natural open spaces are receiving more attention than the previous years from the public because of their irreplaceable functions for benefiting people's physical and mental health (Geng et al., 2021). Parks provide critical services during the pandemic to support outdoor recreations without violating social distancing restrictions and mitigate the stress associated with COVID-19 (Geng et al., 2021; Xie et al., 2020). Accompanied with the pandemic, massive wildfires in 2020 in the western and central US also affect people's mobility patterns to parks and natural open spaces given the public health concern and the loss of recreation in those places. In this study, we explored three metrics that describe human mobility to parks, including the number of visits per capita, the median of minimum dwell time at parks, and the travel distance to park. Additionally, we examined the effects of different factors, such as the COVID-19 pandemic, wildfires, and drought, on those metrics.

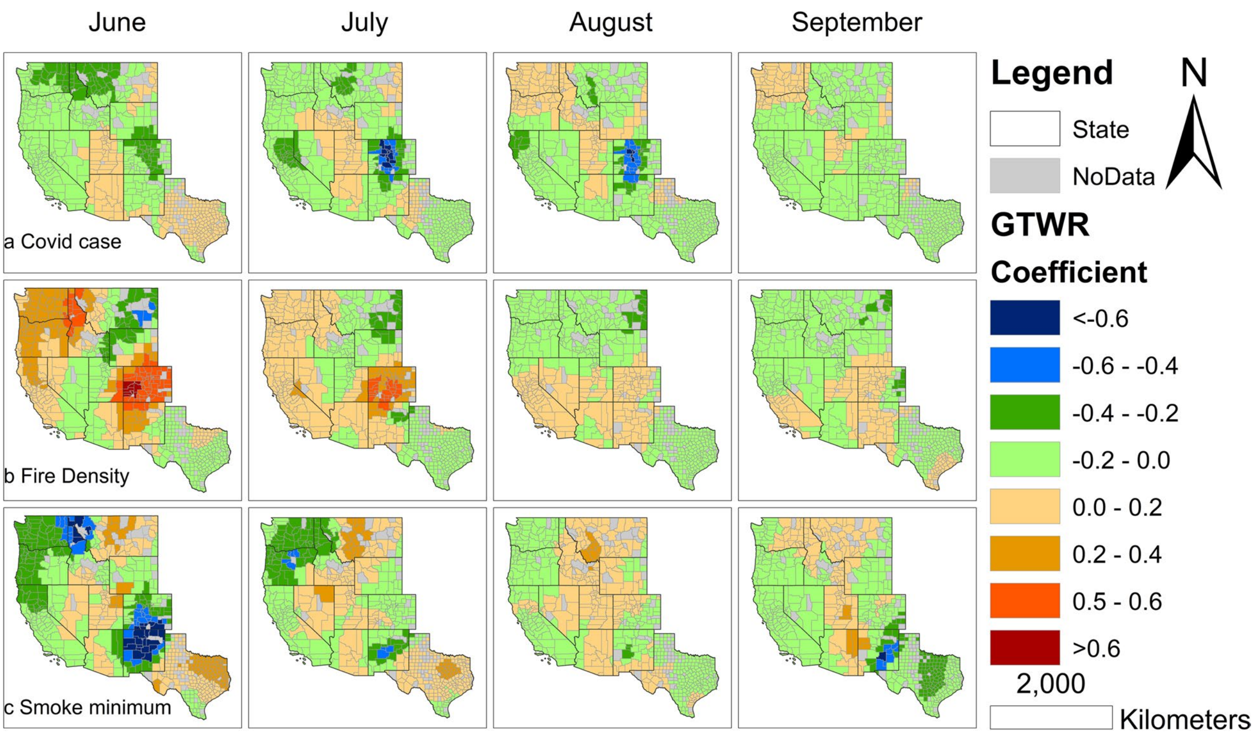


**Figure 3.** Spatiotemporal impacts of (a) COVID-19 cases, (b) fire density, (c) smoke minimum derived from the top-selected geographically and temporally weighted regression model on the pattern of the median minimum dwell time at parks in each county of the western and central US during June–September 2020.

For the effects of the reported COVID-19 cases on how people visit parks, we found local impacts on visits per capita vary significantly over time but with spatial patterns maintained in most counties. Strong negative correlations have been detected in southern Montana, western Wyoming, Colorado, and Utah before the wildfire season, which indicates people avoided visiting the parks when the number of the COVID-19 cases was high in those regions. This reflects similar patterns seen in several previous studies on how infectious diseases might impact the changes in human mobility and behaviors. People who stay at home or avoid places with high disease rates are shown to reduce the links of possible contagion (Funk et al., 2010). However, these strong negative relationships weakened over time from June–September, indicating the decreasing trend of the degree of concern regarding the pandemic, which might result from the increasing registrations and acceptance of vaccines (Al-Amer et al., 2021). In most counties within the study area, people tended to travel closer to parks and spend less time there when more COVID-19 cases were reported, especially in June to August. This pattern might be explained by two possible reasons: people may restrict their long-time outdoor recreation behavior, or, with the stay-at-home order lifted, they spend time doing other things. This is consistent with the findings from Odell (2021), who reported that the time that people spent on physical activity decreased after stay-at-home orders.

We also detected the strong positive patterns between distance to park and COVID-19 incidence rate in Montana and Wyoming in June–July. The COVID-19 cases had a small peak during this period. With some businesses (e.g., public parks, green space, and national parks) reopened as early as June, people might have started to loosen the stay-at-home restrictions and travel to parks or natural open spaces for outdoor recreation following the social distancing practice. The NPI policies and strategies in different states can also affect the spatial variations of COVID-19 impacts on human mobility to parks. For example, with the limited access to national parks and continued restrictive NPI strategies in Wyoming and Utah during June and July, our results indicated the negative relationship between the COVID-19 cases and park visitation (HuschBlackwell, 2021). However, with the slowly reopening parks and more loosened NPI strategies in the southwestern states during June to September, our results showed a positive correlation between COVID-19 cases and park visitation (HuschBlackwell, 2021).

**Table 4**
*Model Performance and Predictive Accuracy for the 10 Top Candidate GTWR Models to Estimate the Effects on the Travel Distance to Park*

| No. | Model structure | K | ΔAICc | Global $R^2$ |
|---|---|---|---|---|
| 3.1 | COVID case + precipitation + wind + fire distance + elevation + smoke maximum + urban + water + agriculture + grass + $NO_2$ + $SO_2$ + state parks | 13 | 0 | 0.405 |
| 3.2 | COVID case + precipitation + wind + fire distance + elevation + smoke maximum + water + agriculture + grass + $NO_2$ + $SO_2$ + number of park + state parks | 13 | 0.86 | 0.404 |
| 3.3 | COVID case + temperature average + minimum humidity + wind + fire distance + smoke minimum + water + agriculture + grass + number of park + national park + state parks | 12 | 4.48 | 0.392 |
| 3.4 | COVID case + precipitation + wind + fire distance + elevation + smoke minimum + urban + water + agriculture + grass + CO + $NO_2$ + $SO_2$ + state parks | 13 | 9.19 | 0.400 |
| 3.5 | COVID case + temperature average + precipitation + vapor pressure deficit + wind + fire distance + smoke minimum + water + agriculture + grass + population + national park + state parks | 13 | 14.86 | 0.380 |
| 3.6 | COVID case + precipitation + wind + fire distance + elevation + smoke minimum + water + agriculture + grass + CO + $NO_2$ + $SO_2$ + number of park + state parks | 13 | 15.42 | 0.411 |
| 3.7 | COVID case + temperature average + precipitation + wind + fire distance + smoke maximum + water + agriculture + grass + $NO_2$ + $SO_2$ + number of park + national park + state parks | 14 | 27.11 | 0.389 |
| 3.8 | COVID case + precipitation + wind + fire distance + smoke minimum + water + agriculture + grass + number of park + national park + state parks | 13 | 40.11 | 0.374 |
| 3.9 | COVID case + temperature average + precipitation + wind + fire distance + smoke minimum + water + agriculture + grass + CO + $NO_2$ + $SO_2$ + population | 13 | 42.35 | 0.392 |
| 3.10 | COVID case + precipitation + vapor pressure deficit + wind + fire distance + smoke minimum + water + agriculture + grass + CO + $NO_2$ + $SO_2$ + number of park + state parks | 14 | 743.02 | 0.404 |

*Note*. We reported the number of covariates included in the candidate models ($K$), the difference of the AICc between the candidate model and the top-selected model (ΔAICc), and the global $R^2$.

Our results also indicated that people who visit parks tended to avoid wildfires and smoke in most counties during the wildfire seasons. Particularly, during the major wildfire season (August to September), more park visits and lower dwell time were found in parks away from wildfires in Washington, Oregon, California, Colorado, and New Mexico. Moreover, we found the travel distances to park were positively correlated with the distance to wildfires during the wildfire season in most of the counties. This indicated that people closer to fires might avoid travel to parks nearby or travel long distance to parks away from wildfires. Previous studies found that wildfires are likely to have negative impacts on recreation, and those impacts could potentially last post-fire for a while (Flowers, 1985; Loomis et al., 2001). However, some studies also suggested that people's curiosity about the wildfire events and their impacts can encourage their visitations close to wildfires (Sánchez et al., 2016), especially for the areas where fires only occasionally occur. In places with a long history of wildfire records, people may be less interested in wildfires and not change their recreation behaviors during the wildfire seasons (e.g., keep visiting the parks or open spaces close to fires).

Wildfire smoke exposure can have serious impacts on human health, causing direct death, respiratory, cardiovascular, mental, and perinatal diseases. Smoke can be transported far away from fires and affect people there (Kollanus et al., 2016). Our findings suggested that between June and July, the monthly average of the daily minimum smoke value was positively correlated with the number of visitors but negatively correlated with the dwell time at the parks, indicating that people still visited parks when the daily minimum smoke was quite large but cut the time they stayed in the park. During the major wildfire season, people tended to visit the parks with less smoke and lower toxic gas levels in the western part of the study area. Given that people follow common sense health protection behaviors, people might avoid outdoor recreation, especially people with respiratory diseases like asthma and chronic obstructive pulmonary disease (Henderson et al., 2011; Moore et al., 2006; Rappold et al., 2011; Reid et al., 2016). Additionally, given the growing evidence of associations between wildfire smoke exposure and the increased risk of respiratory infections (Martin et al., 2013; Reid et al., 2016), people are more likely to feel more stress and concerns about wildfire-induced smoke under the COVID-19 pandemic.

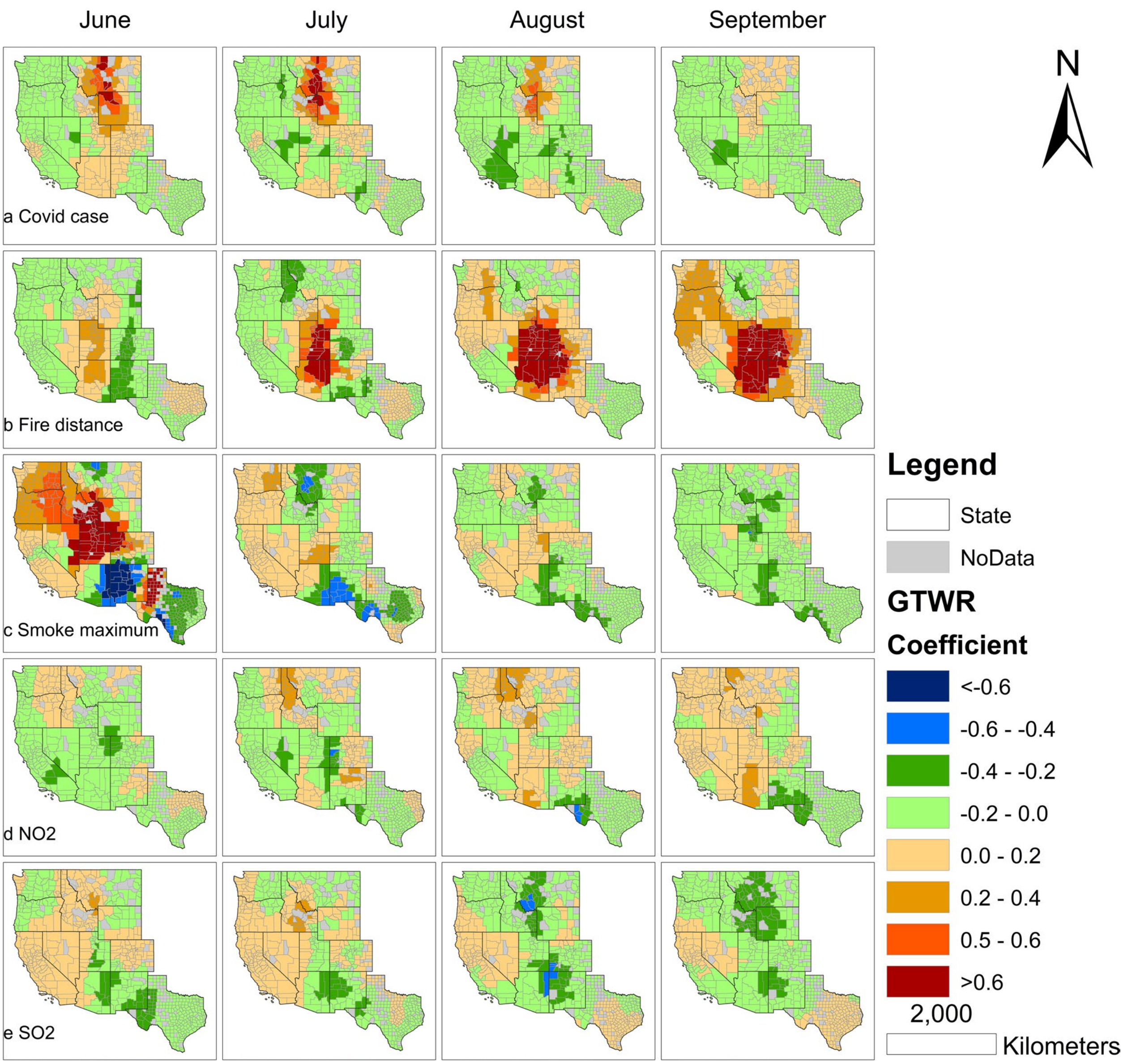


**Figure 4.** Spatiotemporal impacts of (a) COVID cases, (b) fire distance (c) smoke maximum, (d) $NO_2$, and (e) $SO_2$ derived from the top-selected geographically and temporally weighted regression model on the pattern of the travel distance to park in each county of the western and central US during June–September 2020.

Our study is not without limitations. First, to explicitly understand how wildfires impact human recreation behaviors, it is critical to study the historical wildfire records locally, since people's attitudes to the fires can vary in space and time due to many factors like their experience with wildfires and education levels (Edgeley & Burnett, 2020). Second, the top-selected model only explained 19% of the variance in the spatiotemporal patterns of the median of minimum dwell time at parks, indicating that there could be some other factors that might impact the time that people spent. Although we considered national and state parks in each county in the analyses, parks with different recreation purposes, facilities, sizes, and features can also determine the group of visitors they attract, the purpose of their visits, and the time they spend in those places (Larson et al., 2010; Xiao, Lee, & Larson, 2021; Zhai et al., 2018). Thus, consideration of the detailed park conditions is needed for future studies to estimate the spatiotemporal patterns of human

**Table 5**
*The Differences of Local Impacts Between the COVID-19 Incidence Rate and Wildfire Related Variables Based on Welch's t-Test*

| Model | Variable 1 | Variable 3 | *t* | DF | *p*-value |
|---|---|---|---|---|---|
| Model 1.1 | Fire distance | COVID case | 7.3311 | 4,628.6 | <0.001 |
| Model 2.1 | Fire density | COVID case | 21.142 | 4,243 | <0.001 |
| Model 3.1 | Fire distance | COVID case | 14.189 | 3,189.7 | <0.001 |

mobility to parks. Third, this study explored the spatiotemporal patterns of human mobility to parks during the pandemic and wildfire season at the monthly scale without the consideration of the intra-month variations. However, human mobilities, COVID-19 outbreaks, and wildfire situations can vary in daily or even at a much finer scale. Thus, we may expect different spatiotemporal effects of the COVID-19 pandemic and wildfires on human mobility to parks at other scales.

## 5. Conclusions

This study investigated how the cooccurrence of the 2020 COVID-19 pandemic and wildfires impact the spatiotemporal patterns of human mobility to public parks. We employed the GTWR models to examine the effects of the COVID-19 pandemic, wildfires, and the wildfire-induced air pollution on three metrics that describe people's mobility to parks, including the number of visits per capita, their dwell time at parks, and the travel distance to park. Our findings suggested a general trend of avoidance to the parks, with fewer visitors and dwell time in the places with high COVID-19 cases, which is likely due to people's infection protection behavior and risk attitude. However, in June, with the movement restriction orders just lifted, some long-distance travels to parks were observed in some counties in Montana, Wyoming, and Colorado. We also found that people tended to travel further and spend longer time at the parks away from wildfires with less smoke, especially during the major wildfire seasons between August and September. Our findings are helpful to understand the spatiotemporal patterns of human recreation and social behaviors under multiple severe crises, which can support the preparation and mitigation of future threats to people's health and wellbeing.

## Conflict of Interest

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

## Data Availability Statement

All the data being used in this study can be archived from figshare at https://doi.org/10.6084/m9.figshare.15023253.v1.

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