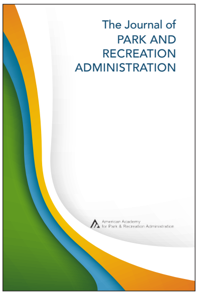
SAGAMORE VENTURE



Journal of Park and Recreation Administration

Print ISSN: 2327-0179, Online ISSN: 2327-0187
Journal homepage: https://js.sagamorepub.com/jpra/index

Using Mobile Device Data to Estimate Visitation in Parks and Protected Areas: An Example from the Nature Reserve of Orange County, California

Christopher Monz, Milan Mitrovich, Ashley D'Antonio, and Abigail Sisneros-Kidd

To cite this article: Monz, C., Mitrovich, M., D'Antonio, & Sisneros-Kidd, A. (2019). Using Mobile Device Data to Estimate Visitation in Parks and Protected Areas: An Example from the Nature Reserve of Orange County, California.*Journal of Park and Recreation Administration*. doi: 10.18666/JPRA-2019-9899

To link to this article: https://doi.org/10.18666/JPRA-2019-9899

Published online: 09/03/2019

 https://doi.org/10.18666/JPRA-2019-9899

Regular Paper

Using Mobile Device Data to Estimate Visitation in Parks and Protected Areas: An Example from the Nature Reserve of Orange County, California

Christopher Monz
Milan Mitrovich
Ashley D'Antonio
Abigail Sisneros-Kidd

Executive Summary

Measuring and monitoring use levels in parks and protected areas (PPAs) remains an ongoing challenge for managers worldwide. Understanding visitation levels is particularly important as contemporary use trends in PPAs have become increasingly dynamic due to many factors that influence demand, including for example, the popularizing of locations via social media. In this paper, we present a novel, mobile device data analysis approach for understanding use levels in PPAs, measured as vehicle arrivals to formal and informal park entrances. We initiated this research in effort to develop an alternative use estimation technique, particularly in situations where visitors may enter a PPA

Christopher Monz is a professor in the Department of Environment and Society at the Institute for Outdoor Recreation and Tourism, The Ecology Center at Utah State University.

Milan Mitrovich is the science director at the Natural Communities Coalition in Irvine, CA.

Ashley D'Antonio is an assistant professor in the Department of Forest Ecosystems and Society at Oregon State University.

Abigail Sisneros-Kidd is a postdoctoral fellow in the Department of Environment and Society at Utah State University.

The authors thank the Natural Communities Coalition for the generous funding support for this project. The lead author (Monz) also thanks the Utah Agriculture Experiment Station (UAES Project 1084) and the Institute for Outdoor Recreation and Tourism at Utah State University for funding support. Mr. James Sulentich provided a helpful review of this manuscript. Orange County Parks provided GIS support in producing the maps in the manuscript.

Please send correspondence to Christopher Monz, chris.monz@usu.edu

in a more diffuse manner, via informal entrance locations that are difficult to monitor by conventional direct counting methods. Our approach uses a readily available mobile data analysis platform, Streetlight *InSight*®, developed for transportation planners that is capable of accessing and processing a vast resource of mobile device data. We tested this approach in a network of urban-proximate PPAs in Orange County, California, via both currently available data processing procedures, and sampling and calibration techniques we developed. Our results compare favorably to available use estimates in the study area that employ standard counting techniques. For example, we statistically compared monthly estimates calculated via the Streetlight model and direct counts at a popular entrance location and found no significant difference. We also examined a time period of a known park closure due to a forest fire event to determine if erroneous data were being collected and estimated use at or near zero. Although our method verification relies mainly on face validity due to limited availability of other use estimates in our study location, our results suggest that acceptable use estimates can be obtained in a wide range of PPA applications. This approach has several substantial advantages to PPA management. First, since mobile data are available, managers can obtain current use level estimates in PPAs with a significantly reduced need for field devices and field staff time and effort. Second, retrospective data back to 2014 are available, making it possible to examine trends over the last several years even if no on-site counts were ever obtained. Last, parks with multiple, diffuse entry locations can be assessed more comprehensively, since locations can be identified and use estimated via a digital map-based interface.

Keywords

Visitor use estimation, park and protected area management, mobile device data, big data

Introduction

The sustainable management of visitors to parks and protected areas (PPAs) has become increasingly complex. Rapidly changing social and technological changes continue to influence how, when, and where visitors use PPAs for recreation and tourism activities, often resulting in dramatic changes in use. These trends are manifest at both a worldwide scale (Balmford et al., 2015) and at the individual unit and system level such as is currently occurring in many U.S. National Parks (NPS, 2018). Managers of national parks, wildlands, and protected areas are often legally required to maintain a high degree of ecological quality while also allowing for an "unconfined" recreation experience—a challenging mandate. With changes in use levels and distribution occurring at unprecedented rates, new knowledge about visitation is constantly needed by managers to serve this mandate in a sustainable manner.

A primary concern is that unmanaged visitor activities in PPAs often have some undesirable consequences to ecological and social conditions. Recreation and tourism activities can cause direct and indirect disturbance to soil, vegetation, wildlife, water and soundscape components of a natural system and minimizing this disturbance to an acceptable level is often a required management objective (Hammitt, Cole, & Monz, 2015). Of equal importance is the maintenance of desirable social conditions. Issues such as overcrowding, conflict, and visitor safety are perennial concerns in many protected areas (Manning 2010). Although the relationships between use level and changes to resource and social conditions are often non-linear and complicated by numerous intervening factors (Monz, Pickering, & Hadwen, 2013), changes in visitation often serve as a useful "early warning" of potential social and ecological management issues.

Fundamental to park management is an understanding of the basic dynamics of visitor use, the numbers of visitors, where they enter and exit, and the spatial attributes of their visit (English & Bowker, 2018). Historically, managers of PPAs were concerned mainly with overall use estimation and various techniques were developed such as self-counting methods (e.g., trailhead registration) and observation-based counting methods (Hollenhorst, Whisman, & Ewert, 1992; Watson, Cole, Turner, & Reynolds, 2000). Automated technology became available in the late 1960s, and the wide application of automatic trail counters and vehicle counters continues in many PPAs today (English & Bowker, 2018; Hollenhorst, Whisman & Ewert, 1992; James & Ripley, 1963; Leonard, Echelberger, Plumley, & Van Meter, 1980). Automated counters are commonplace since they are relatively easy to use, but challenges remain in their application due to the labor effort required in the field and their applicability in many PPA situations (Watson, Cole, Turner, & Reynolds, 2000). As such, efforts at improving methods and approaches continue today in order to improve visitor enumeration. For example, it remains particularly difficult to assess use in PPAs that have unspecified access points and more "porous" boundaries (Ziesler & Pettebone, 2018), and therefore development of new ways of assessing use in these locations remains desirable. Moreover, some large-scale monitoring programs, such as the National Visitor Use Monitoring (NVUM) program in National Forests in the USA, are intending to change from traditional counting methods to a statistical modeling technique for use estimates. This change is being implemented due to the labor effort required in setting up automated counters to determine visitor arrivals at trailhead locations. More efficient use estimation methods could contribute to programs such as the NVUM that have experienced similar data acquisition challenges. (Deng, personal communication)

The information collected from these use estimation techniques is clearly valuable but generally does not provide all of the information desirable to managers such as visitor use patterns, visitor characteristics, motivations, and behavior. Visitor questionnaires, trip diaries, and interview techniques can provide some of this lacking information but require significant time investment from both visitors and researchers and are susceptible to issues of reporting and recall accuracy (Hallo, Manning, Valliere, & Budruk, 2005). Recent advancements in employing GPS-based assessment techniques (D'Antonio et al., 2010; Shoval & Ahas, 2016) have shown considerable promise in determining visitor use patterns and trip characteristics at both small and broad spatial scales, thus eliminating some of the aforementioned issues of reporting accuracy. Current GPS approaches, however, still require the field-based sampling strategies of deploying GPS devices and are often combined with both automated counters in order to correct from sample densities to actual estimates, and survey techniques in order to understand demographic or motivational influences on behavior. Thus, while highly effective, GPS-based approaches remain labor intensive in both the field and in post processing the data for analysis (D'Antonio et al., 2010; Kidd et al., 2018; Newton, 2016).

With the current ubiquity of mobile cellular device use among the general public for navigation, travel, and communication, vast amounts of location-based data are produced resulting in a "digital trace" of the behavior of individuals on the landscape. Available data and associated analysis can yield information on recreation and tourism behaviors, home and work locations, and a range of demographic attributes. Numerous applications for these data are emerging in various aspects of land and infrastructure planning including analysis of travel demand for transportation services (e.g., Çolak, Alexander, Alvim, Mehndiratta, & González, 2015), origin-destination analysis (e.g., Alexander, Jiang, Murga, & González, 2015), land use classification (Pei et al., 2014) and to understand tourist characteristics and movements (Ahas, Aasa, Roose, Mark, & Silm, 2008; Raun & Ahas, 2016). There is also an emerging line of research examining the utility of mobile device data specifically in PPAs since these data are potentially useful to understand visitor use and behavior. Currently there appear to be two major approaches in using mobile device data in PPAs—both involve an "active" participation from the visitor in the use of a specific mobile app or in posting information (commonly photos) to social media. For example, mobile data has been used to understand spatio-temporal patterns within parks via data derived from exercise tracking apps (e.g., Kim, Thapa, & Jang, 2019; Korpilo, Virtanen & Lehvävirta, 2017; Rice, Mueller, Graefe, & Taff, 2019). While these approaches are unique in employing a mobile device to understand visitor use patterns, the data are quite similar to GPS-based approaches that have been deployed for some time (e.g., D'Antonio et al., 2010). A second approach involves the analysis of geotagged, crowdsourced photos as an index of visitor use at specific locations (e.g., Walden-Schreiner, Rossi, Barros, Pickering, & Leung, 2018).

Although the current research in PPAs is clearly useful in examining visitor use and behavior, we argue that the aforementioned digital trace, big data sources may have advantages over most of the previous methods, including the "active participation," app-based approaches. First, since the data sources exist and can be readily obtained from providers, there is a substantially reduced need for field data collection—only for validation and scaling purposes where needed. Second, the data can be passively collected and is not dependent on the visitor to participate, as in visitor questionnaires and GPS tracking, and in other mobile app-based approaches (e.g., Kim et al., 2019; Walden-Schreiner et al., 2018). However, it remains unclear as to the overall availability of digital trace data for PPAs, particularly remote locations lacking in cellular connectivity. Also, new analysis approaches are needed to render the currently available mobile data and associated metrics useful to park and protected area managers.

In this paper we describe an initial effort at using existing mobile device data sources and available analysis tools to answer some fundamental questions about PPA visitation. We make a distinction between our approach and much of the current work in PPAs since the data sources we analyzed did not require direct participation on behalf of the visitor and instead are locations derived from common mobile device usage. Our approach used data purchased from a transportation data analysis provider and an associated web-based analysis tool. This approach allows for the collection of use-related data without the need to deploy field personnel or equipment, and given that these data sources are available for about the last five years, recent trends of changes in use can be examined. We present select examples of our analysis findings as an illustration of an emerging method rather than a full examination of visitation trends at our study location. Our overall goal in this work was to examine whether the available mobile device data could serve as an indicator of use levels that accurately represents differences among sites and changes over time. We focused specifically on determining deliveries of vehicles to entrance location and converting these to estimates of visitor use numbers, analogous to a gate count of visitors common to PPAs.

Methods

Study Site

A total of 22 park units, under various management jurisdictions, are currently designated in Orange County, California, USA (Figure 1). Collectively known as the Nature Reserve of Orange County (referred to throughout this paper as "the Reserve"), the habitat and species conservation of these areas is coordinated by the Natural Communities Coalition (NCC; occonservation.org), a nonprofit organization. The NCC conducts biological research and monitoring, and implements habitat restoration and enhancement programs in coordination with landowners and managers. The overall goal of the Reserve program is to conserve natural, functioning ecosystems at a landscape level in Orange County. The Reserve is part of the California Chaparral and Woodlands Ecoregion and harbors thirty-nine identified species receiving regulatory coverage under federal and state endangered species acts, including nine plant and thirty animal species. The primary vegetation type in the Reserve is coastal sage scrub, coexisting in a mosaic of oak woodland, native grassland, chaparral, Tecate cypress and riparian communities.

The Reserve system parks offer a variety of outdoor recreation opportunities, such as hiking, running, mountain biking, beach recreation and nature appreciation in an urban-proximate setting to the over 3.2 million residents of Orange County (Center for Demographic Research 2019). For this analysis we selected 11 management units within the overall Reserve that are currently experiencing high demand for recreation activities and consequently are considered a high priority for assessment and monitoring of recreation use. These locations are under the respective management of Orange County Parks, California State Parks, City of Irvine, and the Irvine Ranch Conservancy.

Data Sources and Available Analyses

Currently no systematic data collection protocol for visitor use is employed for the entire Reserve system. Several of the management units compile regular estimates of arrivals by automobile at key entry points via manual gate counts, but the accuracy of these estimates is subject to a variety of sources of error, including the diffuse nature of access in many of the Reserve locations. In these urban-proximate PPAs, many undesignated, informal entry points exist, thus complicating standard visitor gate counting approaches. Both this lack of system-wide, consistent use data collection and the diffuse nature of visitor access provided important impetus for this study.

We accessed mobile device data and obtained analysis tools from StreetLight Data, Inc., a transportation and urban planning company located in San Francisco, CA, USA. Streetlight Data provides access to mobile device data primarily focused on road networks to produce transportation-planning analytics. The analysis tools are available via StreetLight InSight,® an online platform that allows the user to more easily access to "big data" resources and custom data processing software (Streetlight Data, Inc. 2019). StreetLight Data, Inc., obtains mobile device data from two types of locational sources, navigation-GPS data and Location-Based Services (LBS) data. The navigation-GPS data is derived from mobile devices running map-based navigation applications and provides a high degree of spatial precision (3-5m) and frequent loca-

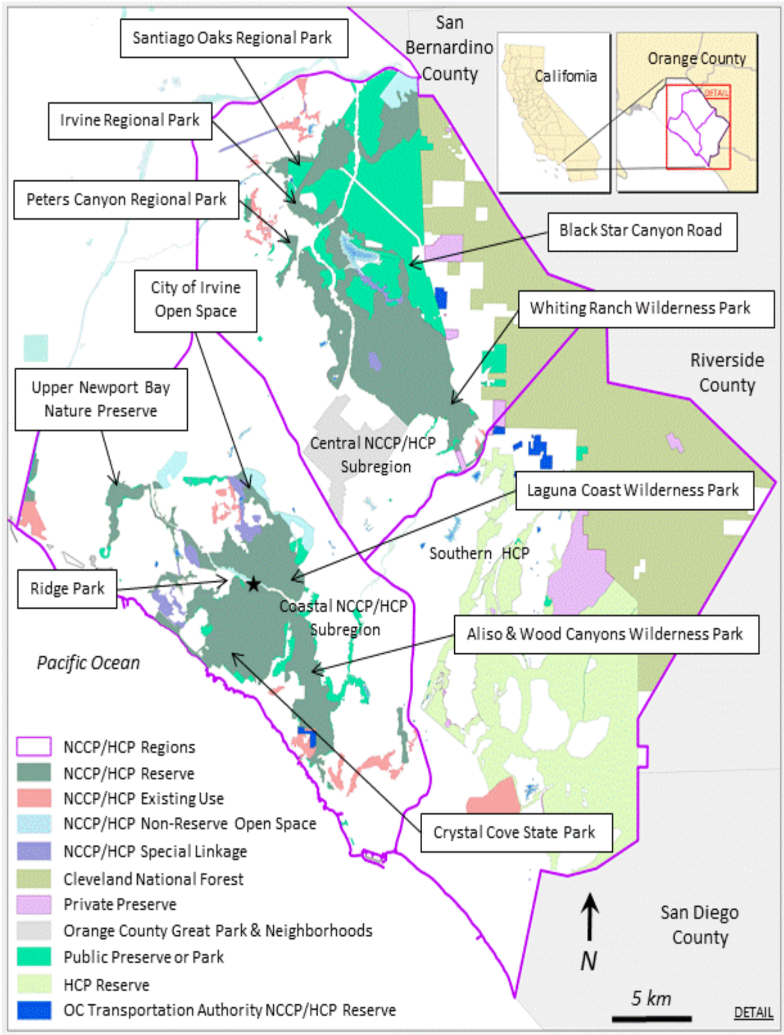


Figure 1. Orange County, California. Shaded and color areas are locations of protected lands under a range of management agencies. Black star indicates location of California State Route 73 Traffic Sensor. NCCP = Natural Community Conservation Plan (State); HCP = Habitat Conservation Plan (Federal); OC = Orange County

tion pings. Location-based services data is derived from a growing number of mobile device applications (e.g., ridesharing apps) that make background use of locational data and yields a 5-25m range of spatial precision. StreetLight obtains the raw data from one major navigation-GPS data supplier, INRIX (http://inrix.co), and one LBS data supplier, Cuebiq (https://www.cuebiq.com). Streetlight has determined that the sample size from all data sources represents about 23% of the travel activity from all modes (e.g., personal auto, commercial vehicles, etc.) on road networks in the U.S. and Canada (StreetLight Data, 2019). For the purposes of this research, we used only navigation-GPS data sources in our analysis, which will be detailed below.

StreetLight links the raw data to specific transportation activities using a proprietary algorithm and then models this output so it is relevant to their standard clients who are primarily transportation planners. Several quality assurance and data cleaning processes that employ spatial and velocity filtering approaches eliminate erroneous data and the data are typically "locked" to known road networks to enhance spatial accuracy. The data are also scaled using population census data and the proportion of devices that appear in these locations. Standard StreetLight *InSight* outputs are always aggregated and cannot be directly examined to track the behavior of any one individual, thus avoiding privacy concerns. For the purposes of clarity in this paper, we refer this proprietary process as the "StreetLight *InSight* model" and for readers interested in more detail on the data sources, algorithm and modeling process, please see the literature available on the Streetlight website (StreetLight Data, 2019). The reader should be aware that as stated, this a proprietary process developed by Streetlight, Inc., and thus many of the exact details of data processing, scaling and the algorithm are beyond the purview of this paper and the authors. Streetlight, Inc. provides access to their analytics via a custom user interface that can be directed to a specific study location by the user and as stated, our goal in this study was to examine the viability of adapting this output to determine use estimates in our study location. As such, we did not directly manipulate the raw mobile device data but instead relied on the output from the *InSight* model and a scaling process that we developed to determine vehicle arrivals and use estimates at our study locations.

Analysis Procedures

Twenty-four park entrance locations across the 11 selected management units were identified by our existing knowledge, field verification of known, formal entrance points and via examination of aerial imagery along the perimeter of each park (Figure 2). In this process we also identified informal, undesignated entrance locations, which are common in this study location, by locating parked cars along adjacent roadsides. Since most visitors arrive by personal auto and may access a particular location not via a formal entrance but by parking along adjacent roadsides, this process provided a more comprehensive identification of arrival locations. Once all formal and informal access locations were identified, spatial delineation of the areas into polygons was accomplished in the InSight platform via the available digital map interface. This process resulted in a suite of 24 formal and informal entrance location polygons across the eleven park management units, and defined the automobile arrival locations for the origin-destination analysis described below. Based on our knowledge of visitor use in these locations, we are reasonably certain that we identified most locations where visitors are accessing these PPAs.

We used one of the analysis approaches readily available via the StreetLight *InSight* platform, "origin-destination analysis" (O-D), in order to understand the total volume of use at specific park access points. The O-D approach describes vehicle trips between any geographic location (trip origin) and the park destination locations we specified. Using the available web-based, platform interface, we generated StreetLight Index (StL Index) values, which are relative use index values based on navigation-GPS data and the primary quantitative output from the platform. We specifically used navigation-GPS due to the need for higher spatial accuracy given the spatial scale of the park entrance locations and availability of consistent measures through time begin-

Figure 2. An example of how destination locations were defined for each park. Here multiple entrance locations for Crystal Cove State park were identified. A destination zone is a fixed geography we defined by parking lots and segments of public streets used by people to access the respective parks. Aerial imagery used for this figure courtesy of Eagle Aerial (https://eagleaerial.com).

ning with 2014. Navigation-GPS data is collected via GPS-enabled devices (e.g., mobile phones, connected cars, truck tracking systems) when using a navigation app on a road network, resulting in frequent location "pings." Mobile apps also frequently "ping" in the background, when the app is not activated, and thus this provides a robust data set. This data is processed by the *InSight* model to represent "vehicle trips" between start and end points. This allows for relative comparisons of visitor use (as measured through vehicular origin-destination trips) across park entrances in our study area. The StL Index, represents all vehicle trips ending in the destination zones we identified. So a destination zone is a fixed geography defined by the location of parking lots and/or segments of public streets where people park to access the respective parks. Trips were analyzed that ended in the destination zone after starting in an any origin zone. Destination zones were not identified as pass-through, thus analysis on each zone only used trips that stopped in the zone. For Navigation-GPS (which accounts for all the data used in the present study), a trip is considered stopped when the device does not move more than 5 meters in 5 minutes and a trip is also required to be at least 3 minutes and 500m in length.

For all annual use totals, we summarized the data by time periods that align with the fiscal years of the management agencies in our study area so our analysis was congruent with their reporting requirements. A paired-sample *T* test used to examine the difference between model estimates and the available gate count data at one location was performed in SPSS version 25 (IBM Corporation, Armonk, NY) using standard procedures.

Data Calibration and Validation Procedures

In order to correct from the StL Index values to use estimates, we had to first develop a calibration procedure that scaled the StL Index values to an actual vehicle count, and then adjust for the number of visitors per auto delivery at each of our sites. We used annual average daily traffic (AADT) values reported by CalTrans (CalTrans, 2018) on a separate calibration zone to develop a correction factor to scale values derived from the *InSight* model to an actual vehicle count. Specifically, we used counts from an established traffic sensor located on California State Route 73 (see Figure 1), which is in close proximity to our study area together with the single-factor calibration component of the *InSight* model to generate calibrated values. Comparison of the model output StL Index values, which only represents a proportion of total volume, to the actual counts over a one-year period (2016-2017) allowed us to determine a correction factor. Thus, to arrive at actual vehicle counts at park entrances, we multiplied the StL Index values by the correction factor we determined of 0.158. Further, to arrive at actual visitor use numbers where needed, we adjusted the vehicle arrival estimates by average group size at each location determined from visitor survey research conducted in 2017 (the authors' unpublished data). These adjustments ranged from 2.01 to 3.04 people per auto depending on the specific location. In cases where the actual site had not been surveyed, we used the lowest observed value on the Reserve (2.01) to avoid over estimation.

We examined the resulting estimates in several ways in order to assess overall validity. In Irvine Regional Park, daily counts of vehicles are reported at the main entrance station and this location served as our best and most reliable means of comparing calibrated *InSight* model estimates to other similar data. The gate count data are unpublished and were determined by a consultant hired by the park who combined information on the number of tallied receipts for cars paying to enter the park, and the number of vehicles tallied by entrance kiosk operators (M. Fuentes, consultant, personal communication). We view these counts as estimates, since there were several possible sources of error and to our knowledge no independent error correction or validation steps were included as part of the protocol.

Next, we examined Ridge Park, a location with a parking area of known capacity, to determine if our estimate of cumulative arrivals by hour at this location were congruent with this known capacity. Last, we again examined Irvine Regional Park during a period where two fire events resulted in parking lot closures. In this analysis we examined 50 days of calibrated vehicular use data from the *InSight* model before, during and after the two fire events (2,500-arce and 10,000-acre wildland fires) that affected multiple locations on the Reserve. This enabled us to determine if our method was over- or underestimating use. Arrivals at Irvine Regional Park were limited to firefighting operations during the first closure, and thus significantly reduced, and then the lot was under complete closure (no use) during the second fire event. We took advantage of these well-documented, random events to examine a very low use situation to determine if erroneous mobile data were being included in our estimates.

Results

Using the StreetLight *InSight* model and the O-D analysis procedure, we estimated the average daily visitation across the 24 entrances for a four-year period (2014-2018; Table 1). Twenty-one of the measured locations increased in use during this timeframe, ranging from 19% to 137%. Entrance locations and overall management units that exhibited increases generally show consistent and continual increases. Three entrance locations and one management unit (Santiago Oaks Regional Park) exhibited overall use declines ranging from 9% to 47%. This decrease was a consistent trend at the two entrances of Santiago Oaks, but was a more sudden decrease at one entrance of Peter's Canyon in 2017-2018—likely due to the aforementioned major fire event that closed this location for two extended periods.

We examined the validity of the average daily visitation data in several ways. First, we compared the number of vehicle arrivals determined by StreetLight *InSight* model and our calibration method to the number of counted vehicle arrivals at Irvine Regional Park—the only location in the study where reliable arrival counts were available (Figure 3). Over the 24 months examined, the corrected *InSight* model reported similar trends and was not significantly different from the count estimates (paired samples t-test, $t(23)$ 1.29, p=.207). Overall, the StreetLight *InSight* model determined 5.7% less vehicle arrivals than the gate count estimate. Next, we compared yearly average hourly arrivals for weekends and weekdays against known parking constraints (defined by parking lot size and the amount of available street parking) at the main entrance to Ridge Park, a prominent coastal park (Figure 4). The number of arrivals at Ridge Park

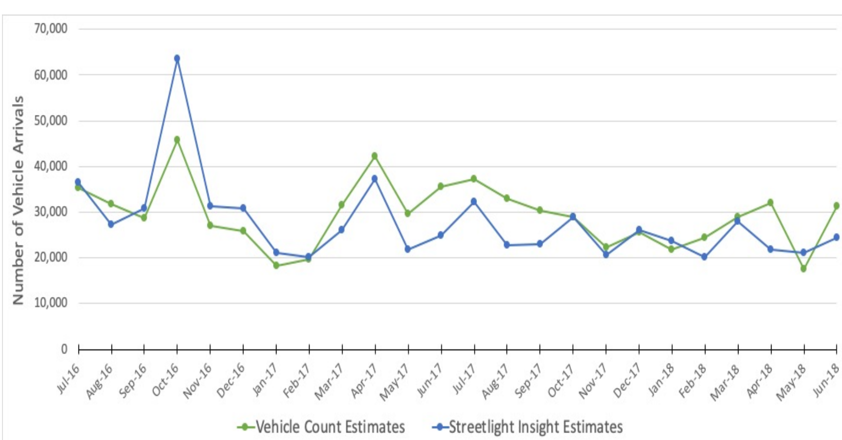


Figure 3. A comparison of total monthly vehicle arrival estimates using the Streetlight InSight model and gate count estimates at Irvine Regional Park over a 24-month period. Observed differences are not significant via a paired samples t-test (t(23) 1.29, p=.207).

Table 1

Annual Visitation Estimates (Total Visitors) by Park Management Unit and Entrance Location as Determined from the Street-Light InSight Model

Park Management Unit and Entrance Location[1]	Annual Number of Visitors[2]				Change (%)[3]
	2014-15	*2015-16*	*2016-17*	*2017-18*	
Crystal Cove State Park	**672,201**	**864,159**	**960,718**	**1,150,937**	**71**
Crystal Cove State Park - Los Trancos	223,140	270,434	295,704	363,051	63
Crystal Cove State Park - Pelican Point	183,032	258,958	279,475	333,145	82
Crystal Cove State Park - Reef Point	103,630	114,642	144,200	156,256	51
Crystal Cove State Park - El Moro Day Use	68,739	91,690	114,642	127,740	86
Crystal Cove State Park - El Moro Ranger Station	59,233	85,662	82,069	112,555	90
Crystal Cove State Park - Campground	34,427	42,773	44,628	58,190	69
Irvine Regional Park	**445,354**	**573,846**	**687,777**	**660,867**	**48**
Aliso & Wood Canyons Wilderness Park	**331,141**	**458,932**	**579,878**	**658,119**	**99**
Aliso & Wood Canyons Wilderness Park - Top of the World	202,442	270,311	384,394	446,885	121
Aliso & Wood Canyons Wilderness Park - Moulton Meadows Park	61,183	83,128	97,806	104,491	71
Aliso & Wood Canyons Wilderness Park - Main Entrance	67,515	105,493	97,679	106,743	58
Ridge Park	**219,530**	**288,055**	**355,602**	**350,439**	**60**
Peters Canyon Regional Park	**98,553**	**150,509**	**139,909**	**111,368**	**13**
Peters Canyon Regional Park - Main Entrance	46,015	57,664	59,761	42,054	-9
Peters Canyon Regional Park - Peters Canyon Road Entrance	52,539	92,845	80,147	69,314	32
Upper Newport Bay Nature Preserve	**77,201**	**103,861**	**129,363**	**120,785**	**56**
Whiting Ranch Wilderness Park	**62,615**	**72,906**	**99,440**	**97,333**	**55**
Whiting Ranch Wilderness Park - Borrego Trail Entrance	55,672	66,335	90,637	85,181	53
Whiting Ranch Wilderness Park - Glenn Ranch Staging Area	6,943	6,571	8,803	12,151	75
City of Irvine Open Space - Quail Hill Trailhead	**34,891**	**46,599**	**91,922**	**82,533**	**137**
Laguna Coast Wilderness Park	**53,587**	**66,285**	**61,159**	**69,547**	**30**
Laguna Coast Wilderness Park - Willow Staging Area	23,532	27,492	22,483	27,958	19
Laguna Coast Wilderness Park - Nix Nature Center	18,056	25,629	21,551	22,483	25
Laguna Coast Wilderness Park - Big Bend	5,242	7,339	9,319	10,950	109
Laguna Coast Wilderness Park - Dilley Preserve	6,757	5,825	7,805	8,155	21
Santiago Oaks Regional Park	**62,247**	**58,422**	**46,019**	**35,471**	**-43**
Santiago Oaks Regional Park - Main Entrance	42,310	40,339	35,123	24,806	-41
Santiago Oaks Regional Park - Santiago Creek Trail Entrance	19,938	18,083	10,896	10,664	-47
Black Star Canyon Road	**14,376**	**19,285**	**35,239**	**28,051**	**95**

[1]Locations in bold type are overall park management units. Where individual entrance locations are listed, management unit totals are the sum of individual entrance locations.
[2]Annual total number of visitors were calculated by calibrating the StreetLight Index values and adjusting for average group sizes. See methods section for full details.
[3]Change is percent change from estimates for the 2014-15 season to 2017-18 season. 2014 is the first year that StreetLight data are available. Note: Some locations exhibited increases and decreases during the study period not fully described by this one measure.

per day averaged 671 for weekend days, and 294 arrivals on the average weekday. The data suggest that peak weekend arrivals occur at 9 a.m. and by 10 a.m. and estimated total of 238 vehicles are parked at one time. This result is congruent with the capacity of parking both in lots and on the street (estimated at ~250 vehicles). Weekday use is considerably less and temporally different, with peak arrivals occurring at 6 p.m., and is also in accord with general observations of use patterns at this location.

A final assessment of validity investigated the sensitivity of our method as an indicator of very low-level use changes by examining a period of park closure during a wildfire at Irvine Regional Park (Figure 5). Prior to the fire events, the *InSight* model determined approximately 400–800 vehicle trips per day during the weekdays and between 2,200 and 3,600 trips on the weekend days. During the first fire event, the parking location was used as a staging area for the firefighters, so some activity remained in the parking area, but a substantial reduction in activity was measured on the first weekend after the fire. This would be expected as firefighters were present during that weekend. The park reopened for a short period the following week and use rebounded to a level similar to that of weekday use prior to closure. A second fire event which swept through the park completely closed this location for six days and our analysis shows no vehicle trips during this time. The park reopened on October 18 and we measured a rebounding of use at comparable levels to that of pre-closure conditions.

Discussion

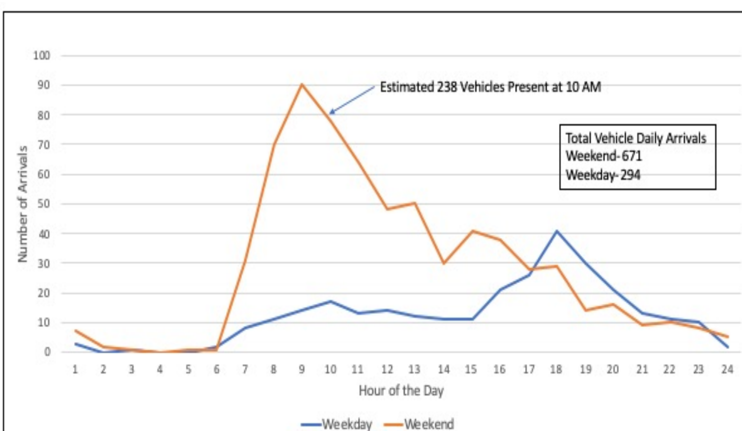


Figure 4. Estimated daily arrivals at Ridge Park by hour using Streetlight *InSight* model. Estimates use one year of data (2016-2017). Total estimated vehicles present at a given time period were obtained by adding hourly estimates and assuming a 3-hour duration of visit.

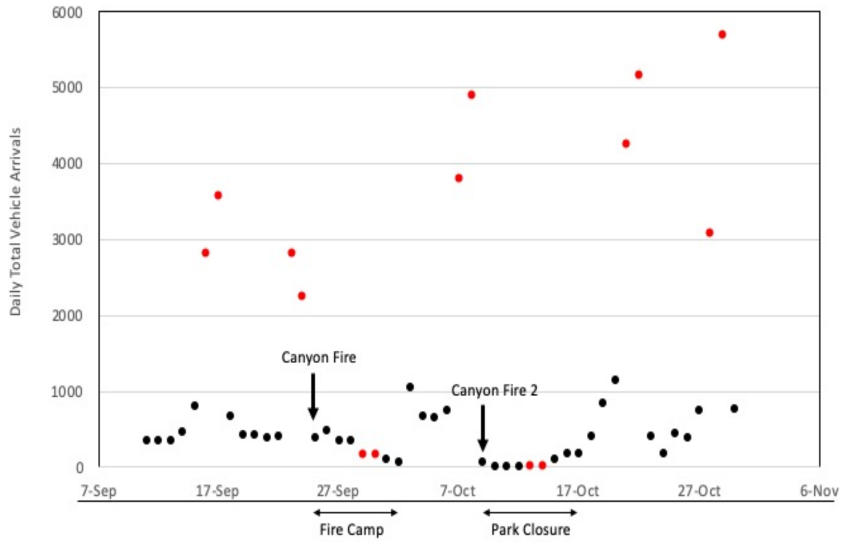


Figure 5. An examination of vehicle arrivals under conditions of park closure. Dates in red are weekends; "Fire Camp" indicates use of park parking areas as a staging location for firefighting operations with no visitation; "Canyon Fire 2" indicates a period of park closure due to a large wildfire. The park reopened on October 18.

The reliable enumeration of the trends of visits to PPAs provides managers with the ability to allocate field staff, plan and manage facilities, and protect sensitive park resources. In addition, understanding travel patterns to and from park locations is becoming increasingly important, as individual units experiencing capacity issues can look to alternative locations to direct visitors in a regional context (Manning, Lawson, Newman, Halo, & Monz, 2014). Consequently, park researchers and managers continuously look for new data sources related to park visitation, and opportunities to improve data collection and analysis. Obtaining readily available data from mobile devices can be helpful in achieving all of these needs and objectives.

Much of the previous work in PPAs using spatially derived measures of visitor use has understandably focused on the spatial, temporal and behavioral patterns that can be derived from the data and resultant experiential and ecological consequences. (e.g., D' Antonio et al., 2010; Kidd et al., 2015; Kim et al., 2019; Rice et al., 2019). While these approaches remain highly valuable, typically studies of this kind involve participation in some way by the visitor, either carrying a GPS device or participation using a mobile device exercise application that tracks use. These approaches also need to be corrected for actual use levels, since they are typically subsamples of the entire population of visitors. The approach used in this study advances mobile device application in PPAs in that we determined total arrivals at parking locations using big data sources that do not require active participation on behalf of the visitor.

The method described here is potentially a significant advancement for visitor use estimation for many park locations. First, mobile device technology continues to improve rapidly as does its adoption by recreationists. Our study area is urban-proximate and well served by mobile networks, and consequently many park visitors rely on mobile devices during their visit—an ideal site for the application of this approach. However, mobile networks serve many PPAs, or at least the park entrance locations, and these services are likely to grow in the future. Although our current method focuses on measuring the use of devices acquiring navigation-GPS data and automobile deliveries, it is well suited for our project area given that most visitors arrive by vehicle. This same approach would be applicable to many national, state and local park settings in the USA and elsewhere. Alternatively, there exists a vast and growing amount of location-based services (LBS) data that is becoming more commonly used by mobile devices—regardless of mode of delivery. Therefore, future development of mobile device analysis strategies may yield similar approaches that could be used in PPAs where auto deliveries are less common and visitors arrive by public transportation or non-motorized means.

A major potential advantage of mobile device data is that use estimation can be accomplished via a desktop analysis, with minimal fieldwork. Destination locations at park entrance areas are delineated in a map-based user interface (e.g., Figure 2) and the StreetLight *InSight* model estimates deliveries to these locations. Eliminating the need for maintenance and calibration of automated counters, data downloading, and other aspects of standard use estimation is a major innovation that can benefit many locations. An additional benefit to this approach is that informal, undesignated entrance locations can also be examined in a similar fashion, although some field work is usually needed in these locations to assure that visitors are actually entering the park. Our findings at the multiple entry locations across the study site (Table 1) are the first of this kind in our study area, that is, at most formal and informal locations managers had no data on visitor use. At the majority of entrance locations, the data suggest trends of increasing use—in some cases very substantial increases—over the four years of the study. The potential for this method to be a viable substitute for traditional, more labor-intensive field methods is significant.

Last, using mobile device data allows access to past data sets and thus the ability to examine recent trends in locations where field-based data were never collected. Data from Streetlight Inc., is available as far back as January 1, 2014, and thus in our study we were able to examine trends over a four-year period starting July 1, 2014 through June 30, 2018. Our approach focused on use estimation but readily available via the *InSight* analysis procedures, are basic demographic analyses on trip origin and home locations, which are often useful to managers in developing and understanding of the visiting public. This kind of information is more typically derived from a visitor questionnaire, which of course requires substantial effort, but can also be derived concurrently with the analysis approach using the same *InSight* platform described here. An analysis comparing the demographic output available from the *InSight* platform and an on-site questionnaire is the focus of ongoing work by our project team.

Our current approach is limited in that it lacks a system-wide calibration validation procedure to translate auto deliveries to actual park visitation. Our overall calibration relied on an existing traffic sensor proximate to the study area and validation to direct counts was only available at one entrance location (i.e., Figure 3). Although there were no statistical differences between the two data sources at this location, we can only speculate that the observed difference of 5.7% was the result of small errors in both types of use estimation approaches. Improved calibration and validation approaches are likely to be best if they are site specific and may involve installing vehicle counters proximate to park entrances and determining a correction for the number of visitors per vehicle. We interpret our current approach as producing an estimate of visitor use—not a direct count—that is particularly useful in examining trends in visitation and making comparisons across sites. It is also very useful in locations where direct counts are difficult to obtain, such as PPAs with diffuse entry locations. Our approach also demonstrates how group size collected from a visitor survey, a metric that could also be collected via entry observations, can be used as part of the calibration approach. We believe that with further development of analysis tools, calibration techniques and associated validation studies, these use estimates will become more accurate and could therefore reliably replace traditional counting techniques over time.

Practitioners interested in accessing mobile device data should be advised that it is generally computationally complex to process and rife with legal and technological issues that need to be handled properly. Data providers, such as StreetLight Data, Inc., make the data and analysis approaches accessible to researchers and practitioners, but adequate funding must be available to pay for such data services. The work presented here provides an initial investigation into the feasibility of adopting readily available tools to estimate use based on vehicle arrivals. Our approach developed a calibration procedure that allows existing transportation metrics to be adapted to a PPA setting and the work also demonstrates an initial approach for validating mobile device data using existing counts and known parking capacities and restrictions. Future development of mobile device data, analysis, and calibration tools will likely to yield approaches that more accurately determine the location and intensity of use to and within PPAs regardless of the mode of arrival.

Conclusions and Management Implications

- Origin-Destination analyses, as available via StreetLight *InSight*, offer an opportunity for park and protected area managers to further understand visitor use levels and trends.
- Current available metrics provide easy and convenient relative comparisons of use levels at access points to a PPA.
- A primary advantage is that these data exist and are readily available from companies such as StreetLight Data, Inc. Use estimates can be obtained without field assessments and visitor direct participation, and trend data can be examined (back to 2014 for data from StreetLight).
- Proper scaling (calibration) techniques need to be developed in order to correct current indices to be representative of actual absolute visitation levels. Calibration approaches are likely to be somewhat site specific and may involve installing counters proximate to PPAs if none are available. Even if counters are needed, the overall approach remains cost effective because one counter location can be applied to multiple PPAs and/or entry points.
- Currently we view the available data and associated analysis as an estimate of visitor use not a direct count. We believe that with further development of analysis tools and calibration techniques and associated validation studies, these use estimates will become more accurate.

- Many park visitors rely on mobile devices during their visit and thus this non-participatory mobile device technology may be useful in spatial and temporal patterns of use within PPAs, off of designated roads. This is the subject of future research by our project team.

References

Ahas, R., Aasa, A., Roose, A., Mark, Ü., & Silm, S. (2008). Evaluating passive mobile positioning data for tourism surveys: An Estonian case study. *Tourism Management, 29*(3), 469–486.

Alexander, L., Jiang, S., Murga, M., & González, M. C. (2015). Origin–destination trips by purpose and time of day inferred from mobile phone data. *Transportation Research part c: Emerging Technologies, 58*, 240–250.

Balmford, A., Green, J. M., Anderson, M., Beresford, J., Huang, C., Naidoo, R., Walpole, M., & Manica, A. (2015). Walk on the wild side: estimating the global magnitude of visits to protected areas. *PLoS Biology, 13*(2), p.e1002074.

Center for Demographic Research. (2019). Orange Range County facts and figures. ,California State University, Fullerton. Retrieved from http://www.fullerton.edu/cdr/ocff.pdf

CalTrans. (2018). Traffic census program. Retrieved from http://www.dot.ca.gov/trafficops/census/

Çolak, S., Alexander, L. P., Alvim, B. G., Mehndiratta, S. R., & González, M. C. (2015). Analyzing cell phone location data for urban travel: current methods, limitations, and opportunities. *Transportation Research Record: Journal of the Transportation Research Board, 2526*, 126–135.

D'Antonio, A., Monz, C., Lawson, S., Newman, P., Pettebone, D., & Courtemanch, A. (2010). GPS-based measurements of backcountry visitors in parks and protected areas: Examples of methods and applications from three case studies. *Journal of Park and Recreation Administration, 28*(3), 42–60.

Deng, J. (2019). Professor in Recreation, Parks, and Tourism Resources Program, School of Natural Resources, West Virginia University. Personal communication, July 30, 2019.

English, D., & Bowker, J. M. (2018). Introduction to the Special Issue on Visitor Monitoring. *Journal of Park and Recreation Administration, 36*(1), ix–x.

Fuentes, M. (2018). Parking Concepts, Inc. Personal communication, July 23, 2018.

Hallo, J. C., Manning, R. E., Valliere, W., & Budruk, M. (2005). A case study comparison of visitor self-reported travel routes and GPS recorded travel routes. In K. Bricker (Ed.), *Proceedings of the 2004 Northeastern Recreation Research Symposium. Gen. Tech. Rep. NE-326.* Newtown Square, PA: US Department of Agriculture, Forest Service, Northeastern Research Station: 172-177.

Hammitt, W. E., Cole, D. N., & Monz, C. A. (2015). *Wildland recreation: Ecology and management.* Chichester, West Sussex: John Wiley & Sons.

Hollenhorst, S. J., Whisman, S. A., & Ewert, A. W. (1992). *Monitoring visitor use in backcountry and wilderness: a review of methods*. Gen. Tech. Rep. PSW-134. Berkeley, CA: Pacific Southwest Research Station, Forest Service, U.S. Department of Agriculture, 10 p. 134.

James, G. A., & Ripley, T. H. (1963). *Instructions for using traffic counters to estimate recreation visits and use.* Res. Pap. SE-3. Asheville, NC: U.S. Department of Agriculture, Forest Service, Southeastern Forest Experiment Station, 14 p. 3.

Kidd, A. M., D'Antonio, A., Monz, C., Heaslip, K., Taff, D., & Newman, P. (2018). A GPS-Based Classification of Visitors' Vehicular Behavior in a Protected Area Setting. *Journal of Park & Recreation Administration, 36*(1), 69–89.

Kidd, A. M., Monz, C., D'Antonio, A., Manning, R. E., Reigner, N., Goonan, K. A., & Jacobi, C. (2015). The effect of minimum impact education on visitor spatial behavior in parks and protected areas: An experimental investigation using GPS-based tracking. *Journal of Environmental Management, 162,* 53–62.

Kim, J., Thapa, B., & Jang, S., (2019). GPS-based mobile exercise application: An alternative tool to assess spatio-temporal patterns of visitors' activities in a national park. *Journal of Park and Recreation Administration, 37*(1), 124–134.

Korpilo, S., Virtanen, T., & Lehvävirta, S. (2017). Smartphone GPS tracking—Inexpensive and efficient data collection on recreational movement. *Landscape and Urban Planning, 157*, 608–617.

Leonard, R. E., Echelberger, H. E., Plumley, H. J., & Van Meter, L. W. (1980). *Management guidelines for monitoring use on backcountry trails* [Forest land recreational use]. Forest Service Research Note NE (USA).

Manning, R. E. (2010). *Studies in Outdoor Recreation- Search and research for satisfaction* (3rd ed.). Corvallis, OR: Oregon State University Press.

Manning, R. E., Lawson, S., Newman, P., Halo, J., & Monz, C. (2014). Sustainable transportation in the national parks: From Acadia to Zion. Hannover, NH: University of New England Press.

Monz, C. A., Pickering, C. M., & Hadwen, W. L. (2013). Recent advances in recreation ecology and the implications of different relationships between recreation use and ecological impacts. *Frontiers in Ecology and the Environment, 11*(8), 441–446.

National Park Service (NPS). (2018). NPS Visitor use Statistics. Retrieved from https://irma.nps.gov/Stats/

Newton, J. (2016). Spatial temporal dynamics of the visitor experience in Grand Teton National Park (Doctoral dissertation, Pennsylvania State University).

Pei, T., Sobolevsky, S., Ratti, C., Shaw, S. L., Li, T., & Zhou, C. (2014). A new insight into land use classification based on aggregated mobile phone data. *International Journal of Geographical Information Science, 28*(9), 1988–2007.

Raun, J., Ahas, R., & Tiru, M. (2016). Measuring tourism destinations using mobile tracking data. *Tourism Management, 57,* 202–212.

Rice, W. L., Mueller, J. T., Graefe, A. R., & Taff, B. D. (2019). Detailing an approach for cost-effective visitor-use monitoring using crowdsourced activity data. *Journal of Park and Recreation Administration, 37*(2), 144–154.

Shoval, N., and Ahas, R. (2016). The use of tracking technologies in tourism research: The first decade. *Tourism Geographies, 18*(5), 587–606.

Streetlight Data, Inc. (2019). *StreetLight* Metrics Resource Library. Retrieved from https://www.streetlightdata.com/metrics/

Walden-Schreiner, C., Rossi, S. D., Barros, A., Pickering, C., & Leung, Y. F. (2018). Using crowd-sourced photos to assess seasonal patterns of visitor use in mountain-protected areas. *Ambio,* 1–13.

Watson, A. E., Cole, D. N., Turner, D. L., & Reynolds, P. S. (2000). *Wilderness recreation use estimation: A handbook of methods and systems.* USDA Forest Service General Technical Report RMRS-GTR-56. Rocky Mountain Research Station.

Ziesler, P. S., & Pettebone, D. (2018). Counting on visitors: A review of methods and applications for the National Park Service's Visitor Use Statistics Program. *Journal of Park and Recreation Administration, 36*(1), 39–55.