Understanding drivers of change in park visitation during the COVID-19 pandemic: A spatial application of Big data

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Abstract

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. This dataset offers vast application potential, containing aggregated information from location data collected via smartphones around the world. However, empirical analysis of these data is limited. Namely, the factors causing reported changes in mobility and the degree to which these changes can be directly attributable to COVID-19 remain unknown. The goal of this study is to address these gaps in our understanding of both the changes in park visitation and the causes of these changes. Results suggest that seasonality, not the COVID-19 pandemic, serves as the primary driver of reported changes in park visitation. Specifically, latitude-driven seasonal changes significantly influence visitation trends. Median age of a county is also a statistically significant driver.

Keywords: COVID-19, big data, outdoor recreation, parks, Google, spatial analysis

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The COVID-19 pandemic presents an unprecedented health crisis to the global community (Stier et al., 2020). The rapid, 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 & 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 (i.e., Salama, 2020; Samuelsson et al., 2020). Outdoor recreation and park visitation data, specifically, are important for understanding compliance with safer-at-home orders (Tufan & Kayaaslan, 2020), economic impacts of the pandemic (Jamal & Budke, 2020), and communities' capacities for coping with it (Rung et al., 2011). 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 recreation, parks often serve as places of restoration for those dealing with crisis (Samuelsson et al., 2020). Additionally, both outdoor recreation and park visitation are robustly linked to mental, physical, and social well-being (see reviews by Holland et al., 2018; Thomsen et al., 2013). It is thus imperative that decision-makers have quality data insights concerning park use during the COVID-19 pandemic to not only ensure proper management, but also to provide an indicator of public health. Big data has 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 the use of big data to understand how park visitation is changing during the pandemic and what is influencing changes in park visitation. These insights could improve the management of parks and increase community resilience to the health crisis (Salama, 2020). However, such analysis has been sparse. Hence, the goal of this study is to address these gaps in our understanding of the factors contributing to park visitation during this pandemic and, at the same time, assess the efficacy of Google's community mobility data in providing meaningful insights.

Big data for Park and Outdoor Recreation Research

Li et al. (2018) assert that big data have a low value density. This means that these data have comparatively low utility per unit. However, if available in mass quantities, high amounts of value can be extracted—thus making up for this limitation. Principally, three primary forms of big data exist: transaction data, device data, and user-generated data (Li et al., 2018). 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 towards measuring park visitation include Flickr (Fisher et al., 2018), Instagram (Tenkanen et al., 2017), Strava (Norman & 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.

Throughout the COVID-19 pandemic, big data sources have been heralded as a necessary tool in combating the advance of the virus (Ienca & 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), data generated via the Strava fitness app to assess changes in urban park use (Venter et al., 2020), and social media data to explore rhetoric surrounding responses to the pandemic (Li et al., 2020). However, 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). 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 clearly communicating exactly what the data represent (Zook et al., 2017).

Google's Community Mobility Reports

On April 3, 2020, Google released their first set of Community Mobility Reports (Fitzpatrick & 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 & 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 population size or the percentage of Google users who have their location history turned on is unknown. The reports breakdown mobility 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). Following their 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 & 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.

Study Purpose

Limited attempts have been made to analyze the Community Mobility Report data (see Chan et al., 2020). Therefore, the data remain largely unexplored and the efficacy of the big data source remains 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 research questions:

R1: What factors are causing changes in park visitation in the Western United States during the COVID-19 pandemic?

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

Methods

Study area

The geographic scope of this research was determined by data availability. Google's park mobility data is unavailable throughout much of the United States due to a lack of location history data as allowed by Google users (Google, 2020c), which made a national spatial model unfeasible (Chi & Zhu, 2019). It was hence determined that the largest continuous swath of available data be used instead. This determination yielded 111 counties in the Western region of the United States, including Arizona, California, Nevada, Oregon, and Washington (Figure 1). This area has substantial variation across the rural-urban continuum and a large spectrum of latitudes (see Table 1).

[INSERT FIGURE 1 ABOUT HERE]

Data

Dependent Variable

The dependent variable in the spatial model was sourced from Google's COVID-19 Community Mobility Reports (Google, 2020c). The park visitation portion of this dataset provides county-level activity "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 number of visits and length of stay at parks on an aggregated county level. Change is calculated from the "baseline" or "the median value, for the corresponding day of the week, during the 5-week period Jan 3–Feb 6, 2020" immediately prior to COVID-19's widespread emergence in the U.S. (Google, 2020a, p. 52). In this way, a coefficient was generated for 821 of 2,791 U.S. counties (29%) for each day of the week ranging from April 24-30, 2020. For the 111 counties within the study area, the available daily coefficients across one week were averaged for each individual county to control for any outliers in the data. In this way, a single coefficient was generated for each of the 111 counties representing average change from the baseline during the week of April 24, 2020. A summary of this variable can be found in Table 1.

[INSERT TABLE 1 ABOUT HERE]

Independent Variables

Table 1 summarizes the independent variables included in the model. Each of these variables were selected based on: 1) previous research or policy goals related to controlling and adapting to the COVID-19 pandemic or 2) park visitation. Variables directly related to the COVID-19 outbreak included: population density, median age, the presence of 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 for (Rogers, 2002). It has also been posited that the amount of confirmed cases within an area may be impacting behavior and decision-making (Tufan & Kayaaslan, 2020). The total number of confirmed cases were operationalized instead of cases per capita to account as it was determined that it best captured of the effect of the virus's spread. 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 & Kayaaslan, 2020). Additionally, variables directly-related to park visitation were included in the model. The proportion of county residents living within one-half mile of a park was used as a measure of park access (Sato et al., 2019;

Ussery et al., 2016) and the latitude of counties was included to account for different seasonal change during the studied week (Hewer et al., 2015; 2016).

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 & Patry, 2017). Additionally, visitation across counties and relationships of county governments may lead to spatial autocorrelation (Chi & Zhu, 2019). Therefore, a spatial regression was selected for this analysis to account for spatial dependence and autocorrelation (Chi & Zhu, 2019). This analysis followed the study procedure of Chi and Marcouiller (2013), whereas 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.

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 & 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 & Patry, 2017), a data-driven approach was adopted. Following the guidelines provided by Chi and Zhu (2019), a variety of spatial weight matrix styles were tested, each with varying levels of orders or distance. These included: Rook's Continuity, Queen's Continuity, Distance, and Inverse Distance (Table 2). For the distance-based weight matrices, the shortest distance included—200 miles—was determined based on the shortest distance from a county's centroid whereas all counties would have at least one neighbor. Following Chi and Zhu (2019), matrices were assessed based on their resulting Akaike info criterion (AIC), Schwarz criterion (BIC), and Moran's *I* in relation to the park visitation variable

(Table 2). Rook's Continuity (Order 1) and Queen's Continuity (Order 1) captured similar levels of spatial dependence, however the AIC and BIC were lower for Queen's Continuity. Therefore Queen's Continuity (Order 1) was selected as the spatial weight matrix for subsequent analysis.

[INSERT TABLE 2 ABOUT HERE]

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 0.5728, the data were determined to be clustered, or positively autocorrelated (Chi & 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 (Chi & Zhu, 2019). LM tests revealed a non-significant spatial lag effect and a significant spatial error effect. In turn, it was determined that a spatial error model (SEM) should be used in our final regression:

$$Y = C + (\text{Population density})\beta_1 + (\text{Median age})\beta_2 + (\text{Safer\_at\_home order})\beta_3 + (\text{Cases per captia})\beta_4 + (\text{Latitude})\beta_5 + (\text{Pop. within .5 mi. of park})\beta_6 + u, u = \rho W u + \varepsilon$$

In this model, Y represents the dependent variable—park visitation changes as reported Google Mobility Reports. The regression coefficients are represented by β_x. The vector for the error term is represented by u. The scalar spatial error parameter is represented by ρ. The spatial weight matrix is represented by W. The constant is *C*. And the error terms that are not identically distributed are represented by the vector ε (Chi & Zhu, 2019).

Results

A comparison between the descriptive results of the OLS model and SEM is listed in Table 3. AIC and BIC statistics indicate that the SEM had better model fit. Full results of the SEM are summarized in in Table 4. The multicollinearity condition number is less than 30, indicating that significant multicollinearity is not present in the model (Chi & Zhu, 2019). The R^2 for this model indicates that the variance of the independent variables account for 53% of that within the dependent variable. On average, among 111 counties in the study area, there is a 2.5% increase in park visitation, as compared to the baseline period prior to the pandemic.

R1: What factors are causing changes in park visitation in the Western United States during the COVID-19 pandemic?

Two variables were found to have statistically significant predictive relationships with change in park visitation. Median age of a county was negatively related to change in park visitation at a 95% confidence interval. Latitude was positively related to change in park visitation at a 99.9% confidence interval. All other variables had non-statistically significant relationships. Examining the effects of median age and latitude on park visitation, results suggest that a one year increase in median age of a county results in nearly a 1% decrease in park visitation from the baseline period. Conversely, a one-degree increase (or movement north) in latitude results in a nearly 4% increase in in park visitation from the baseline period. The spatial error lag term, Lambda, was significant at 99.9% confidence. This indicates that if the change in park visitation in surrounding counties increases an average of 10%, the neighboring counties' changes in park visitation will increase 5.4%, all else being equal.

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

Of the independent variables directly related to COVID-19, only median age was shown to have statistically significant prediction of park visitation. Population density, the presence of safer-at-home orders, confirmed cases, and access to parks were not significantly predictive of changes in park visitation. This result—paired with the strong effect of latitude—suggests that much of the change in park visitation reported in Google's park mobility data is not the direct result of the pandemic but is instead the result of seasonality.

[INSERT TABLES 3 AND 4 ABOUT HERE]

Discussion

Latitude's impact on park visitation

Results of this analysis indicate that the impact of COVID-19 accounts for only a portion of the change in park visitation reported by Google. Seasonality, by way of latitude, is also a significant force of change, as noted in previous research (see Hewer et al., 2016). Google's baseline period from which COVID-19 era mobility data are compared falls from January 3 to February 6, 2020. In 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 was 45ºF (National Weather Service, 2020). In Bend, Oregon it was 36ºF (National Weather Service, 2020). During the week for which the data in this study were collected—April 24 to April 30—the average temperatures in Seattle and Bend had risen to 55ºF and 54ºF, respectively (National Weather Service, 2020). January temperatures in these northern latitudes are substantially colder than those experienced in large population centers in the southern portion 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 & Yli-Pelkonen, 2019). The results of this analysis confirm that this phenomenon is present within the study area, whereas park visitation is lower in the winter. Therefore, Google should be controlling for seasonality in their mobility data to demonstrate the real changes in park visitation directly due to the pandemic. Such practices are now fairly standard in recreation and tourism research (i.e., Boyer et al., 2017; Pan & Yang, 2017).

By not controlling for latitude-induced seasonality differences in park visitation, Google's park mobility data is biased by geography and is therefore misleading. The results of this study reveal that these data are not representative of the slogan Google uses in their marketing: "See how your community is moving around differently due to COVID-19" (Google, 2020b). In turn, Google's marketing of the data is not accurate. This study sheds light on the larger debate about the responsible dissemination and use of big data. The causal relationship likely assumed by the disseminators of this data at Google is overshadowed by the relationship between latitude and seasonal changes in park visitation. 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.

Age's impact on park visitation

The results of this study also indicate that the heightened risk for severe symptoms associated with COVID-19 among older adults (Lloyd-Sherlock et al., 2020) has caused them to reduce their park visitation, more so than younger individuals. This finding has serious implications. 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, it also important to consider the broader implications of their significant decline in outdoor recreation. Aspects of park visitation have been linked to the health of older populations (Orsega-Smith et al., 2004). Yang et al. (2020) argue that older adults—having less access to internet connectivity than younger individuals—in China have are already more susceptible to lapses in mental healthcare as a result of quarantine and social distancing. Similar issues have raised concerning reduced access to community spaces like parks in the United Kingdom (Armitage & 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.

Limitations and Future Research

This study is limited in the quality of the data as reported by Google Mobility Reports. The details of the underlying algorithm on how Google defines “parks” is unknown, though Google claims that “parks” include amenities like “national parks, public beaches, marinas, dog parks, plazas, and public gardens” (Google, 2020a). In addition, the percentage or 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 population who achieved a 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 & Pan, 2012; Arora et al., 2019). Without it, the researchers are handicapped in adopting those big data sources.

This analysis is based on weekly average of daily data due to limitations in the resolution of county-level data on safer-at-home orders. The data resolution does not allow for understanding how these orders changed on a daily basis throughout the study period. It is reasonable to assume that a hierarchal analysis of daily data (i.e., daily confirmed cases and safer-at-home orders) would offer more accurate insights (Chi & Zhu, 2019). However, this was not feasible due to the data resolution available at the time of this study.

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 is possible that as time goes by, the sink-in effect will result in significant changes of park visitation since most of the country has been be ordered stay home. In addition, the nearby green space outside one's house or apartment might be the only outdoor activities available after a longer period of confinement in home. A longer-term analysis may reveal different results. Park visitation is also influenced by the temperature and the amount of rainfall/snowfall one area receives (Hewer et al., 2016). We did not include those variables in the model due to the worry of multicollinearity with latitude (Schultz & Halpert, 1993). Considering weather conditions, especially the average temperature and rainfall/snowfall, 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.

In general, our modeling efforts are limited by the availability of data sources, the length of the study period, the level of aggregation on a temporal level, and limited variables on weather conditions. Future research may consider incorporating more big data sources such as mobile phone data, investigating on a longer period of time, dissecting the impact on a daily level, and including more weather-related variables for modeling effort.

Conclusions

This research offers a timely investigation on the factors impacting park visitation on a county-level in the Western United States at the early stage of COVID-19 pandemic. Based on

Google Mobility Reports, this study revealed that the factor of latitude-driven seasonality serves as the main source of park visitation changes in late-April, 2020 for 111 counties in the Western United States, instead of the fear of contracting the virus based on reported confirmed cases, or “safer-at-home” orders issued. Counties with an older population have signficantly decreased park visitation due to the fear of more severe symptoms for those who contract the desease. This calls for better intervention on mental and phsyical health of seniors amidst this pandemic, and possibly offering safer park visitation and outdoor recreation opportunities (Levy-Storms et al., 2018).

The study also highlighted the limiation of big data: without couching the big data within a longer period of time with a more representative baseline and considering the seasonality factor, the changes in park visitation could be misleading, at least at the early stage of the pandemic. The Google Mobility Reports could be more valid for other types of mobility activities in demonstrating the impact of the pandemic, such as visits to retail and indoor recreation facilities, and grocery stores and pharmacies, which are less affected by outdoor weather. For outdoor recreation and park visitation, without comparision to mulitple 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 comparision from past few years as well as a few weeks prior to the pandemic is feasible and should be a better approach, at least for park visitation data.

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Tables

Table 1

Variable Summary

Variable Name	Definition	Source	Min.	Max.	Mean
Park Visitation	Average percent change in daily park use among county residents in the week of April 24 to April 30, 2020 from base line numbers. The baseline numbers are the median values, for the corresponding day of the week, during the 5-week period Jan 3rd to Feb 6, 2020.	Google	-72.0	88.3	2.5
Population density	Population per square mile based on 2018 census data	U.S. Census Bureau	1.8	18,537.2	462.0
Median age	Median age of county residents based on 2018 census data	U.S. Census Bureau	30	54	39
Safer-at-home order	Binary, dummy variable for counties issuing safer-at-home orders as of most updated version available on April 24, 2020. 0 = No. 1 = Yes.	National Association of Counties	0	1	0.22
Confirmed Cases within county	Total confirmed cases within county as of April 24, 2020	Centers for Disease Control / USA Facts	0	1,8517	592.51
Latitude	Centroid latitude of county	ESRI	31.53	48.82	40.46
Pop. within ½ mile of park	Percent of population within a buffer of ½ mile radius of a park	Centers for Disease Control	0.12	0.99	0.59

Table 2

Spatial dependence captured by spatial weight matrices

Spatial Weight Matrix	AIC	BIC	Moran's *I*	Mean Number of Neighbors
Rook's Continuity, Order 1	1028.86	1047.83	0.5744***	4.11
Rook's Continuity, Order 2	1051.71	1070.67	0.3271***	6.86
Rook's Continuity, Order 3	1053.86	1072.83	0.2629	8.45
Queen's Continuity, Order 1	1028.38	1047.35	0.5730***	4.20
Queen's Continuity, Order 2	1052.09	1071.06	0.3226**	7.03
Queen's Continuity, Order 3	1048.08	1067.04	0.3522***	19.87
Distance – 200 miles	1042.55	1061.51	0.3639***	26.74
Distance – 400 miles	1054.60	1073.56	0.2668**	49.44
Distance – 600 miles	1047.59	1066.56	0.1618***	73.28
Inverse Distance – 200 miles	1042.55	1061.51	0.3640***	26.74
Inverse Distance – 400 miles	1054.60	1073.56	0.2670**	49.44
Inverse Distance – 600 miles	1047.59	1066.56	0.1620***	73.28

*p < .05, **p < .01, ***p < .001
AIC = Akaike info criterion, lower = better
BIC = Schwarz criterion, lower = better
Moran's *I*, higher = better

Table 3

Comparison of Model Fit

Model	R^2	AIC	BIC
OLS	0.3506	1054.64	1073.60
SEM	0.5306	1028.38	1047.35

AIC = Akaike info criterion
BIC = Schwarz criterion

Table 4

Results from SEM regression

Variable	Coefficient	Standard Error
Population density	0.00091	0.00126
Median age	-0.96298*	0.41621
Safer-at-home order	4.14382	5.37586
Confirmed Cases	-0.00157	0.00115
Latitude	3.8407***	0.94603
Pop. within ½ mile of park	6.51679	14.4704
Lambda	0. 54563***	0. 0889
Constant	-120.10*	40.6985

*p < .05, **p < .01, ***p < .001
$R^2 = 0.5306$
AIC = 1028.38
BIC = 1047.35
Multicollinearity condition number = 26.66

Figure

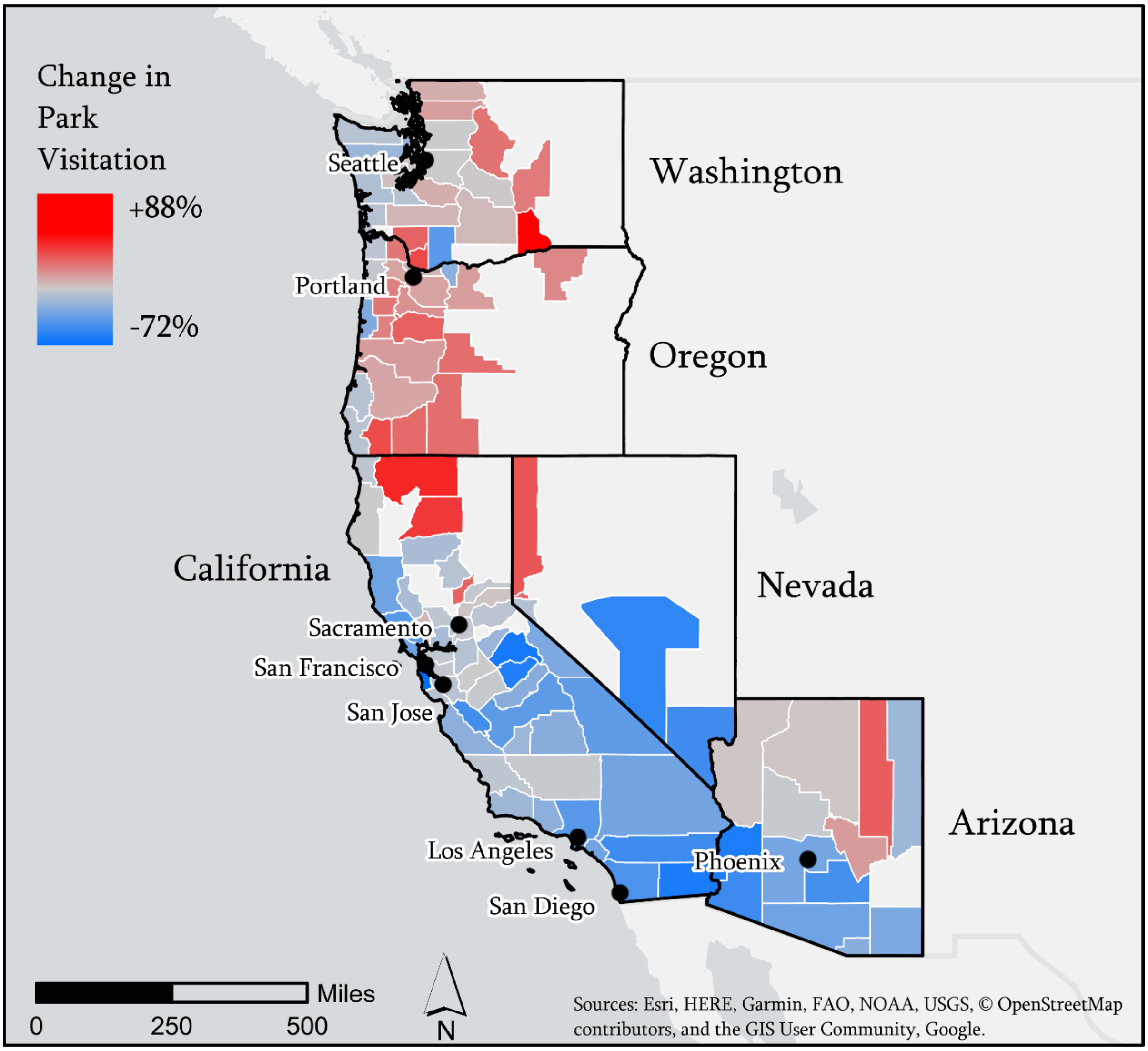

Figure 1. Change in park visitation across the study area