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# Estimating Trail Use and Visitor Spatial Distribution Using Mobile Device Data: An Example From the Nature Reserve of Orange County, California USA

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# Estimating trail use and visitor spatial distribution using mobile device data: An example from the nature reserve of orange county, California USA

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ABSTRACT

Monitoring visitor use in parks and protected areas (PPAs) provides essential information for managers of PPAs to evaluate aspects of the visitor experience and balance the ecological disturbance that use creates. Traditional methods for quantifying visitation and spatial use of PPAs are resource intensive and thus are conducted infrequently or at cost-effective intervals which may fail to capture the dynamic nature of modern visitor use trends. This paper provides an addition to a growing literature using mobile-device data to quantify visitation and spatial density of use of urban-proximate PPAs in Orange County, California, USA using the analysis platform *Streetlight, Inc.* The results of our analysis compared favorably with well-established automatic trail counting and GPS-based monitoring methods, and illustrate several advantages of mobile device data to inform the management of PPAs. Mobile device data provide reliable estimates of visitation and spatial density of use and can augment and compliment existing social and resource monitoring for PPA management and planning.

## 1. Introduction

Recreation and tourism use in parks and protected areas (PPAs) continues to change dramatically as visitation trends fluctuate in response to dynamic social and technological influences. These increases have been observed worldwide across many PPAs (Balmford et al., 2009; 2015) and by park systems such as U.S. national parks NPS (2021) and U.S. state parks (Smith et al., 2019). Additionally, recent trends suggest that many urban-proximate locations are experiencing dramatic increases in visitation during the COVID-19 pandemic compared to historical trends (Geng et al., 2020). Managing agencies of many PPAs are often legally required to protect natural resources and provide high-quality opportunities for recreation experiences, while also accommodating visitor use in a manner as unrestricted as possible NPS (2017). The frameworks and adaptive management processes used to balance these competing demands require knowledge of the current amounts and types of use and identification of where use results in impacts to the resource or desired conditions (IVUMC, Interagency Visitor Use Managment Council). Additionally, knowing how and where visitors enter and use PPA landscapes can help park managers in planning of infrastructure and target minimum impact messaging to mitigate the impacts of recreation use.

A considerable literature suggests that without monitoring and management, visitor activities in PPAs frequently have some unintended and often undesirable consequences to both ecological and social conditions (Hammitt et al., 2015; Manning and Corvallis, 2011). Recreation use almost always results in direct and indirect disturbances to soil, vegetation, wildlife, water, and natural sound resources. Managing use with the expectation of some level of disturbance enables the maintenance of desirable and sustainable resource conditions (Hammitt et al., 2015). Increased visitor use can also introduce issues from a social or visitor experience perspective, with over-crowding, conflict, visitor safety, and diminished experience quality becoming challenges for managers in many PPAs (Manning and Corvallis, 2011). Monitoring changes in use often can suggest potential experiential and ecological management issues, but should not be considered causal as the relationship between use level and disturbance is often non-linear and location-specific (Monz et al., 2013).

There is broad agreement among PPA managers that understanding aspects of visitor use, such as the total number and temporal dis-

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tribution of visitors, entrance and exit behaviors, and the spatial attributes of recreation activities, is vital to management (English and Bowker, 2018). Historically, approaches focused mainly on total use estimation, with reliance on techniques such as self-counting, trailhead registration, and observation counts (Hollenhorst et al., 1992; Watson et al., 2016). In contrast, automated counter technology has been available for over five decades and automatic trail counters and vehicle counters continue to be widely employed in many PPAs today (English and Bowker, 2018; Hollenhorst et al., 1992; James and Ripley, 1963; Leonard et al., 1980). The spatial consequences of visitor use have been considered for some time (Monz C., 2018), but the more recent availability of inexpensive GPS devices and the application of spatial analysis (e.g., Antonio et al., 2010; Shoval and Ahas, 2016) has greatly expanded the ability to understand visitor use patterns across a variety of scales. When coupled with field-based surveys to add the context of visitors' attitudes and motivations, GPS tracking studies provide the opportunity to understand the factors that influence spatial behaviors and patterns of use in PPAs (D'Antonio et al., 2020; Sisneros-Kidd et al., 2021). Despite many advantages, GPS approaches still require the labor, thoughtful planning, and staffing for field-based sampling strategies to yield a statistically valid sample. Thus, although highly accurate and valuable to research and management, GPS-based approaches remain labor intensive in both the sampling phase and in the analysis phase given the extensive post processing of data that is required (Antonio et al., 2010; Kidd et al., 2018).

More recently, there is a growing interest in using mobile device data in PPAs in order to understand visitor use levels and distribution (Leggett et al., 2017). Currently the majority of published work that has used mobile device data in PPAs involves "active" participation from the visitor. In other words, visitors are asked to use a specific mobile app, such as a fitness app, or post information (e.g., photos) to social media, which can be gathered and analyzed. For example, mobile data has been used to understand spatio-temporal patterns within parks via data derived from exercise tracking apps (e.g., Kim et al., 2019; Korpilo et al., 2017; Rice et al., 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., Antonio et al., 2010. A second approach involves the analysis of geotagged posts on social media to estimate visitor use at both PPA-specific and regional scales (e.g., Runge et al., 2020; Walden-Schreiner et al., 2018; Wilkins et al., 2020). However, one limitation of estimating visitor use from fitness apps and other social media platforms is that only a small portion of visitors post about their trips online, and these visitors may not be representative of all park visitors (Wilkins et al., 2020). Further, using mobile device data that does not require active participation may be more representative of all visitors to PPAs. Mobile device data serves as vast network of sensors for understanding human mobility to inform transportation planning (Calabrese et al., 2011; Raun, et al., 2016; Jiang et al., 2017) and valuation of PPA recreational ecosystem services and benefits (Jaung and Carrasco, 2020) to integrate into outcomes-focused management techniques (Driver, 2008; Rice et al., 2020).

According to the U.S. Census Bureau, (Ryan, 2017), 76.5% of households in the United States have a smartphone and 90.2% of respondents to a 2017 survey in Orange County,CA PPAs reported carrying their cell phones during their visit (Sisneros-Kidd et al., 2019). Smartphones connected to cellular networks generate enormous volumes of spatially-explicit data. Every time a cell phone connects to a cellular network, a call detail record is automatically created; this stores information such as the time and location of the user (Leggett et al., 2017). This can provide information about people's travel patterns and behaviors. Emerging approaches in PPA contexts involve accessing mobile device data and employing available analysis tools to examine total use, visitor demographics, and use patterns in PPAs (Merrill et al., 2020; Monz et al., 2019,2020). Data sources are readily obtained from providers, and consequently field data collection is only needed for validation and scaling purposes. The data can be passively collected and is not dependent on the visitor to directly participate, as in visitor questionnaires and GPS tracking, and in other mobile app-based approaches (Kim et al., 2019; Walden-Schreiner et al., 2018). Some PPAs in remote locations are lacking in cellular connectivity and thus these emerging methods may be somewhat limited in geographic scope.

In this paper, we present a novel approach to examine the total use and spatial distribution of use *on trails* within a PPA setting. This paper complements our previous work examining arrivals to PPA trailhead parking areas (Monz et al., 2019)and demographic analysis of visitation (Monz et al., 2020) with mobile device data. This paper advances the application of mobile device data in PPAs since the data sources we analyzed did not require direct participation on behalf of the visitor. Our approach uses data purchased from a transportation data analysis provider, *Streetlight Data, Inc.* (San Francisco, CA, USA), and an associated web-based analysis tool, *Streetlight InSight*. This allows for determination of use and distribution-related data without the need to deploy field personnel or equipment, and given that these data sources are available for about the last six years, recent trends of changes in use can be examined. In this paper, we compared our mobile device analysis methods with more established protocols of automated trail counters and GPS tracking. Our overall goal was to examine whether the available mobile device data could serve as a reliable measure of trailhead visitation counts and spatial distribution and density of use along trail corridors. As stated, this paper builds on previous work and we refer the reader to (Monz et al., 2019, 2020) for examinations of vehicle arrivals at PPA locations and demographic analyses.

## 2. Methods

### 2.1. Study sites

Orange County, California (CA) is situated between the metropolitan areas of Los Angeles, CA and San Diego, CA. The planned development of the city of Irvine, CA and Orange County created large open space parks and preserves to provide critical habitat for coastal migratory birds, as well as for fauna migrating between the coast and the interior Santa Ana Mountains (Schoenherr et al., 2005). In 1991, the State of California passed the Natural Community Conservation Planning (NCCP) Act formally prescribing collaborative state and federal habitat management of these open-space preserves (C. A. FGC§, 2013). The initial focus of the NCCP was to balance urban-development with critical habitat protection for threatened and endangered species. However these open space lands also provide year-round outdoor recreation opportunities to the nearly 3.2 million residents of Orange County. Demand for recreational use of these highly accessible open space preserves is very high and as such, this use requires visitor use monitoring and management, particularly during native and migratory bird nesting.

The state and county PPAs in this study are collectively managed under the NCCP and provide diverse recreation opportunities including beach access and watersports, developed and backcountry camping, and an extensive multi-use trail system for hiking, running, mountain biking, and equestrian use. The four PPAs in this study, shown in Fig. 1, were selected because of the availability of extensive datasets of visitation and visitor spatial behavior to compare to similar metrics of visitation and density of use available via the Streetlight platform.

### 2.2. Trailhead counts and spatial density of use estimation

The analysis in this study compares estimates from *TRAFx* (TRAFx Research Ltd, Canmore, Alberta, Canada) infrared automatic trail counters and visitor GPS tracks that we obtained in the field with *Streetlight* (StreetLight Data, 2020) mobile device data of visitation counts. We measured visitation using TRAFx trail automated counters at four trailhead or entrance locations in three PPAs: Aliso Wood Canyons (ALWO),

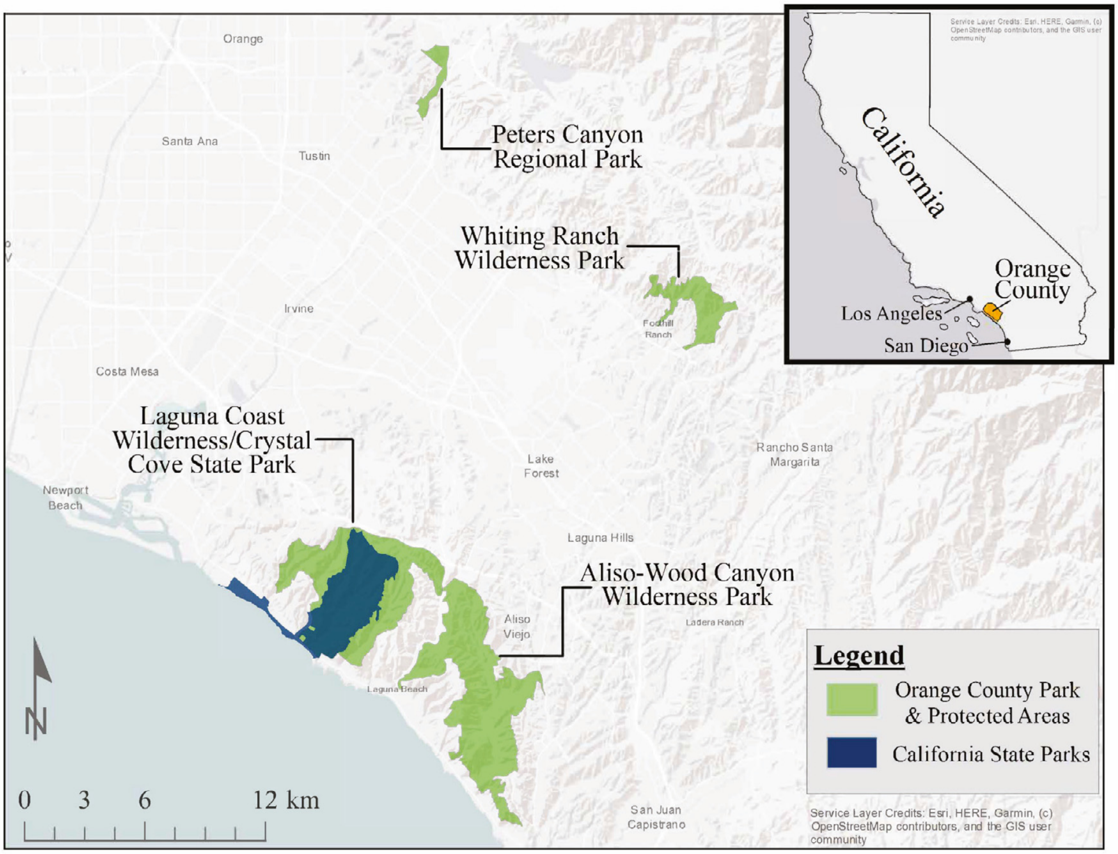


**Fig. 1.** Reference map indicating the four PPA study sites administered by state and county land managers.

Peter's Canyon (PECA), and Whiting Ranch (WHRA). Counts were collected over six days (Thursday to Tuesday) continuously during the month of May 2018 calibrated via a systematic comparison with manual counts in accordance with manufacturer recommendations. We stratified the calibration periods across days and throughout the day across the period the counters were deployed, providing proportions of activity type (pedestrian and bicycle) observed at each location. These proportions were then used to estimate the number of bicyclists and pedestrians on an average weekday and average weekend day at four counter locations across the three PPAs.

Mobile device data from StreetLight Data, Inc were accessed through a web-browser based interface using *StreetLight's Pedestrian Tool*. The *Pedestrian Tool* provides algorithm-based classifications of a mobile device's travel mode and estimates of the number of pedestrians or bicyclists passing through a user-defined "geofence" or polygon (StreetLight Data, 2020). Rectangular polygons extending across the trail sections were created at the same locations the *TRAFx* counters were installed and the *Pedestrian Tool* provided an estimate of average weekday and weekend use. At the time analysis was conducted, the data availability of *Streetlight Pedestrian Tool* use estimates in these locations were limited to mean daily estimates between April through June and September and October 2018. Data were entered into SPSS for analysis to compare *StreetLight* and *TRAFx* estimations of visitor counts for the average weekday and weekend day for both pedestrians and cyclists. We assessed distributions for the assumption of normality using Shapiro-Wilk tests which indicated normal distributions for the pedestrian counts; however bicycle counts violated this assumption for weekdays (0.851, $p=.038$) and weekends (0.769, $p=.004$). As a result, the Wilcoxon signed-rank test, a non-parametric equivalent of the paired-samples *t*-test for paired observations was selected to analyze use-estimates between the *StreetLight* and *TRAFx* data. Paired observations at each of the twelve counter locations were analyzed to determine if there were statistically significant differences between the *Streetlight* and *TRAFx* estimates of visitation. Finally, in order to understand the strength of the relationships between the *TRAFx* and *Streetlight* use estimates we selected the Spearman's rank-order test of correlation due to its independence of the assumption of normal distributions.

Similar to the analysis for visitor counts using pass-through zones, the *Streetlight Pedestrian Tool* was used to estimate spatial distribution and density of visitor use on trails in the PPA study areas. In order to conduct this analysis, a tessellation grid with 100x100m cells was generated in ArcMap 10.7 (ESRI, 2020) and clipped to a boundary shapefile for each of the four PPA study areas: Aliso Wood Canyons (ALWO), Peters Canyon (PECA), Laguna Coast Wilderness/ Crystal Cove State Park (LCW/CCSP), and Whiting Ranch (WHRA). The *Streetlight Pedestrian Tool* produced two sets of estimates of spatial distribution and density of visitor use, pedestrian activity types (i.e., walkers, runners, hikers) and bicycle activity types, for each of the PPA study areas. We compared the *StreetLight* use estimates of trail use to visitor GPS tracks from 594 pedestrians (hikers and runners) and 251 mountain bikers. These GPS tracks were obtained via a systematic random sample of visitors across the months of May and October 2017 and May 2018 in each of the parks. GPS tracks of visitors whose primary activity was hiking or running, collected in 2017, were added to the same 100x100m tessellation grid for the respective PPA where the track was collected and the sum of tracks passing through each cell was calculated providing an analogous metric of spatial density of use produced by the *Streetlight Pedestrian Tool*. GPS tracks of visitors whose primary activity was biking, collected in 2018, were prepared and summed using the same method. Use estimates for corresponding sections of trail which fell within a grid cell from the *StreetLight* and GPS datasets for both pedestrians and bicycles were exported to an SPSS (IBM Corp., 2020) dataset for statistical analysis.

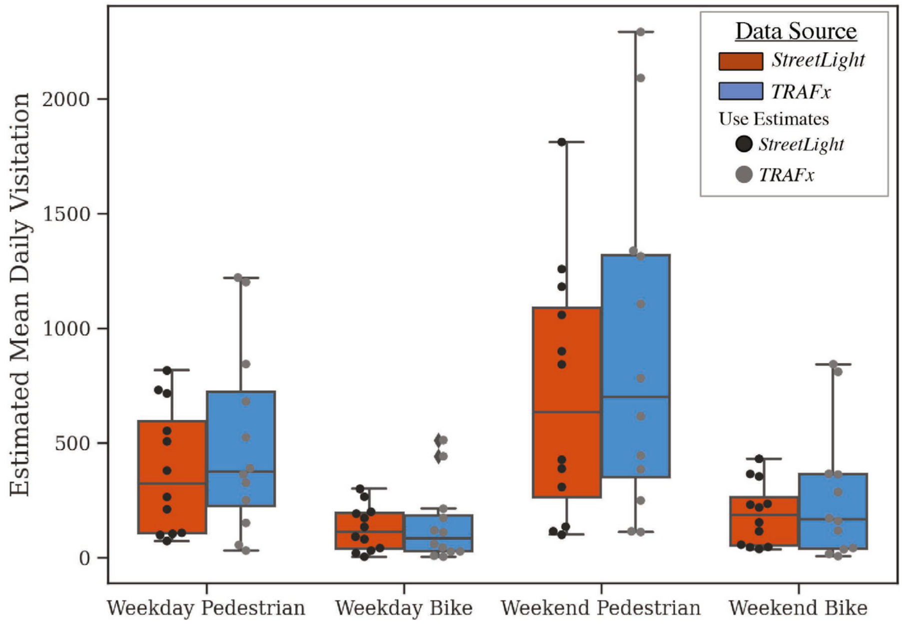


**Fig. 2.** *Streetlight* and *TRAFx* estimates of mean daily visitor use across the three parks in this analysis (n=12). Dots overlaid on the boxplots illustrate use estimate observations at four trailheads in three parks.

**Table 1**
Results of Wilcoxon signed-rank test comparing Weekday/Weekend Bike and Pedestrian Use estimates between *Streetlight* and*TRAFx*..

| | | Z | Sig. |
|---|---|---|---|
| Weekday | Pedestrian | -1.490 | 0.136 |
| | Bike | 0.000 | 1.000 |
| Weekend | Pedestrian | -1.334 | 0.182 |
| | Bike | -.392 | 0.695 |

**Table 2**
Spearman's ranked correlations between average *TRAFx* counts and *Streetlight* counts.

| | | n | Spearman's rho | Sig. |
|---|---|---|---|---|
| Weekday | Pedestrian | 12 | 0.775 | 0.005 |
| | Bike | 12 | 0.741 | 0.006 |
| Weekend | Pedestrian | 12 | 0.769 | 0.003 |
| | Bike | 12 | 0.811 | 0.001 |

**Table 3**
Spearman's ranked correlations between GPS and Streetlight estimates of trail use. *Note: The number of 100m x 100m grid cells in analysis is expressed by (n).Only includes grid cells that have established trails within them.*

| Park | Activity Type | n | Spearman's rho | Sig. |
|---|---|---|---|---|
| ALWO | Pedestrian | 865 | 0.527 | <.001 |
| | Bicycle | 864 | 0.907 | <.001 |
| PECA | Pedestrian | 230 | -.023 | 0.732 |
| | Bicycle | 230 | 0.734 | <.001 |
| LCW/CCSP | Pedestrian | 867 | 0.848 | <.001 |
| | Bicycle | 867 | 0.688 | <.001 |
| WHRA | Pedestrian | 295 | 0.872 | <.001 |
| | Bicycle | 295 | 0.870 | <.001 |

We assessed the distributions of use estimates for pedestrian and bicycle activity types with a Shapiro-Wilk test, which indicated violations of the assumption of normality for both *Streetlight* and GPS based estimates of pedestrian and bicycle densities for the four parks. In order to evaluate the strength and direction of the relationship between the *Streetlight* and GPS based estimates, a Spearman's rank-order test of correlations was performed to overcome the violation of the assumption of normality

## 3. Results

### 3.1. *Comparisons of* streetlight *and* TRAFx *estimations of trailhead counts*

After performing the Wilcoxon signed-rank test, we found *Streetlight* and *TRAFx* median estimates of pedestrian and bicycle use across weekdays and weekends were not significantly different (Table 1; Fig. 2)

Results from the Spearman's rank test indicated strong positive and statistically significant correlations between the *Streetlight* and *TRAFx* estimations of weekday/weekend pedestrian and bike use (Table 2).

### 3.2. *Spatial density of use estimates*

The spatial distribution and density of pedestrian and bicycle trail use estimates from the *StreetLight* and GPS samples were tabulated for four PPAs (ALWO, PECA, LCW/CCSP, and WHRA). Results indicate statistically significant moderate to very strong positive correlations between the Streetlight and GPS based estimates (Table 3). However, we found no significant relationship between *Streetlight* and GPS based estimates of pedestrian use at PECA.

Data are presented in Figs. 3–6 and suggest a high degree of face validity in the spatial patterns and density estimates in the *Streetlight* and GPS.

## 4. Discussion

The monitoring of visitation in PPAs provides managers critical information to balance the social and ecological implications of recreation use with the wide-ranging benefits to physical, mental, and social well-being. The most perspicuous of this information is quantifying the number of visitors to PPAs and where they are entering which can inform planning, provisioning of resources, and education (Newsome et al., 2012). Next, understanding the spatial and temporal patterns and in-

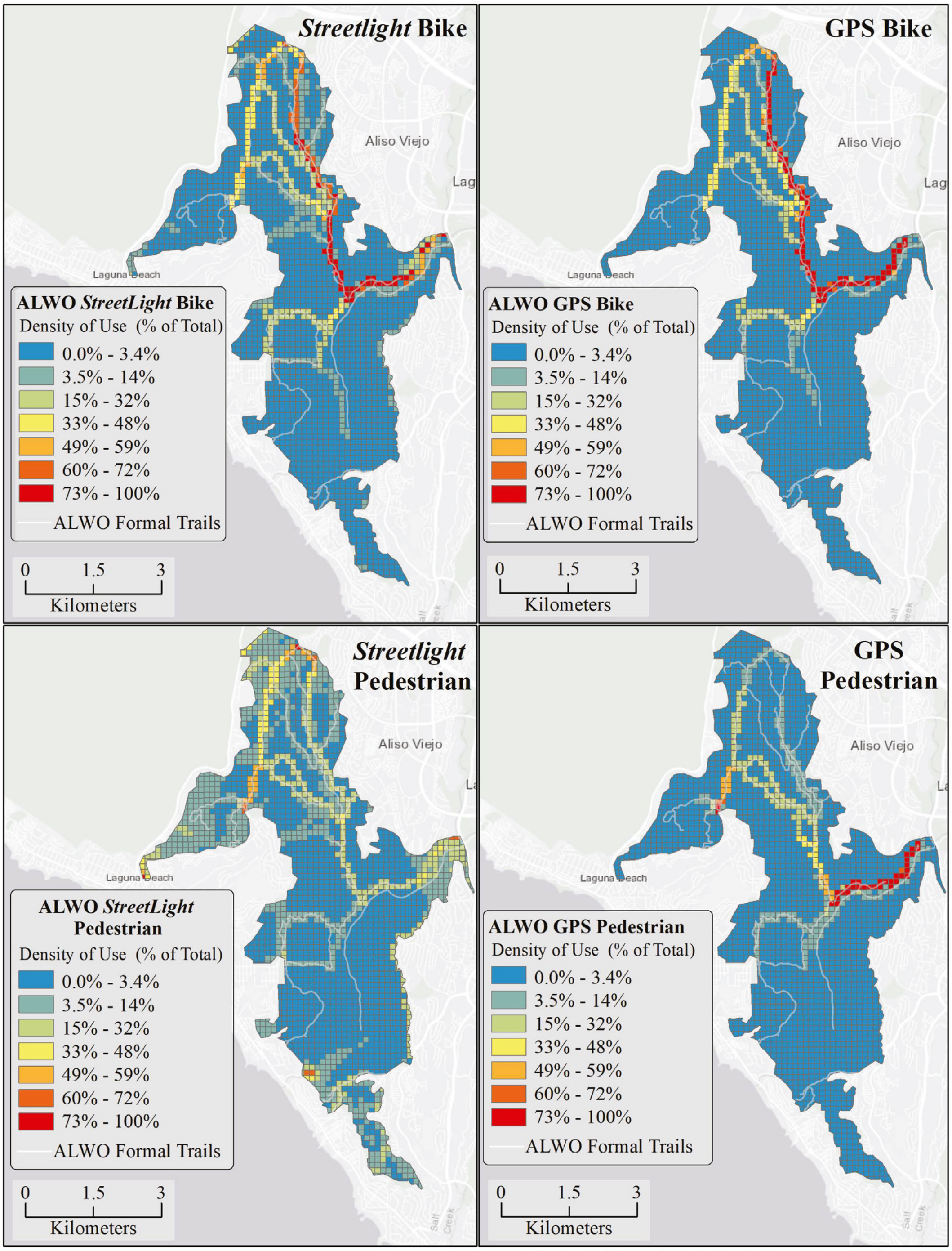


**Fig. 3.** Aliso Wood Canyons Wilderness Park (ALWO) comparisons of *StreetLight* and GPS spatial distribution and density of use.

tensity of use aids in management and mitigation of the ecological disturbances to soils, water, vegetation, and wildlife (Hadwen et al., 2007). A recent development to monitor and quantify human movement to inform planning has employed mobile-device data via smartphones which are passively collected, requiring no active participation from the population of interest (Kim et al., 2019). This study provides a novel contribution to visitor use monitoring methodologies in PPAs by illustrating a direct comparison of mobile device data with more established monitoring techniques.

In the first analysis we compared *Streetlight* estimates of trailhead counts with *TRAFx* infra-red automatic trail counters. We found the *Streetlight Pedestrian Tool* to provide similar estimates, with no significant differences in medians. The distributions of *Streetlight* use-estimates were less dispersed, which we attribute to variations in use-levels in the months the *Streetlight* data were sampled (April through June and September and October 2018). However, given the small sample size ($n$=12) the statistical power of this test is small, so there may be a difference that we were unable to detect. Nevertheless, we found strong correlations between the *Streetlight* and *TRAFx* estimates of visitor use, and the correlation values are similar to studies that have used social media data to estimate visitor use in urban-proximate PPAs (Teles da Mota and Pickering, 2020; Wilkins et al., 2020). Currently, advantages of social media data compared to mobile device data are that it is free and available on fine spatial scales (e.g., within a few meters) (Barros et al., 2020). However, mobile device data contain contextual information

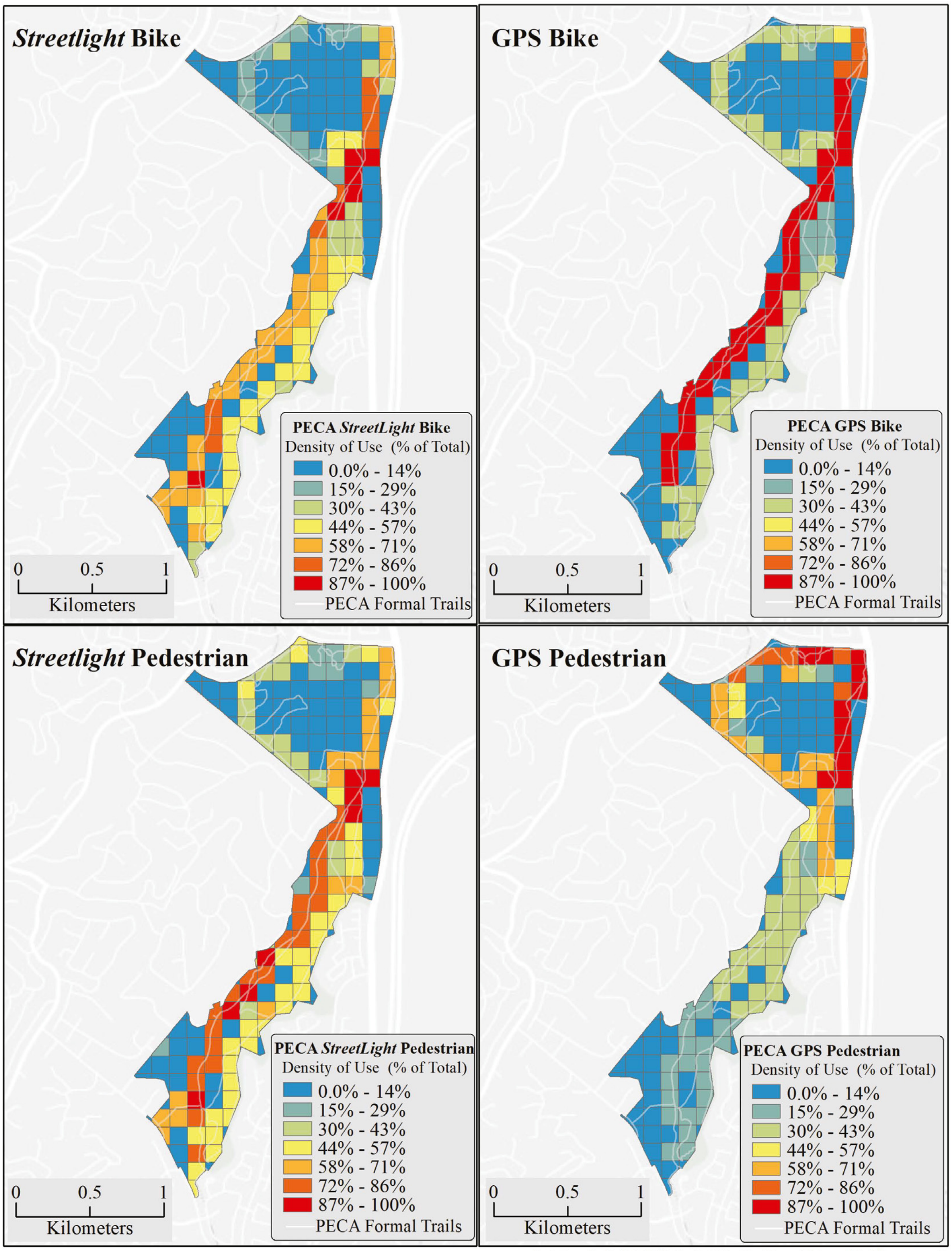


**Fig. 4.** Peters Canyon Regional Park (PECA) comparisons of *StreetLight* and GPS spatial distribution and density of use.

about visitor demographics (Monz et al., 2020), may be more representative than social media data, and can differentiate activity type between pedestrians and cyclists.

The second analysis compared the spatial distribution and intensity of use on trails across the parks. The analysis was conducted using a similar grid-based approach as Kim et al. (2019), however the size of the cells in our analysis was much smaller (0.01 km$^2$ vs 9 km$^2$), providing a finer spatial resolution of visitor use and density. The *StreetLight Pedestrian Tool* uses algorithms to sample mobile device location data, classify its activity type, and return probabilistic use estimates across the study area. We found strong, positive correlations for both pedestrian and bicycle use types across the four PPAs in this study, with the exception of pedestrian use in PECA. The extent of visitors' spatial use of the parks in the GPS sample were influenced by the sampling location where visitors were intercepted at the formal entrances to the PPAs. This effect is more pronounced with pedestrians in the GPS sample than with cyclists, who did not travel as far away from the locations where visitors were intercepted. This may provide one explanation of why pedestrian use in PECA was the only non-significant and low correlation measure in the analysis. However, in our previous work using Streetlight to estimate visitor demographic characteristics (Monz et al., 2020), our survey sampled visitors at the main, formal entrance at the north of PECA and was significantly different than *StreetLight* estimates. The pedestrian GPS tracks for PECA collected in 2017, like the aforementioned survey sam-

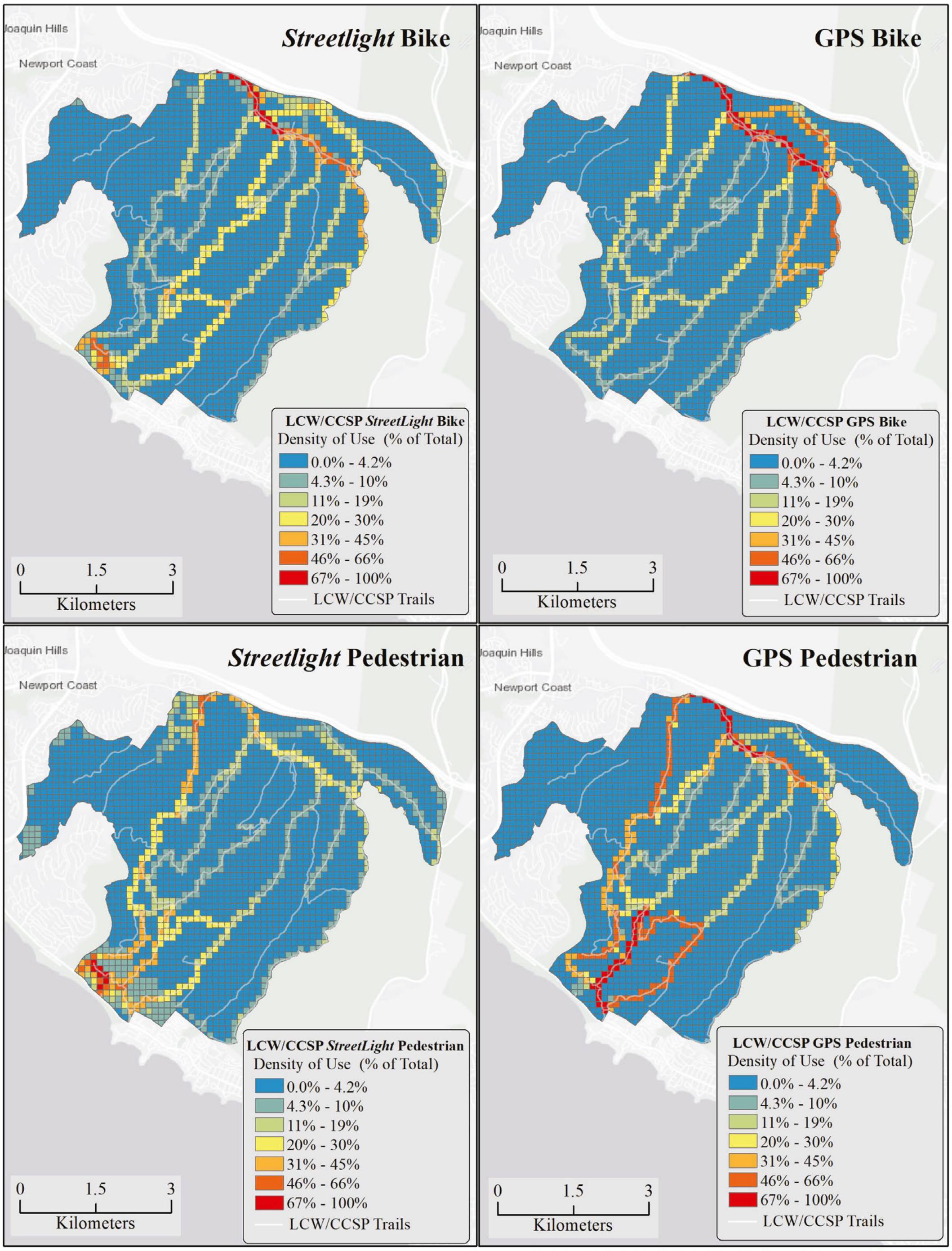


**Fig. 5.** Laguna Coast Wilderness and Crystal Cove State Park (LCW/CCSP) comparisons of *Streetlight*and GPS spatial distribution and density of use.

ple, may suffer from coverage error where visitors were sampled and may not capture the full amount of variation in spatial behavior across the park. However, in 2018 the bicycle GPS tracks were sampled from the north entrance and a trailhead at the southern end of PECA to intercept visitors accessing the park from a secondary entrance with street parking. Our sample of bicyclists in 2018 illustrates similar patterns of use as *Streetlight*, with the greatest intensities of use in the southern portion of the park and lower intensities of use at the northern entrance.

The *StreetLight* density of use estimates illustrate the locations where visitors entered the park from surrounding neighborhoods and secondary entrances, which the sample of GPS tracks did not reflect because visitors were intercepted only at primary entrances to the parks. However, the *StreetLight* estimates for pedestrian use indicate some low to moderate use in areas near edges of the PPAs which are proximate to office and retail areas (e.g., North border of Fig. 3 or shopping centers (e.g., South border of Fig. 6) which we attribute to error in classification of vehicle vs human movement of a mobile device. *Streetlight* algorithms snap or "lock" trips to the closest road or trail catalogued in the Open Street Map(OSM) network (StreetLight Data, 2020). Vehicles traveling at lower speeds near the periphery of PPAs may have been misclassified as pedestrians whose movements are processed with fewer rules about directionality and speed while bicycle trips are processed with these trip parameters. Nevertheless, *Streetlight* estimates captured use at a golf course and scenic overlook trails at the southern portion of Aliso

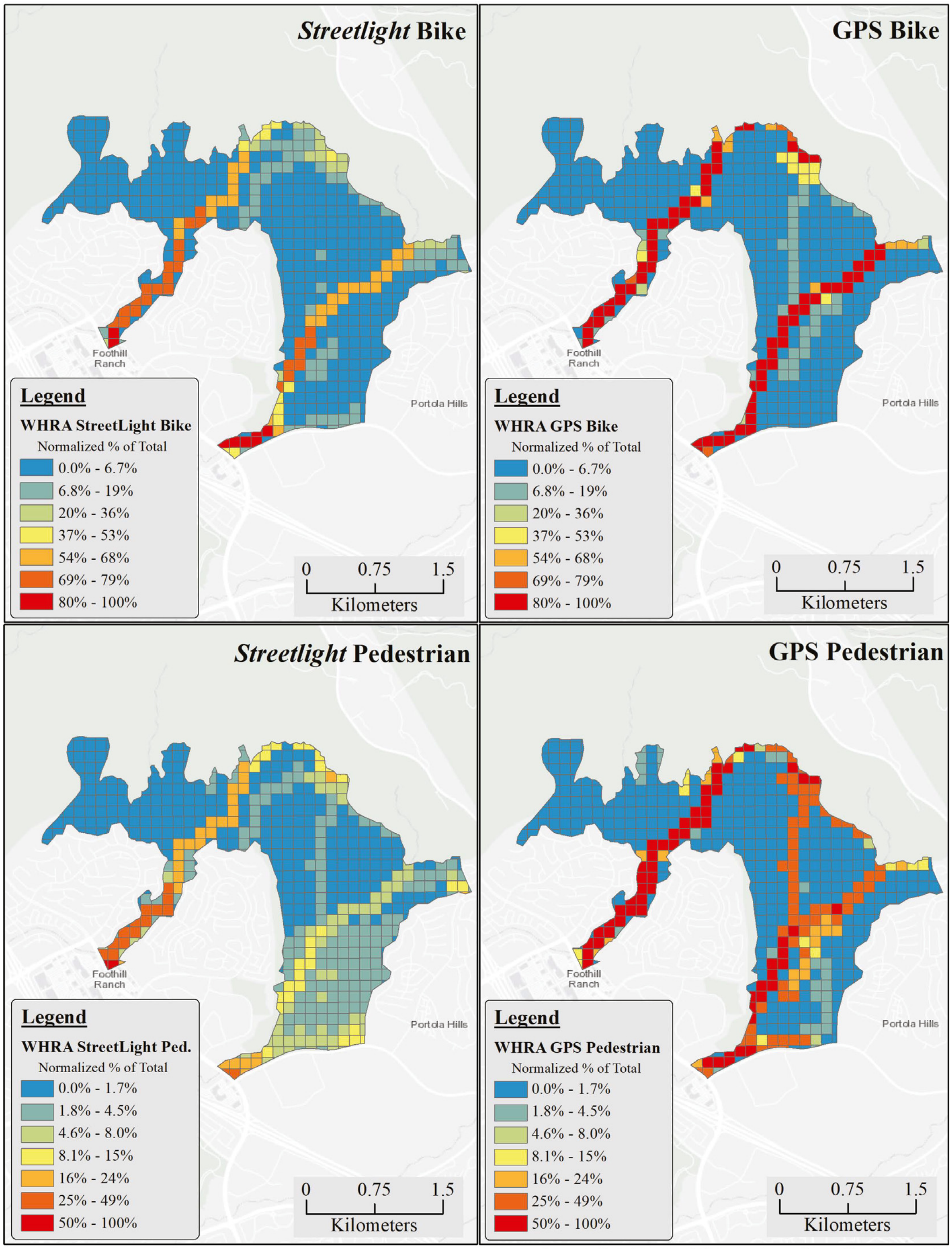


**Fig. 6.** Whiting Ranch Wilderness Park (WHRA) comparisons of *StreetLight* and GPS spatial distribution and intensity of use.

Wood Canyon (Fig. 3) and -indicated high densities of use from neighborhood entrances along the western border of Peters Canyon (Fig. 4). Ultimately, we constrained the analysis to the grid cells with formal trails because the GPS track sample was not designed to measure this neighborhood and periphery use.

While the focus of this analysis was to demonstrate the utility of mobile device data as an instrument to quantify visitation and spatial density of use within PPAs, the utility of mobile device data to managers goes beyond the boundaries of the PPAs they manage. Mobile device data has been particularly practicable in transportation literature with examples of origin-destination analysis (Alexander et al., 2015; Jiang et al., 2017) which can illustrate relationships with PPAs and surrounding communities, activity and mobility analysis (Calabrese et al., 2011; Jiang et al., 2017), and travel-cost studies (Jaung and Carrasco, 2020) that inform urban-planning and development of transportation infrastructure. A recent report published by the National Park Service using *StreetLight* data demonstrates the utility of mobile device data for regional transportation planning, visitor use trends and patterns, and origin-destination to inform PPA transportation planning and management (NPS, 2020). With this information, PPA managers alongside regional transportation planners might consider how visitors' travel in the multiphasic recreation experience contributes to the PPA's management objectives, and where and how active and sustainable modes of transportation could connect PPAs and vistors' communities to meet those objectives (Orsi, 2015). Furthermore, the strengths of mobile device data could provide a useful complement to traditional visitor counting methodologies and be useful as an inferential tool to understand more complex issues in protected area management.

## 5. Conclusion

In this study we found *StreetLight* estimates of visitation and spatial use and intensity of urban-proximate PPAs to reflect trends and patterns we observed with traditional visitor use monitoring techniques. The analysis of spatial distribution and intensity of visitor use in this study was constrained to trails but the use levels we observed around the periphery and through secondary or neighborhood access points represent an advantage of Streetlight and mobile device data to measure visitation to PPAs with "porous" boundaries, like seashores (Merrill et al., 2020), which make use estimation using traditional methodologies difficult to operationalize (Ziesler and Pettebone, 2018). This more complete understanding of where and how many visitors enter and spatial and temporal use within PPAs can help inform resource allocation, visitor-use management, and planning (Newsome et al., 2012). With information regarding the location and amount of visitor use PPA managers could target visitors entering through secondary or neighborhood entrances and effectively position signage to communicate relevant managerial regulations, minimum impact practices, and natural resource interpretation. However, more research is needed to determine the availability and quality of this data source in other park locations, particularly in undeveloped recreation areas or where cellular coverage may be limited.

Mobile device data present a wide-range of applications to advance research and inform PPA and visitor use management. Because of *StreetLight*'s ability to query mobile data from 2016 or 2018 to the present for vehicles and pedestrians respectively, managers using this tool for visitor monitoring could conduct longitudinal analyses to understand long term trends and changes in visitation particularly as (Monz et al., 2019) suggest when no field-based data exists, the effects of climate change (Wilkins et al., 2021) as well as social and cultural factors (Jaung and Carrasco, 2021) on changes in seasonal visitation, or to understand displacement and behavior as a result of direct management interventions which limit visitation or alter visitor patterns of spatial use in PPAs (Wesstrom et al., 2021). Mobile device data provide a spatio-temporal context to visitation data to quantify daily or seasonal use trends which can be integrated into adaptive management frameworks measuring visitor experience indicators of crowding or congestion (Kim et al., 2019). Finally, mobile device data have potential applications in quantifying the spatial scale of recreation as an ecosystem service and its demand (Cortinovis and Geneletti, 2018), as well as social and environmental justice considerations to understand who benefits from recreation and protected areas.

## 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.

## CRediT authorship contribution statement

**Noah E. Creany:** Data curation, Formal analysis, Writing - original draft. **Christopher A. Monz:** Conceptualization, Methodology, Investigation, Supervision, Project administration, Writing - review & editing. **Ashley D'Antonio:** Conceptualization, Methodology, Investigation, Supervision. **Abigail Sisneros-Kidd:** Conceptualization, Methodology, Investigation, Supervision. **Emily J. Wilkins:** Validation, Writing - review & editing. **Jordan Nesbitt:** Data curation, Software, Resources. **Milan Mitrovich:** Project administration, Supervision, Funding acquisition.

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