A toolbox to quantify human activity in protected areas for park management

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Abstract

1. Recreation in protected areas (PAs) is growing worldwide, potentially conflicting with wildlife and ecosystem protection. Efficiently estimating human activity in PAs is crucial for balancing a dual mandate of supporting visitor access and biodiversity, but managers lack clear recommendations about how best to monitor spatial and temporal trends in human activity.
2. Through two case studies, we reviewed several key tools for measuring human activity in PAs to assess the impacts on wildlife: camera traps, day passes, trail counters, and social media. We measured human activity across multiple scales and compared spatial and temporal activity estimates within and between PAs.
3. We found strong correlations between tools across PAs and a combination of tools may be better suited to understand finer-scale trends within parks. Individual tools, and their combination, can be tailored to specific research and management goals.
4. Synthesis and applications: Our case studies provide insights into the effectiveness of tools for measuring human activity in PAs and informs practitioners and researchers about how they can be used to address real-world management decisions. Tools varied in their strengths and their weaknesses and looking forward, the widespread adoption of multiple, integrated measures of human activity is needed to develop evidence-based park management strategies, benefitting both humans and nature.

Keywords: camera trap, human activity, protected area management, recreation, social media, trail counter, Western Canada

Introduction

As visitation to protected areas (PAs) grows (Balmford et al., 2015), efficient tools for managing human access while optimizing social and ecological benefits are increasingly needed. Visitor data can quantify non-consumptive recreation benefits for people (e.g., Romagosa *et al.* 2015), and the potential wildlife impacts (e.g., Reed & Merenlender, 2008).

At one extreme, managing human activity might exclude people from PAs to prevent negative ecological impacts (e.g., Manenti *et al.* 2020). However, such approaches risk disenfranchising local communities or outdoor recreationists (West & Brockington, 2006). On the other hand, unmanaged PA visitation can lead to ecological degradation and defaunation (Larson et al., 2019). Management approaches to mitigate impacts include education, seasonal timing restrictions, zonation or visitation limits, invasive species management, and infrastructure maintenance (Lewis et al., 2021; Lucas, 2020). Regardless, human activity effects on PAs are context-dependent (Granados et al., 2023) so tools to monitor trends should address the research and management questions of interest. Monitoring approaches can help identify thresholds of human activity on ecosystem functions and acceptable activity levels in PAs. This can inform management strategies that optimize the socioeconomic and human wellness benefits from outdoor recreation, while minimizing undesirable ecological impacts (Miller et al., 2022).

A fundamental challenge of PA management is measuring spatial and temporal trends in human activity including how visitors use PAs (e.g., entry points, routes followed, activity type) (Cessford & Muhar, 2003). PAs are often established in remote and rugged locations with relatively poor infrastructure, making direct counts of people difficult and expensive (D'Antonio et al., 2010). Porous PA boundaries and a lack of available tools to monitor access also complicate efforts to determine spatial patterns of activity after the point of entry (Ziesler & Pettebone, 2018). To address issues with on-site visitor counts in PAs (i.e., day passes or traffic counters), remote sensing tools (i.e., data collected by remote sensors without the need for on-site human presence) are increasingly used (Fisher et al., 2018). For example, camera traps produce fine-scale human activity information and can simultaneously monitor wildlife (Fennell et al., 2022) and vegetation (Sun et al., 2021) but they lack spatial breadth required to predict PA spatial and temporal trends in human activity. Conversely, activity tracks from fitness applications can provide spatially explicit information about human activity (Toivonen et al., 2019), and user-contributed social media data from geotagged photos or posts can be used (Fisher et al., 2018) independently or with data collected on-site to parameterize models that predict visitation (Wood et al., 2020). Remotely sensed tools could be cost- and time-efficient options for monitoring human activity, but whether they reflect true levels of human activity and complement each other is less understood (Fisher et al., 2018).

PAs have diverse management objectives (e.g., ecological, conservation value, and recreation values), and accessibility and management budgets, so the applicability of tools and their effectiveness in measuring human activity at multiple scales also varies. A comparative analysis of these tools can answer crucial questions about where the most popular trails are, peak activity times, spatiotemporal trends, and potential impacts on wildlife movement. Answers could affect the allocation of funding for park infrastructure and wildlife management (Northrup et al., 2016). Ecological processes shaping wildlife habitat selection can vary with scale thus wildlife responses to human activity could also be scale-dependent (McGarigal et al., 2016). To enhance tool adoption, testing and comparing methods for monitoring park visitation at various scales is crucial, offering clear recommendations for real-world management decisions to advance our understanding of human-wildlife coexistence.

To address the need to define how remote sensing tools can be linked to specific PA management objectives, we convened a working group of 18 conservation practitioners working in western Canada (Appendix 1). We reviewed key tools, then compared trends in human activity across multiple scales measured by camera traps, trail counters, and social media. The case studies showcase the links between data collected from each of these methods. Our work informs practitioners and researchers about the tools available to measure PA human activity, and how to use them to address real-world management decisions.

How can human activity be measured?

Table 1 lists tools for monitoring human activity (camera traps, trail counters, day passes, and social media), selected because they are actively used by the co-authors. Deciding which to use depends in part, on research and management objectives (Table 1, Appendix 2). Tools vary in accuracy, influencing whether human activity is directly or indirectly measured (e.g., photos vs. self-reporting), and the spatial or temporal scale of data collection. The scale(s) at which data are collected is influenced by park manager or personnel capacity and research or management goals (Appendix 2). Cost-effectiveness considers the need for fieldwork or how labour-intensive that fieldwork is. For example, PA-wide camera trap surveys are more labour-intensive than smaller-scale (e.g., trail segments) surveys. Automated trail counters offer easy deployment at multiple sampling points, but may have accuracy or performance issues (Marion et al., 2021).

Increasingly, camera traps deployed to monitor wildlife are also used to estimate human activity. Images of people provide information about the type of activity visitors engage in (e.g., hiking, ATVs, horseback riding, cycling) as well as spatiotemporal information about those activities (Ladle et al., 2018; Naidoo & Burton, 2020), unlike trail counters, which cannot distinguish between animal and human detections, and activity type (e.g., motorized vs. non-motorized) (Marion et al., 2021). However, we acknowledge that tools like camera trapping come with privacy concerns related to human data collection (Sandbrook et al., 2018).

Human activity data scraped from social media are downloaded from an external source (e.g. Instagram, Twitter, Facebook, AllTrails, Strava), requiring less labour than fieldwork, and covering broad geographic regions beyond PAs (Obar & Wildman, 2015). However, it is unclear how well they reflect true activity levels. Extracting data from these platforms requires advanced knowledge of computing and coding (e.g., web scraping, APIs) and access requirements frequently change.

In contrast to remote sensing tools, tools counting visitors on-site, like day passes, are easy to collect and require little technical expertise. However, permits and passes may not necessarily reflect attendance as online pass sales may not correlate to physical visitation. Day pass counts may be less informative about spatial human activity trends, and be less useful if not accompanied by specific user reporting criteria.

Table 1: Comparisons of tools used to measure human activity in protected areas. Colours: green = relatively better; orange = relatively worse; white = neutral; * = characteristics which can vary depending on context. For full justification and additional detail, see Appendix 2.

Human activity monitoring tools	**Data characteristics**							
	Spatial resolution	*Temporal resolution*	*Type of human activity*	*Wildlife activity*	*Data from in & outside PAs*	*Privacy issues*	*On-site presence of researchers*	*Data processing burden*
Camera traps	High*	High	Yes	Yes	Yes	Yes	Low	High*
Trail counters	High	High	No*	No*	Yes	No	Low	Low
Day Passes	Low	High	No*	No	No	No	Low	Low
Social media data	Low to high	Low to high	Yes*	No	Yes	Yes	None	High*

Methods

What can existing tools tell us about trends in human activity?

We illustrate the advantages and limitations of tools for estimating large and fine-scale trends in PA human activity through two case studies. First, we measured temporal activity patterns within Joffre Lakes Provincial Park, British Columbia (BC) to assess the similarity of information provided by camera traps, trail counters, and day passes. Next, we evaluated within- and between-park spatial visitation trends across four provincial parks in southwestern BC (Garibaldi, Joffre, Golden Ears, and Cathedral; see Table A2, Figure 1), comparing human activity estimates from social media with camera traps. In both cases, camera traps were specifically deployed to monitor human activity.

Case study 1: Characterising temporal patterns in human activity within PAs

One objective for PA researchers and managers is characterizing temporal patterns in human activity, involving measurements of broad temporal patterns, (e.g., annual) or finer-scale patterns (e.g., daily, monthly or seasonal) in visitation. We compared camera traps, trail counters, and day passes to measure fine-scale temporal patterns in human activity in Joffre Lakes Provincial Park (Figure 1). Visitation to this park has increased dramatically in the last decade (222% increase from 2010 to 2019) (Canadian Parks and Wilderness Society, 2021). Joffre Lakes is renowned for its “Instagram worthy” glacier blue alpine lakes and provides habitat for many species, including wolverine (*Gulo gulo),* grizzly bear (*Ursus arctos),* cougar (*Puma concolor*), and black-tailed deer (*Odocoileus hemionus*) (Figure 3). Data collection spanned May to September 2021, coinciding with the park’s re-opening in June after a COVID-19 shutdown. Further details are provided in Appendix 3.

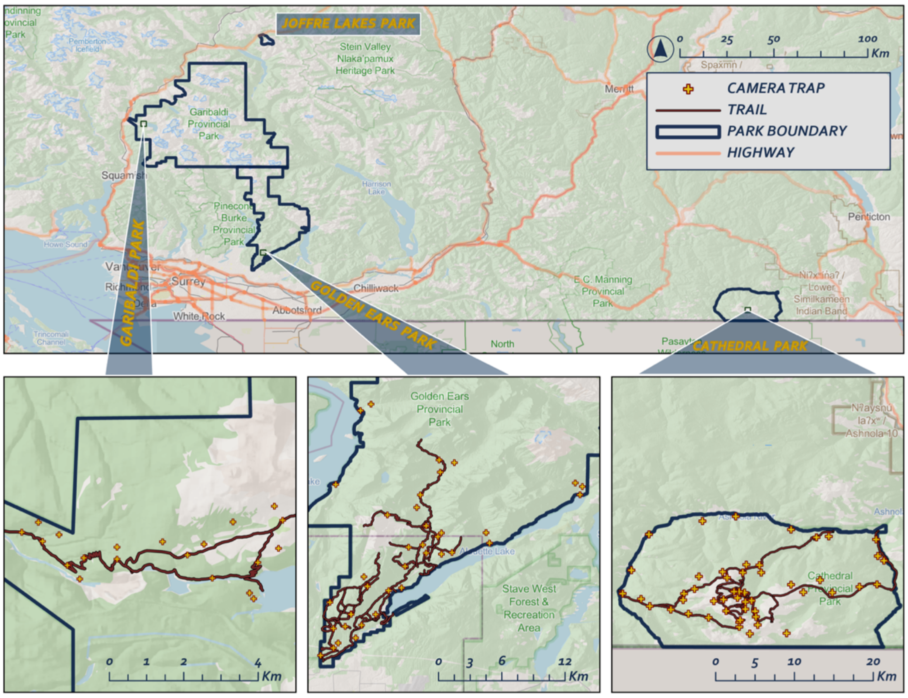

Figure 1. Provincial parks in British Columbia used in our case studies (Joffre Lakes, Garibaldi, Cathedral, and Golden Ears). Locations of camera trap sampling points used to measure human activity are also shown.

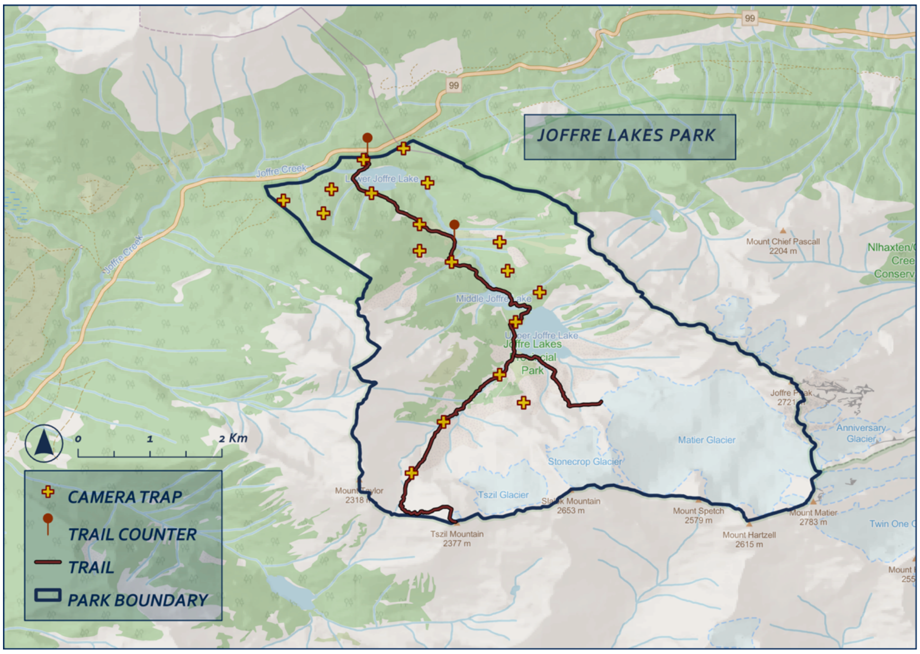

Figure 2. Locations of camera trap and trail counters sampling points in Joffre Lakes Provincial Park used for analysis in Case Study 1.

Figure 3. Camera trap images of wildlife detected at Joffre Lakes Provincial Park: A) Wolverine (*Gulo gulo*), B) Black-tailed deer (*Odocoileus hemionus*), C) Grizzly Bear (*Ursus arctos*), and D) Cougar (*Puma concolor*).

Camera traps, trail counters, day passes provided similar human activity estimates at monthly (Figure 4A) and daily (Figure 4B) scales, with correlation coefficients $\geq$ 0.92. However, trail counters had higher error rates with false triggers compared to the other methods. Trail counters and camera traps showed marked day-to-day variation in human activity. For day passes, daily human activity estimates showed that maximum quotas of 1056 passes per day were reached August to September. All three tools revealed a similar 'weekend effect', where human activity is greater during weekends and holidays, potentially causing negative effects on wildlife (Green et al., 2023). Human activity increased by roughly 10% on weekends relative to weekdays (Figure 4C). Finally, diel human activity patterns were highly correlated between cameras and trail counters (correlation coefficient = 0.98;

Figure 4D). It was not possible to obtain similar information from day passes, as the time passes are redeemed was not recorded.

TAKE HOME MESSAGE: For broad temporal patterns, the choice between camera traps, trail counters, or day-passes does not influence conclusions about human activity. Decisions should consider context-specific costs and logistical considerations for implementing different methods. For example, camera trap deployment requires more fieldwork than trail counters, making it less feasible for monitoring large-scale human activity trends, particularly in rugged landscapes. However, camera traps provide more informative fine-scale temporal data, crucial for management decisions, such as monitoring nighttime recreationist activity (Blundell et al., 2020). Camera traps also have the advantage of distinguishing activity types and simultaneously monitoring wildlife, facilitating assessments of human-wildlife interactions.

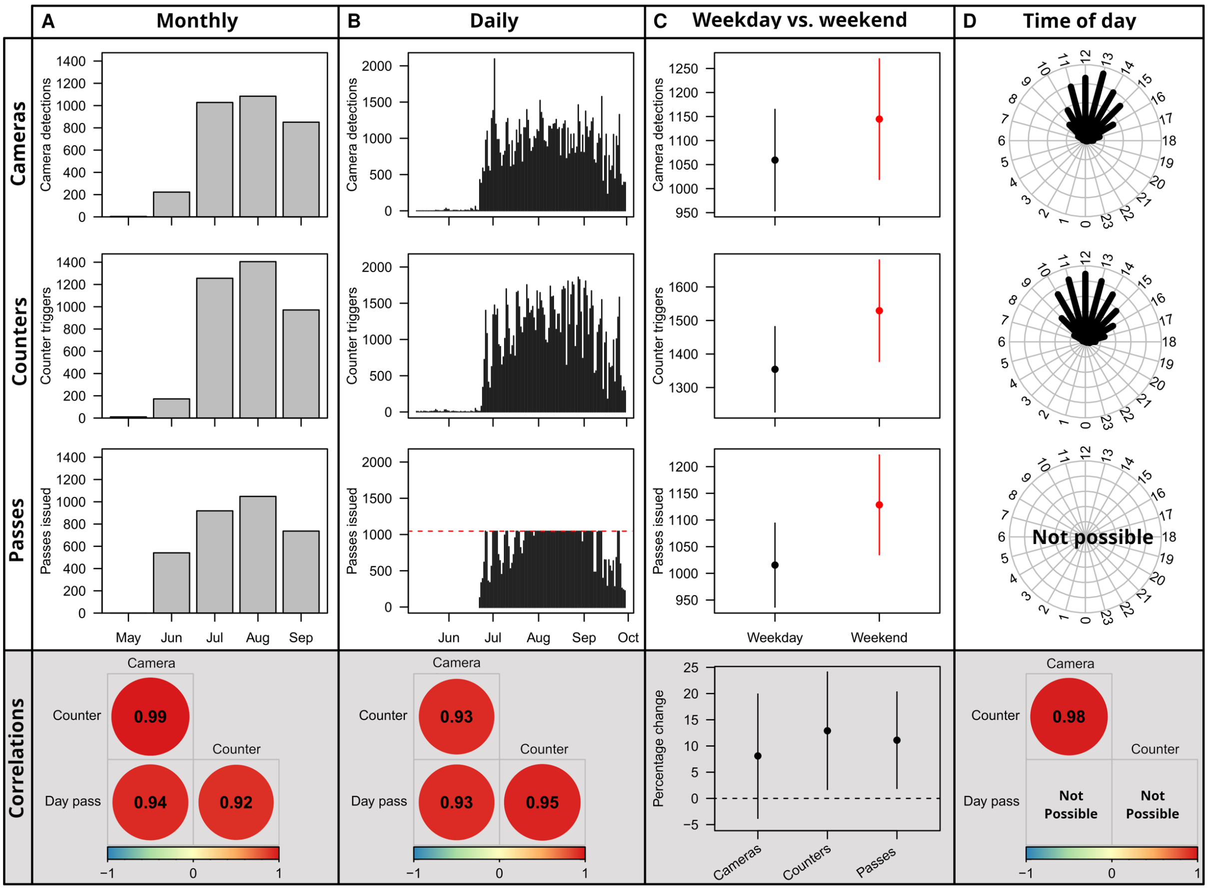

Figure 4. Comparison of camera traps, trail counters, and day passes to monitor monthly (A), daily intervals (B), weekday vs. weekend (C), and at different times of day (D) in Joffre Lakes Provincial Park at monthly. Column A column heights = monthly average number detections/triggers/passes issued per day. Column B heights = camera detections/triggers/passes issued per day. The horizontal dashed line represents the maximum day pass quota (n = 1056). Column C panels show the mean estimated number of detections/triggers/passes issued for a weekday or weekend day in August, with 95% confidence interval of the estimate as whiskers. Column D shows the relative number of detections/triggers per hour of the day across the whole time period. For columns A, B, and D, the estimates are compared using correlation plots with the sign and magnitude of the correlation coefficients represented by colour (blue = negative, red = positive) and circle size (larger = stronger correlation). In Column C, methods are compared through contrasting the percentage change in human activity estimated through each method.

Case study 2: Characterising spatial patterns in human activity across multiple PAs

Quantifying the relative intensity of PA human activity provides insights into how large-scale differences in accessibility or ecological conditions affect recreation area popularity and crucially, thresholds in recreation impacts. Human activity can be measured through deployment of monitoring devices (e.g., camera traps) within PAs, or through data scraped from social media platforms (e.g. AllTrails and Strava) (Toivonen et al., 2019). We compared human activity estimates from camera traps, AllTrails, and Strava in Joffre Lakes, Cathedral, Garibaldi, Golden Ears Provincial Parks (Figure 5) to generate spatially explicit human activity indices. These parks are popular for recreation and contain important wildlife habitat but they differ in visitation due to proximity to urban centres, access points, camping facilities, topography, etc.

For the average intensity of human activity, camera traps and AllTrails ranked PAs in the same order: Garibaldi (greatest), Joffre Lakes, Golden Ears, and Cathedral (least). In contrast, Strava suggests there is substantially more activity in Golden Ears relative to the other two methods, while underreporting activity at Joffre Lakes (Figure 5A). The popularity of social media platforms among recreationists varies regionally and for Strava, there are socioeconomic and demographic biases resulting in underreporting of hikers and other specific groups (Garber et al., 2019; Venter et al., 2023). The three metrics showed high agreement in human activity spatial patterns in some PAs (correlation coefficients >0.8 for Garibaldi and Joffre Lakes; Figure 5B & 5C), whereas other PAs showed significant disagreement between different tools (correlation coefficients between -0.01 and 0.91 for Golden Ears and Cathedral; Figure 5D & 5E). The locations where the three metrics were in strong agreement were PAs with single access points and simple, linear trail structures (Garibaldi and Joffre). Locations with high disagreement had multiple access points and more complex interconnected trail structures, likely driving higher variability in estimated human activity.

TAKE HOME MESSAGE: Correlations between tools depended on trail system complexity. Camera traps provided finer-scale information relative to social media data and showed more spatial variation for within-park human activity. Social media data may under or over-report human activity, depending on socioeconomic factors and activity type. For example, AllTrails collects more hiker traffic, whereas Strava was more accurate for running and biking. Furthermore, while social media excels at providing information about the spatial distribution of human activity, these data may not reliably address temporal trends if the proportion of trail users that contribute to social media data varies through time.

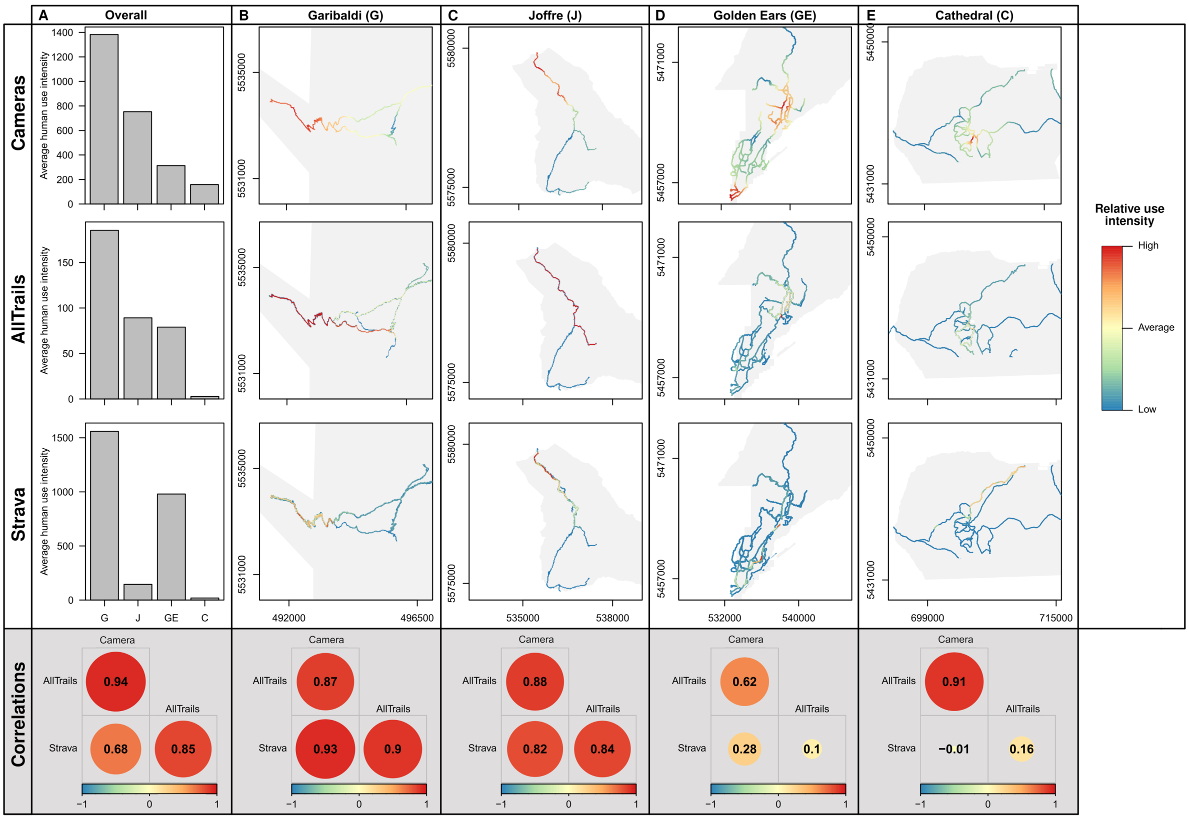

Figure 5. Overall average human activity intensity (A) and spatial patterns across PAs with four methods (columns B-E). AllTrails =the number of reviews of different trails, Strava = number of athlete 'efforts' per year for each trail segment. Column A bar heights = average use intensity across all trails in the analysis. Columns B-E show the spatial patterns in estimated human activity standardised and scaled to between 0 (low -blue) and 1 (high - red). Across all columns, the spatial estimates are compared using correlation plots with the sign and magnitude of the correlation coefficients represented by both colour (blue = negative, red = positive) and circle size (larger = stronger correlation).

Discussion

How can we link measurements of human activity to management actions?

Our case studies illustrate that fine-scale temporal (Figure 4) and spatial (Figure 5) trends in human activity within and between PAs can be estimated with existing tools, with accuracy and utility varying by method and context. Tool selection should align with practitioner needs, emphasising the need to link tools to PA management objectives. This involves mitigating the negative effects on wildlife, for example, through seasonal timing restrictions, zonation, or visitation limits in specific areas, while identifying habitat restoration needs. Understanding spatiotemporal patterns of human activity and recreation impacts on wildlife are critical for informing effective legislation, policy, and authorization processes (e.g., permitting with reporting requirements, species at risk or critical habitat policies), and allocation of staffing and financial resources.

Our working group identified three broad management categories: characterising human activity patterns, investing in land use planning, and understanding trade-offs between visitation and ecosystem health (Appendix 2). For each, potential management actions are included. For example, researchers quantifying human activity patterns may use tools in Table 1 to measure trail visitation over short (e.g., seasonal) or long (e.g., annual) periods. Based on trends from those data, practitioners can implement trail use restrictions if, for example, human activity is high on specific trails near sensitive wildlife habitat (Thorsen et al., 2022). Areas with low human activity may require greater understanding of potential ecological impacts and increased resource allocation including additional staff time and financial resources for outreach and human-wildlife conflict mitigation (e.g., garbage left on trails), and enforcement action. New infrastructure and ongoing maintenance may be needed to address unanticipated damage from increased human presence (e.g., trail rutting, erosion).

Future directions and opportunities

Our case studies provide insights into the effectiveness of tools for measuring PA human activity and highlight where more work is needed. For example, identifying thresholds can inform management strategies to predict negative wildlife impacts. This may involve identifying thresholds causing demographic impacts on wildlife (e.g., population decline due to reduced survival or reproduction), thresholds above which wildlife can no longer co-exist with people or recreation levels above which wildlife can adapt through behavioural flexibility (e.g., shift habitat use or timing of activity) (Lewis et al., 2021) and where sensitive species can no longer persist (displacement, filtering) (Dertien et al., 2021). Thresholds can guide practitioners to enable quality recreational user experiences while mitigating negative ecological impacts. Analysing historical human activity trends may also inform predictions about future activity, given weather or temporal trends (e.g., seasonal, weekend) or real-time monitoring about how a location is trending online (e.g., clicks, likes) (Clark et al., 2019). Given the strengths and weaknesses of each tool, integrating data from multiple tools within a cohesive framework may provide reliable and generalisable predictions (e.g., Wood *et al.* 2020).

We focused on PAs because of their dual mandate to support recreation and biodiversity, but information about human activity outside PA boundaries is lacking. Furthermore, large-bodied mammals require home ranges larger than the size of most PAs, so characterising human activity across larger, mixed-use landscapes is a priority. This can assist in developing practical management actions relevant to people and wildlife, including how and where new trails are sited, restrictions on activities, infrastructure needs (bear-proof food caches, garbage receptacles, etc.,), and signage design (i.e., wayfinding, educational, regulatory).

This work focused on legal recreation activities within PAs. However, PAs are susceptible to illegal uses including poaching of flora and fauna and encroachment (Rija et al., 2020). Such activities likely occur away from trails and access points used by legal visitors, exhibiting spatial and temporal patterns differing from legal activities. In such cases, trail counters, day passes, and social media are not reliable for capturing such human activity. Camera traps deployed off-trail, monitoring wildlife patterns relative to areas with higher human activity, may more effectively detect illegal activity. Remote sensing data may also effectively quantify impacts of human activity on landscape condition like erosion, fire, and habitat loss (Watson et al., 2014). Although illegal activities are a small minority of human activity in PAs predominantly characterized by authorized recreation, they can disproportionately impact biodiversity (Hilborn et al., 2006).

Sustainable recreation requires careful planning and there is a clear need for land use and recreation planning in North America, particularly with respect to management objectives. Efforts to monitor human activity trends should identify specific objectives prior to tool selection (Appendix 4). Developing and implementing management plans requires more funding, which has historically been under-resourced. To alleviate costs, increased engagement with community scientists could assist with monitoring efforts (Cheung et al., 2022). Several emerging networks promote a coordinated sampling approach across large scales, including camera traps (e.g. WildTrax, WildCAM, Wildlife Insights) (Buxton et al., 2018; Granados et al., 2023; Hedley et al., 2022). There is a growing need to better understand how tools can accurately monitor human activity in PAs to determine the ecological impacts to parks and open spaces. While this requires increased funding and labour for field surveys, our work provides valuable insights into the conditions under which tools quantify trends in human activity in PAs.

Conclusion

As visitation to PAs globally increases, identifying tools to accurately estimate human activity becomes critical for understanding impacts on wildlife and natural areas. Multi-scale visitor data are lacking in much of North America, yet understanding trends within and between parks is needed for evidence-based management plans. We addressed this knowledge gap by presenting case studies highlighting various tools for measuring human activity, making them relevant for park managers and decision-makers. Baseline information about human activity can reveal for example, crowding patterns and help managers and researchers predict future trends. In turn, this information can guide investments in new park infrastructure, maintenance and ongoing monitoring needs, and staffing resources. Additionally, this information can support decisions related to regulation and management changes. We argue that data collection on human activity in and around PAs is urgently needed. Our case studies emphasize the need for careful tool selection, guided by issues relevant to specific PAs.

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Ethics Statement

Data collection on human activity in parks was conducted under protocol H21-01424 from the University of British Columbia's Behavioural Research Ethics Board.

Open Research Statement

Upon acceptance for publication, data will be available for download on https://github.com/WildCoLab/.

Conflict of Interest

None.

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