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Understanding changes in park visitation during the COVID-19 pandemic: A spatial application of big data

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A R T I C L E I N F O

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A B S T R A C T

In the spring of 2020, the COVID-19 pandemic changed the daily lives of people around the world. In an effort to quantify these changes, Google released an open-source dataset pertaining to regional mobility trends—including park visitation trends. Changes in park visitation are calculated from an earlier baseline period for measurement. Park visitation is robustly linked to positive wellbeing indicators across the lifespan, and has been shown to support wellbeing during the COVID-19 pandemic. Therefore, this dataset offers vast application potential, containing aggregated information from location data collected via smartphones worldwide. However, empirical analysis of these data is limited. Namely, the factors influencing reported changes in mobility and the degree to which these changes can be directly attributable to COVID-19 remain unknown. This study aims to address these gaps in our understanding of the changes in park visitation, the causes of these changes (e.g., safer-at-home orders, amount of COVID-19 cases per county, climate, etc.) and possible impacts to wellbeing by constructing and testing a spatial regression model. Results suggest that elevation and latitude serve as primary influences of reported changes in park visitation from the baseline period. Therefore, it is surmised that Google's reported changes in park-related mobility are only partially the function of COVID-19.

The COVID-19 pandemic presents an unprecedented health crisis to the global community (Stier et al., 2020). The rapid and volatile evolution of the crisis has been met with widespread calls for quality big data sources and analytics concerning all aspects of its spread and related impacts (i.e., Ienca and Vayena, 2020; Ting et al., 2020). Additionally, numerous requests have been made concerning the need for data on outdoor recreation patterns, travel behavior, and park visitation (e.g., Salama, 2020; Samuelsson et al., 2020). Outdoor recreation and park visitation data, specifically, are important for understanding compliance with safer-at-home orders (Tufan and Kayaaslan, 2020), economic impacts of the pandemic (Jamal and Budke, 2020), and communities' wellbeing and their capacities for coping with the crisis (Rung et al., 2011). Park visitation is robustly linked with wellbeing indicators across the lifespan (Dzhambov et al., 2020; Holland et al., 2018; Thomsen et al., 2013), including mental health (see reviews by Collins et al., 2020; Houlden et al., 2018; Vanaken and Danckaerts, 2018), obesity (see review by Jia et al., 2020), asthma (see review by Hartley et al., 2020), and host of other medical outcomes (see review by Kuo, 2013). Additionally, outdoor recreation and access to parks increase communities' resilience to crisis and aid in their coping process (Rung et al., 2011; Samuelsson et al., 2020). By providing spaces for nature-based leisure experiences, parks often serve as places of restoration for those dealing with crisis (Samuelsson et al., 2020). As demonstrated by Buckley and Westaway (2020), these experiences are vital for maintaining wellbeing during the COVID-19 pandemic. Thus, it is imperative that decision-makers have quality data and timely insights concerning park use during the pandemic to ensure proper management and provide indicators of public health. Big data have already proved useful in understanding and controlling the spread of the virus (Wang et al., 2020). Therefore, parties such as public health officials, park managers, tourism operators, and other decision-makers might also benefit from using big data to understand how park visitation is changing during the pandemic and what is influencing the changes in park visitation. These insights could improve parks' management and increase community resilience to the health crisis (Salama, 2020). However, such analysis (reviewed in the succeeding section) has been sparse. Hence, this study aims to address these gaps in our understanding of the factors contributing to changes in park visitation during this pandemic and, at the same time, assess the efficacy of Google's big data source in providing valid insights.

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1. Big data for park and outdoor recreation research

Big data have three dimensions: volume, velocity, and variety (Miller and Goodchild, 2015). Therefore, big data are not necessarily defined by their sheer size. Miller and Goodchild (2015) define big data as those data that "outstrip our capabilities to analyze" (pp. 449–450). Three primary forms of big data exist in leisure and tourism studies: transaction data, device data, and user-generated data (Li et al., 2018). Li et al. (2018) assert that big data have a low-value density. This means that these data have relatively low utility per unit compared to more traditional datasets (e.g., surveys), where each unit within a sample may provide a depth of information on a number of issues of interest. However, when units are available in mass quantities, high amounts of value can be extracted from the total sum—thus making up for this limitation. For example, a twenty-question survey taken by 300 respondents contains a high-value density per unit (respondent). However, it is possible that a similar or greater volume of information can be gathered from analyzing tweets from 30,000 individuals.

Monz et al. (2019) note that device data have been used most often to collect data associated with park visitor use, often in the form of GPS tracking. Examples of big data sources applied toward measuring park visitation include Flickr (Fisher et al., 2018), Instagram (Tenkanen et al., 2017), Strava (Norman and Pickering, 2019), Twitter (Tenkanen et al., 2017), and national park campground reservations (Rice et al., 2019). These studies have been able to utilize big data to assess differences in visitation between sites and seasons. Additionally, a growing number of studies have demonstrated the value of park-related big data toward understanding linkages to wellbeing—a concept defined in this context as being inclusive of “the basic materials for a good life, freedom of choice and action, health, good social relationships, a sense of cultural identity, and a sense of security” (Díaz et al., 2006). Herrera et al. (2017) and Rasolofoson et al. (2018) examined how proximity to protected areas influences children’s health in developing countries using data from hundreds of thousands of households in 35 and 27 countries, respectively. Engemann et al. (2019) used health records data from nine hundred thousand individuals and remote sensing data from Denmark to assess how access to green space influences mental health among children. Rice et al., 2020b used data from over one hundred thousand parks and protected areas in the eastern United States to assess how conservation status of parklands influences the abatement of noise in surrounding communities. Ferster et al. (2021) examined bicyclists’ exposure to safety risks along greenways, pathways, and roadways throughout Ottawa, Canada using eight million activities recorded on Strava—a spatially enabled physical activity-focused social media app.

Throughout the COVID-19 pandemic, big data sources have been heralded as a necessary tool in combating the advance of the virus (Ienca and Vayena, 2020; Zhou et al., 2020). Applications include using health insurance and customs datasets to generate alerts for clinical visits based on health and travel histories (Wang et al., 2020), smartphone location data to support government decision-making (Gao et al., 2020), and social media data to explore rhetoric surrounding responses to the pandemic (Li et al., 2020). Venter et al. (2020) used data generated via the Strava fitness app to examine changing patterns in urban park use in Oslo, Norway. However, the authors did not directly examine the sources of these changing use patterns, unlike the present study. Instead, we move beyond descriptive analysis by using aggregated location data from smartphones, like Gao et al. (2020), to examine the factors influencing changes in park visitation, not just the changes themselves.

Big data—regardless of its application—has limitations. Primary among its epistemological issues is the question of causality (Ekbia et al., 2015). As noted by Xiang et al. (2017), this issue centers around "the validity of claims about causal relationships, as opposed to mere statistical correlations, within the data" (p. 52). In short, without proper theory to guide big data analysis and field experiments, false assumptions about causality can be made (Ekbia et al., 2015). Previous research using big data to examine park visitation has noted additional limitations. Venter et al. (2020) note that park visitation data that is sourced from social media (e.g., Strava, Twitter, Flickr, Facebook, etc.) often fails to contain information about who the data is sourced from, therefore potentially hiding biases across socio-economic gradients. Fisher et al. (2018) confirmed the presence of such a bias in their study of visitor use in Mt. Baker National Forest (USA), finding that age demographics of Flickr users posting in the forest were not representative of recreationists at large. Tenkannen et al. (2017) provide another common example of bias from a park visitation perspective—inconsistencies in connectivity. In their study of park visitors in Finland and South Africa using Instagram, Twitter and Flickr data, the authors note considerable differences in the wireless connectivity across parks (Tenkannen et al., 2017). Therefore, the amount of data across park sites are biased by cell reception.

With the COVID-19 pandemic, additional concerns have been made about responsible gathering and analysis of big data. Ienca and Vayena (2020) note, "Authorities should be mindful that precisely because personal data may contain valuable information about the social interactions and recent movements of infected people, they should be handled responsibly" (p. 464). This responsibility includes drawing reasonable conclusions from data concerning causality and communicating what the data represent clearly (Zook et al., 2017).

2. Google’s community mobility reports

On April 3rd, 2020, Google released its first set of Community Mobility Reports (Fitzpatrick and DeSalvo, 2020). These reports were issued in response to public health officials who reached out to Google, positing that "aggregated, anonymized data could be helpful as they make critical decisions to combat COVID-19" (Fitzpatrick and DeSalvo, 2020, para. 1). The heading on the reports’ website beckons visitors to "see how your community is moving around differently due to COVID-19" (Google 2020b). The reports are based on location data from "aggregated, anonymized sets of data from [Google] users who have turned on the Location History setting, which is off by default" (Google 2020b). However, the percentage of Google users who have their location history turned on is unknown. The reports breakdown mobility locations into six categories: grocery and pharmacy, parks, residential, retail and recreation, transit, and workplaces (Google, 2020a). Along with their reports, Google provides open-source data for all regions where reports are available (Google, 2020c). The sizes of these datasets themselves are not overwhelming since they can be handled comfortably with a spreadsheet on a computer; however, they represent the aggregation of at least tens of millions of users’ location history in Google Maps. Following the release, the reports received continued interest from syndicated news sources around the world, including The New York Times (i.e., Dave, 2020), the British Broadcasting Corporation (i.e., Kelion, 2020), Forbes (i.e., Togoh, 2020), The New Zealand Herald (i.e., Collins, 2020), The Peninsula (Doha, Qatar) (i.e., Ataullah, 2020), the Daily Nation (Nairobi, Kenya) (i.e., Nanjala, 2020), and the Financial Express (India) (i.e., Bhandari and Chaudhary, 2020). Representative headlines include: "Google location data for Seattle shows decline in work, transit and retail trips — but not park visits" (Nickelsburg, 2020) and "Mobility data shows a massive boost for Blount parks after COVID-19 outbreak" (Jones, 2020). However, issues of causation remain unclear concerning users’ mobility patterns with the pandemic. Specifically, park mobility (or visitation) is strongly linked to seasonality (Hewer et al., 2015; 2016). It is possible that changes in park visitation reported by Google are not entirely attributable to the COVID-19 pandemic.

3. Study purpose

Limited attempts have been made to analyze the Community Mobility Report data (see Chan et al., 2020; Zhu et al., 2020). Therefore, the data remain largely unexplored in the areas of wellbeing and leisure activities, and the efficacy of the big data source remains

Table 1
Variable summary.

Variable Name	Definition	Source	Min.	Max.	Mean
Park Visitation	Average percent change in daily park use among county residents during the study period (April 1st – June 30th, 2020) from the baseline period. Baseline use is calculated are the median values, for the corresponding day of the week, during the 5-week period January 3rd to February 6th, 2020.	Google (2020b)	−59.0	101.8	20.2
Population density	Population per square mile based on 2018 census data	United States Census Bureau (2018)	1.8	18,384.2	514.5
Median age	Median age of county residents based on 2018 census data	United States Census Bureau (2018)	29.6	53.9	39.1
Duration of Safer-at-home order	Number of days throughout the study area where county-level safer-at-home order was in place	Killeen et al. (2020)	38	72	46.7
Confirmed COVID-19 Cases within county	Total confirmed cases within county as of June 30th, 2020	Centers for Disease Control and Prevention (2020)	5	103,529	3,737.2
Latitude	Centroid latitude of county	ESRI (2020)	37.0	62.5	49.3
Elevation	Average elevation (meters) of county	ESRI (2020)	1	2,118	356.1
Population within $\frac{1}{2}$ mile of park	Portion of population within a buffer of $\frac{1}{2}$ mile radius of a park	Centers for Disease Control (2019)	0.12	0.99	0.59

untested. The factors causing these changes in mobility and the degree to which these data represent changes directly due to COVID-19 remain unknown. Therefore, the purpose of this study is to answer calls by Salama (2020) and Samuelsson et al. (2020) for COVID-19-related research concerning outdoor recreation and park visitation by using Google's park mobility data to assess the following two related research questions:

R1: What factors influenced changes in park visitation in the western United States during the spring of 2020 in the midst of the COVID-19 pandemic?

R2: To what degree are Google's data on changes in park visitation attributable to the COVID-19 pandemic?

4. Methods

4.1. Study area

The geographic scope of this research was determined by data availability. Google's park mobility data are unavailable throughout much of the United States due to a lack of location history data as turned on by Google users (Google, 2020c), making a national spatial model unfeasible (Chi and Zhu, 2019). It was hence determined that the largest continuous swath of available data be used instead. This determination yielded 97 counties in the Western region of the United States—including Arizona, California, Nevada, Oregon, and Washington—that had park mobility data available for at least half of the days throughout the study period (Fig. 1). This area has substantial variation across the rural-urban continuum and a large spectrum of elevations and latitudes (see Table 1).

4.2. Data

4.2.1. Dependent variable

The dependent variable in the spatial model was change in park visitation at a county-level. This variable was sourced from Google's COVID-19 Community Mobility Reports (Google, 2020c). The park visitation portion of this dataset provides county-level "mobility trends for places like national parks, public beaches, marinas, dog parks, plazas, and public gardens" (Google, 2020a, p. 1). Trends are presented as daily percentages of the change in the number of visits and length of stay at parks on an aggregated county level. Counties, political sub-units within U.S. states, within our study area ranged from 122 km^2 to 51,960 km^2, with an average area of 9,025 km^2 and median area of 4,873 km^2. Change in park visitation is calculated from the "baseline" or "the median value" for the corresponding day of the week during the 5-week period January 3rd–February 6th, 2020 immediately preceding COVID-19′s widespread emergence in the U.S. (Google, 2020a, p. 52). In this way, a coefficient was generated for 2,791 U.S. counties representing the average daily change in park mobility from April through June 2020. Those counties with mobility data available for at least half of the days within the study period were considered for further analysis, ultimately yielding 97 counties in the western region of the United States.

4.2.2. Independent variables

Table 1 summarizes the independent variables included in the model. These variables were selected based on 1) previous research or policy goals related to controlling and adapting to the COVID-19 pandemic and preserving wellbeing or 2) park visitation. Variables directly related to the COVID-19 outbreak included: population density, median age, the duration of county-level safer-at-home orders, and the number of confirmed cases. Population density is linked to the transmission rate of the COVID-19 (Stier et al., 2020). Age is also linked to the severity of illness associated with COVID-19 (Lloyd-Sherlock et al., 2020). Given that both median age and population density were included within the model, the trend of rural areas generally having a higher proportion of older individuals is controlled (Rogers, 2002). It has also been posited that the number of confirmed cases within an area may impact behavior and decision-making (Tufan and Kayaaslan, 2020). The total number of confirmed cases was operationalized instead of cases per capita, as it was determined that it best captured the effect of the virus's spread. Van Bavel et al. (2020) noted that gross reporting of the numbers of cases is potentially most impactful on human behavior. Per capita reporting may be less impactful as it can appear to present numbers of lower magnitude. In an effort to control the virus, stay-at-home (or safer-at-home) orders have been issued by various scales of governments around the world (Tufan and Kayaaslan, 2020). County-level restrictions were operationalized to assess the impact of safer-at-home orders. However, it should be noted that all states within the study area also had active safer-at-home orders at times during the study period. Additionally, variables directly-related to park visitation were included in the model. The proportion of county residents living within one-half mile of the edge of a park boundary was used as a measure of park access (Sato et al., 2019; Ussery et al., 2016), and the centroid latitude and mean elevation of counties were included to partially account for different climates (Hewer et al., 2015; 2016).

Additional variables were initially included in the model but were removed stepwise according to their multicollinearity with other variables. The duration of state-level safer-at-home orders was initially included but was removed due to high multicollinearity with county-level safer-at-home orders. Additionally, variables representing differences in

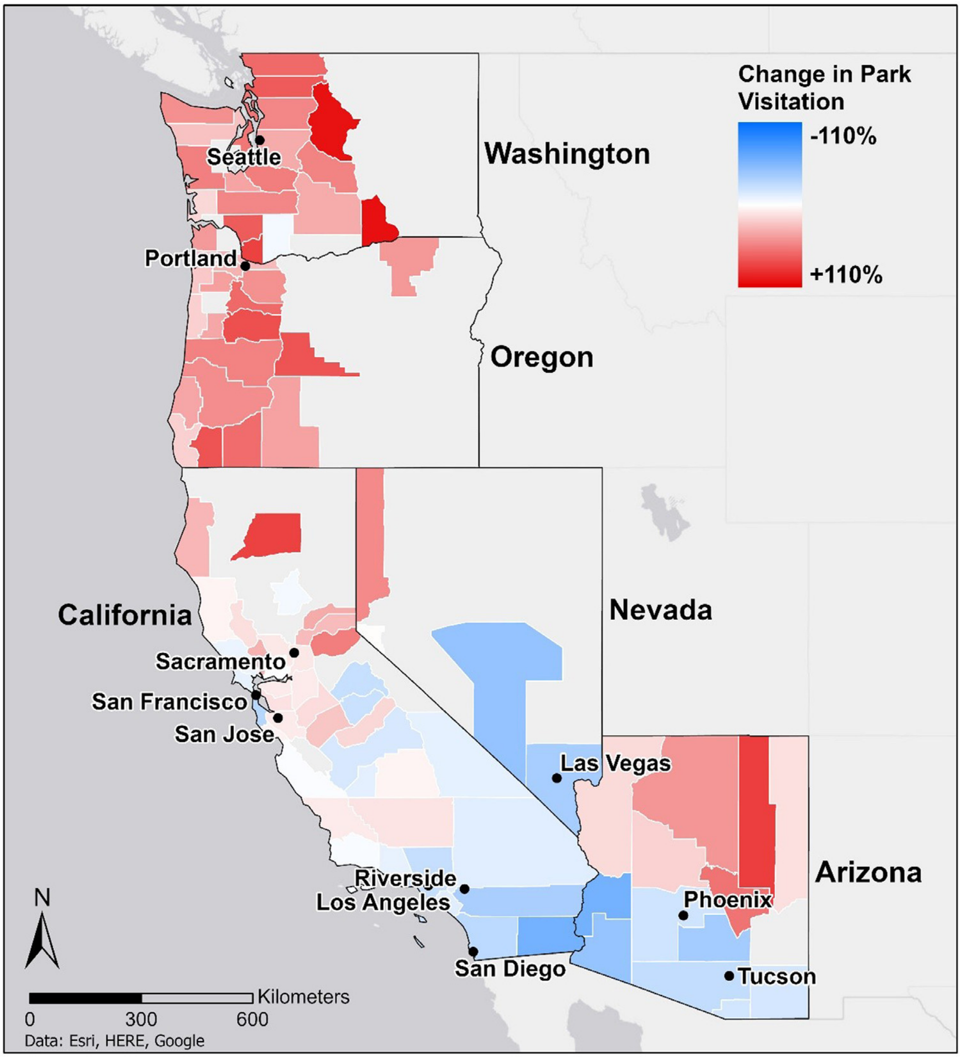

Fig. 1. Change in park visitation across the study area from the baseline period (January 3rd - February 6th, 2020) to the study period (April 1st - June 30th, 2020).

1) monthly average precipitation from April-June 2020 and January-February 2020 and 2) average daily temperature from April-June 2020 and January-February 2020 were initially included but were removed due to high multicollinearity with latitude and elevation. Each of the three removed variables was selected for removal instead of their related remaining variable(s) based on their lesser observed impact on the dependent variable. Finally, cases-per-capita was trialed in lieu of gross cases. However, no substantive change was observed in the significance of its impact on the dependent variable.

4.3. Spatial model

Given that park visitation is a spatial phenomenon, it is important to analyze it within the context of space (see Schägner et al., 2016; Wuepper and Patry, 2017). Additionally, visitation across counties and relationships among county governments may lead to spatial autocorrelation (Chi and Zhu, 2019). Therefore, spatial regression techniques were used for this analysis to account for spatial dependence and autocorrelation (Chi and Zhu, 2019). Variables were combined into a common shapefile using ArcGis Pro (ESRI, 2020). Subsequent analysis was undertaken in Geoda and Geoda Space (Anselin et al., 2006). This analysis followed the study procedure of Chi and Marcouiller (2013), where a neighborhood structure was first established through a spatial weight matrix followed by testing for autocorrelation and spatial dependence, and lastly, a spatial regression model was formulated based on the results of the previous steps.

4.4. Spatial weight matrix

Prior to assessing autocorrelation and spatial dependence, a spatial weight matrix must be generated to establish a system projecting how counties relate to their neighbors (Chi and Zhu, 2019). Since there is no established theory to guide the creation of spatial weight matrices related to park visitation (see Schägner et al., 2016; Wuepper and Patry, 2017), a data-driven approach was adopted. Following the guidelines provided by Chi and Zhu (2019), various spatial weight matrix styles were tested, each with varying levels of orders or distance. These included: Nearest Neighbor Continuity, Queen's Continuity, Distance, and Inverse Distance (Table 2). Each of these matrix styles determines what units can be considered neighbors (referred to as a neighborhood structure) in different ways (see Chi and Zhu, 2019). A neighbor is a unit that interacts with a proximate unit in a meaningful way (Kelejian and Piras, 2017). These neighborhood structures may be produced for multiple orders. In a first-order spatial weight matrix, only true neighbors of a unit as defined by the underlying matrix may be considered its neighbors. In a second-order spatial weight matrix, the neighbors of a unit's true neighbors are also considered its neighbors. Following Chi and Zhu (2019), matrices were assessed based on their resulting Moran's I—a measure of similarity between neighboring units—in relation to the park

Table 2
Spatial dependence captured by spatial weight matrices.

Spatial Weight Matrix	Moran's *I*	Mean Number of Neighbors
2 Nearest Neighbors	0.647***	2.00
3 Nearest Neighbors	0.614***	3.00
4 Nearest Neighbors	0.595***	4.00
2 Nearest Neighbors, Inverse	0.647***	2.00
3 Nearest Neighbors, Inverse	0.648***	3.00
4 Nearest Neighbors, Inverse	0.622***	4.00
Queen's Continuity, Order 1	0.667***	3.63
Queen's Continuity, Order 2	0.563***	9.15
Distance – 85 kms	0.550***	2.45
Distance – 100 kms	0.612***	3.48
Distance – 115 kms	0.615***	4.72
Distance – 130 kms	0.590***	5.96
Inverse Distance – 85 kms	0.593***	2.45
Inverse Distance – 100 kms	0.601***	3.48
Inverse Distance – 115 kms	0.596***	4.72
Inverse Distance – 130 kms	0.590***	5.96

*$p < .05$. **$p < .01$.
*** $p < .001$. Moran's *I*, higher = better.

visitation variable (Table 2). Queen's Continuity (Order 1) captured the greatest amount of spatial dependence (0.667, $p < .001$). Therefore, it was selected as the spatial weight matrix for subsequent analysis. Within this matrix, only two counties were isolated—having no neighbors.

4.5. Model specification

Given that a first-order Queen's Continuity spatial weight matrix resulted in a Moran's *I* of the dependent variable equal to 0.647, the data were determined to be clustered or positively autocorrelated (Chi and Zhu, 2019). An Ordinary Least Squares (OLS) regression was conducted to determine the nature of the spatial dependence within the data. Robust Lagrange Multiplier (LM) tests were used to assess spatial lag and spatial error effects within the OLS results at a 95 percent confidence interval (Chi and Zhu, 2019). LM tests revealed a significant spatial lag effect (5.91, $p = .015$), meaning that the value of the dependent variable in one county is affected significantly by independent variables in both that county and its neighboring counties. In turn, it was determined that a spatial lag model (SLM) should be used in our final regression:

$$
\begin{aligned}
&Y = C + \beta_1(\text{Population density}) + \beta_2(\text{Median age}) \\
&+\beta_3(\text{Safer\_at\_home order}) + \beta_4(\text{Cases}) + \beta_5(\text{Latitude}) + \beta_6(\text{Elevation}) \\
&+\beta_7(\text{Pop. within 0.5 mi. of park}) + \rho W Y + \varepsilon
\end{aligned}
$$

In this model, Y represents the dependent variable—park visitation changes from the benchmark period reported by Google Mobility Reports. The regression coefficients are represented by β_x. The scalar spatial lag parameter is represented by ρ. The spatial weight matrix is represented by W. The spatially lagged variable is represented by WY. The constant is *C*. The error terms that are not identically distributed are represented by the vector ε (Chi and Zhu, 2019). This model was assessed for multicollinearity. Collinearity is a measure of the non-independence of independent variables in a model. Multicollinearity refers to the positive linear relation between independent variables that can lead to unstable parameter estimates, inflated standard errors, and biased inference statistics (Dormann et al., 2013).

5. Results

A comparison between the descriptive results of the OLS model and SLM is listed in Table 3. AIC—a measure used to compare fit between models—and R^2 statistics indicate that the SLM had a better model fit. The full results of the SLM are summarized in Table 4. The multicollinearity condition number (27.12) is less than 30, indicating that significant multicollinearity is not present in the model (Chi and Zhu, 2019; Dormann et al., 2013). However, it does fall within the bounds of moderate collinearity (> 10) (Dormann et al., 2013). The non-significant results ($p > .05$) of the Breusch-Pagan and likelihood ratio tests show that the spatial lag model resolved the issues of heteroskedasticity and spatial lag. The R^2 for this model indicates that the independent variables' variance account for 62% of that within the dependent variable. On average, among 97 counties in the study area, there is a 20.2% increase in park visitation compared to the baseline period prior to the pandemic.

Table 3
Comparison of Model Fit.

Model	R^2	AIC	BIC
OLS	0.576	896.614	917.212
SLM	0.623	895.699	918.871

AIC = Akaike info criterion. BIC = Schwarz criterion.

Table 4
Results from SLM regression.

Variable	Coefficient	Standard Error	p-value
Population density	−0.0004	0.0013	0.7450
Median age	−0.7954+	0.4123	0.0537
Duration of safer-at-home order	−0.4693+	0.2613	0.0726
Confirmed Cases	−0.0002	0.0002	0.2645
Latitude	3.33057***	0.5757	< 0.0001
Elevation	0.0135**	0.0049	0.0063
Pop. within $\frac{1}{2}$ mile of park	−4.5577	14.4969	0.7532
Spatial lag effect	0.2090+	0.1140	0.0667
Constant	−96.0302***	27.4610	0.0005

+ $p < .075$.*$p < .05$.
** $p < .01$.
*** $p < .001$$R^2 = 0.623$AIC = 895.699BIC = 918.871Multicollinearity condition number = 27.12Breusch-Pagan test: 13.26, $p = .066$Likelihood Ratio Test: 2.92, $p = .088$.

5.1. R1: What factors influenced changes in park visitation in the western United States during the spring months of 2020 in the midst of the COVID-19 pandemic?

Two variables were found to have statistically significant predictive relationships with the change in park visitation. Elevation and latitude were positively related to change in park visitation at 99% and 99.9% confidence intervals, respectively. Median age and duration of safer-at-home orders were negatively related to change in park visitation at a 92.5% confidence interval, below 95%, but still worthy of note given their borderline significance. All other variables had non-statistically significant relationships. Regarding the effects of elevation and latitude on park visitation, results suggest that a 100-meter increase in elevation results in a 1.3% increase in park visitation from the baseline period. Conversely, a one-degree increase (or movement north) in latitude results in a 3.33% increase in park visitation from the baseline period. The spatial lag effect indicates that a county can expect to experience a 2.1% increase in park visitation for each 10% increase among its neighbors.

5.2. R2: To what degree are Google's data on changes in park visitation attributable to the COVID-19 pandemic?

Of the independent variables directly related to COVID-19, only median age and duration of safer-at-home orders were shown to have a borderline significant prediction of park visitation. Population density, confirmed cases, and access to parks were not significantly predictive of park visitation changes. This result—paired with the strong effects of elevation and latitude—suggests that much of the change in park visitation reported in Google's park mobility data during the spring months of 2020 is not the direct result of the pandemic, but is instead the result of possible climatic effects.

6. Discussion

On average, park visitation increased 20.2% at a county-level from the baseline period to the study period. All else being equal, this purveys that study area residents—on the whole—were able to visit and recreate in parks despite the impacts of the COVID-19 pandemic. This provides key insight into the well-documented concern that wellbeing may be negatively impacted by disconnection with park spaces during the pandemic (e.g., Slater et al., 2020; Soga et al., 2020). The findings of this study are consistent with those from East Asia (Lu et al., 2020), Germany (Derks et al., 2020), and Norway (Venter et al., 2020). However, our results reveal that this increase in visitation is neither uniform across space nor demographics.

6.1. Elevation and Latitude's impact on park visitation

The results of this analysis indicate that COVID-19 accounts for only a portion of the change in park visitation reported by Google. Climate, by way of elevation and latitude, is also a significant force of change, as noted in previous research (see Hewer et al., 2016; Smith, 1993). Google's baseline period—from which COVID-19 era mobility data are compared—spans from January 3rd to February 6th, 2020. At higher elevations and more northern latitudes of the study area, January weather can be rather inhospitable to outdoor recreation and park visitation. In January 2020, the overall average temperature in Seattle, Washington (latitude: 47.6° N) was 45°F (National Weather Service, 2020). In Flagstaff, Arizona (elevation: 2,106 m) it was 30.2°F (National Weather Service, 2020). During the spring months of 2020, the average temperatures in Seattle and Flagstaff had risen to 57.8°F and 53.5°F, respectively (National Weather Service, 2020). January temperatures in higher elevations and northern latitudes within the study area are substantially colder than those experienced in large population centers in the lower elevations and more southern portions of the study area (e.g., Los Angeles, Las Vegas, and Phoenix) (National Weather Service, 2020). Large seasonal changes in outdoor recreation demand at northern latitudes have been well-documented in the literature (i.e., Chen et al., 2003; Rice et al., 2019; Vierikko and Yli-Pelkonen, 2019). This analysis confirms that this phenomenon is present within the study area, whereas park visitation is more seasonally variable at higher elevations and northern latitudes. Therefore, Google should control for the climate in their mobility data to demonstrate the real changes in park visitation directly due to the pandemic. Such practices are now fairly standard in leisure research (i.e., Boyer et al., 2017; Pan and Yang, 2017).

By not controlling for elevation—and latitude-induced climactic differences in park visitation—Google's park mobility data are biased by geography and are therefore misleading. The results of this study reveal that these data are not representative of the slogan Google uses in their description of the reports: "See how your community is moving around differently due to COVID-19" (Google, 2020b). In turn, Google's depiction of the implications of the data is not accurate. While Google notes the importance of calibrating your region's mobility data to account for weather changes, this disclaimer is not obvious to the casual viewer. It requires an exploration of the "Help" portion of the webpage (Google, 2020b). Google should, therefore, take strides to control for multiple sources of seasonality (e.g., elevation, latitude, weather, etc.) in their data. The suggested methodology is certainly feasible given that Google likely has access to Google Maps history data for at least a few years before 2020. This study also sheds light on the larger debate about the responsible dissemination and use of big data. As asserted by Zook et al. (2017), responsible big data research requires that researchers ground their data in the proper context and clearly communicate this context. The authors contend, "While it is tempting to interpret findings based on big data as a clear outcome, a key step within scientific research is clearly articulating what data or an indicator represent and what they do not" (Zook et al., 2017, p. 5). Specific to the use of big data in studying COVID-19, Ienca and Vayena (2020) argue that while its critical role in understanding the virus and related impacts is undisputed, there remains a need for responsible data collection and processing. The findings of this study suggest that responsible dissemination and communication are also essential to providing decision-makers with the best possible data insights.

6.2. Age and safer-at-home order's impacts on park visitation

The results of this study also indicate that counties with an older population and those with longer durations of safer-at-home orders have experienced less increasing park visitation during this stage of the pandemic, albeit at 92.5% confidence—considered borderline significance (Amrhein et al., 2019; Andrade, 2019). One possible reason for the observed age effect is that older adults are at a heightened risk for severe symptoms associated with COVID-19 (Lloyd-Sherlock et al., 2020). This risk may cause them to reduce their park visitation—at a county level—more so than younger individuals. This finding has serious implications on wellbeing. While the results of this study suggest that older adults are adhering to safer-at-home orders and social distancing recommendations by reducing their park visitation at a county level, it also important to consider the broader implications of their significant decline in outdoor recreation. Aspects of park visitation have been linked to the wellbeing of older populations (Orsega-Smith et al., 2004). Yang et al. (2020) argue that older adults in China—having less access to internet connectivity than younger individuals—are already more susceptible to declines in mental health as a result of quarantine and social distancing. Similar issues have been raised concerning reduced access to community spaces like parks in the United Kingdom (Armitage and Nellums, 2020). As noted by Van Bavel et al. (2020), isolation behaviors among older adults "threatens to aggravate feelings of loneliness and could produce negative long-term health consequences" (p. 7) during and after the COVID-19 pandemic. The relationship between park use and health among older adults is well-established (see review by Levy-Storms et al., 2018). Therefore, decreases in park use specifically will likely only exacerbate the negative impacts of isolation. Van Bavel et al. (2020) suggest that these impacts might be somewhat mitigated through training programs targeted at teaching older individuals to use digital communication technologies. Additionally, Matias et al. (2020) recommend that quarantined individuals develop in-home exercise routines to continue gaining some of the benefits attained through outdoor exercise activities. Public health and park agencies should also improve communication to older individuals surrounding how to engage in safe outdoor recreation during the pandemic and preserve wellbeing.

The impact of safer-at-home orders has similar implications for public health and park management. If accepted at the borderline 92.5% confidence interval, the longer safer-at-home orders are in place, the larger the reduction in park visitation becomes across the study period. While this result indicates that safer-at-home orders are an effective intervention to reduce park-related travel during the COVID-19 pandemic, it also suggests that those in counties with safer-at-home orders in place are less likely to engage in park-related leisure activities that support mental, physical, and social wellbeing and coping during the crisis (Holland et al., 2018; Rung et al., 2011; Thomsen et al., 2013). While necessary to control the pandemic, these orders have unintended consequences. As demonstrated by (Rice et al., 2020a), urban residents in the United States living in areas with heightened travel restrictions at the start of the COVID-19 pandemic were significantly more impacted in their outdoor recreation behaviors than rural residents. Therefore, the authors recommend taking measures (e.g., instituting quotas, transforming streets to greenways, etc.) to ensure that outdoor recreation can proceed during periods where local travel restrictions are in place (Rice et al., 2020a).

6.3. Limitations and future research

This study is limited in the quality of the data, as reported through Google Mobility Reports. The details underlying the algorithm of how Google defines "parks" is unknown. However, Google claims that "parks" include amenities like "national parks, public beaches, marinas, dog parks, plazas, and public gardens" (Google, 2020a). In addition, the percentage of the population of Google users who have their "Location History" turned on is also unknown. Thus, a caveat in the reports states that "…the data represents a sample of our users. As with all samples, this may or may not represent the exact behavior of a wider population" (Google, 2020a). Since "Location History" is turned off by default, it is reasonable to assume that Google users who turned it on possess a higher level of technical capability; thus, the data may over-represent the part of the population who achieved higher technical expertise (Leon et al., 2012). The reported mobility patterns may not be able to represent the whole population of those counties. Future studies using survey data or mobile phone location data beyond the Google platform may offer more validation. Big data research calls for greater transparency in the underlying algorithms and population penetration to make the data truly useful (Tierney and Pan, 2012; Arora et al., 2019). Without it, researchers are hindered in adopting those big data sources. Additionally, the geographical area is not exhaustive of the counties of those states included in the study. Each state contains counties where mobility data was not available. Therefore, the results of this study may be biased by a lack of data availability in rural counties where not enough mobility data was available to make estimates of changes in mobility.

This study operationalizes the spring months of 2020 as a "snapshot" of the pandemic to immediately inform management and future research. This analysis is based on an average of daily data. It is reasonable to assume that a hierarchal regression model of daily mobility data throughout the length of the entire pandemic might offer more accurate insights (Chi and Zhu, 2019). Therefore, we recommend that future research—following the conclusion of the pandemic—use repeated-measures spatial models to capture changes across the entire pandemic. The COVID-19 pandemic is still in progress, and this research only captured the early stage of this phenomenon and Americans' response to it.

It must also be noted that elevation and latitude are not perfect proxies for seasonality. Temperature and precipitation also influence park visitation (Hewer et al., 2016). However, there was a concern that their inclusion in the model might lead to issues of multicollinearity (see Schultz and Halpert, 1993). To this end, differences in average daily temperature from April-June 2020 and January-February 2020 and monthly average precipitation from April-June 2020 and January-February 2020 were initially included in an intermediate model along with elevation and latitude. Both were ultimately dropped due to excessively high multicollinearity condition numbers in models including one or both of these additional variables. Elevation and latitude were thus retained, alone, as both serve as sources of multiple climatic phenomena and both resulted in greater observed impacts on the response variable. The greater observed impacts of these variables may possibly be due to historic seasonal use patterns that are the function of climate rather than weather (Smith, 1993). Additionally, many park-based activities rely on reservations or permits that require decisions to be made well in advance, thus requiring visitors to make long-term predictions of future weather conditions based on climate (Smith, 1993; Rice et al., 2019). Therefore, the data-driven decision to retain elevation and latitude in the model also rests on a theoretical foundation. Still, considering weather conditions in any future modeling efforts will likely help researchers tease out all the influencing variables and result in more precise measurements of the park visitation due to the pandemic—following its conclusion, once more data becomes available. Future analysis should consider controlling for climate and weather's impacts on the Google Community Mobility Reports data.

In general, our modeling efforts are limited by the availability of data sources, the length of the study period, and the level of aggregation on a temporal level. Future research may consider incorporating more big data sources such as mobile phone data, investigating a longer period, dissecting the impact on a daily level, and including more weather-related variables for modeling effort. Additionally, future COVID-19 leisure research must approach the comparison of time periods with caution. As evidenced here, various rapidly changing variables make comparisons challenging (e.g., restrictions to travel, confirmed cases, weather, etc.).

7. Conclusions

This research offers a timely investigation of the factors impacting park visitation on a county-level in the western United States at an early stage of the COVID-19 pandemic. Based on Google Mobility Reports, this study revealed that elevation- and latitude-driven climactic differences serve as main sources of park visitation changes in the spring months of 2020 for 97 counties in the western United States. Additionally, counties with an older population and longer safer-at-home orders significantly decreased their park visitation, likely due to the fear of more severe symptoms among older adults and adherence to county-level travel restrictions. Future research should further examine both the impacts age and safer-at-home orders had on park visitation during the COVID-19 pandemic, and the impacts to wellbeing resulting from reduced park visitation among older individuals and those subject to long-running safer-at-home orders. In addition to those implications for future research, this study also provides implications for future policy. Communities and policymakers must provide improved support and better intervention for seniors' wellbeing during future health crises. Additionally, urban planners and park managers must design parks to allow for adequate social distancing. Finally, given these results, we recommend that health policymakers consider not only the potential risk outdoor recreation poses toward spreading infection, but also outdoor recreation's vital role in supporting human health and wellbeing during a pandemic.

The study also highlights the limitations of the Google Community Mobility Reports. Without couching the data within a longer period with a more representative baseline and considering the seasonality factor, park visitation changes could be misleading. The Google Mobility Reports could be more valid for other types of mobility activities in demonstrating the pandemic's impact, such as visits to retailing, indoor recreation facilities, grocery stores, and pharmacies, which are less affected by the weather and climate. For outdoor recreation and park visitation, without the comparison to multiple years of history, the change of season is likely causing the different mobility patterns. Google surely possesses multiple years of location data based on Google users' history; offering the comparison from the past few years as well as a few weeks before the pandemic is feasible and should be a better approach, at least for park visitation data.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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