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PERSPECTIVE

A case for human mobility data applications in wildlife management

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Abstract

1. Human activities have significantly altered terrestrial ecosystems, leading to biodiversity loss and habitat fragmentation. Traditional methods for measuring human impacts often lack the precision required for localized assessments, fail to capture temporal dynamics or are scale-limited. Human mobility data (HMD) from GPS-enabled smartphone applications offers a valuable approach to understanding human movement patterns, overcoming many of these limitations.
2. We present case studies demonstrating the use of HMD in assessing human activity within ecologically sensitive habitats (e.g. winter ranges and breeding grounds) and evaluating where human-wildlife interactions are likely to occur to inform proactive conflict management. We also discuss how HMD can improve inference from habitat connectivity analyses and provide detailed, timely insights on how HMD can broadly support conservation and wildlife management goals.
3. HMD revealed patterns of recreational use in bighorn sheep (*Ovis canadensis*) winter range and helped inform the timing and scope of protective measures for sheep. HMD also allowed us to quantify the frequency and timing of potential wildlife-human interactions, such as cougar (*Puma concolor*) proximity to human activity, identifying high human-wildlife conflict areas and opportunities to mitigate mortality risks (e.g. road crossings).
4. We discussed how future uses of HMD can improve conservation and connectivity, allowing managers to assess barriers to movement, identify critical thresholds of human disturbance and refine strategies for mitigating impacts on species sensitive to human disturbance. We provided a simple example by highlighting

differences in human use of a migration corridor for pronghorn (*Antilocapra americana*).

5. *Synthesis and applications*. Human mobility data provides a transformative tool for wildlife management by offering scalable, dynamic insights into human activity that traditional methods cannot fully capture. These data enable managers to prioritize intervention areas, improve compliance with management zones, mitigate conflict risks, and enhance connectivity for sensitive species, supporting effective conservation strategies in a human-dominated world.

KEYWORDS

conservation strategies, dynamic human footprint, human mobility data, human-wildlife interactions, landscape connectivity, recreation, wildlife management

1 | INTRODUCTION

Human activities have altered 58.4% of terrestrial ecosystems globally, leading to biodiversity loss and habitat fragmentation through widespread landscape modifications such as urbanization and land use changes (Seto et al., 2012). Between 2000 and 2013, an estimated 1.1 million km^2 of natural areas were lost, highlighting the accelerating rate of ecosystem degradation and the pressing need for more effective conservation strategies (Williams et al., 2020). Beyond direct habitat alteration, human disturbances from activities like resource extraction, energy development, and recreation exacerbate biodiversity loss through indirect impacts, such as sensory pollution through noise and traffic, which can reduce habitat usability and quality (Francis & Barber, 2013; Zeller et al., 2024). As these trends continue, measuring and managing human disturbances will become increasingly critical for effective management and conservation planning.

Traditionally, human presence in natural landscapes has been quantified using static metrics such as human footprint indices and infrastructure density (Mu et al., 2022). While these broad-scale indices provide valuable insights, they often lack the spatial and temporal precision necessary for localized assessments (Toews et al., 2017). Furthermore, these static metrics may overlook the dynamic nature of human activity over time (Ellis-Soto et al., 2023; Oliver et al., 2024). Audio recordings, trail counters, camera traps and GPS tracking offer more temporal detail, but their limited spatial scope and high costs restrict their widespread application (Cardona et al., 2024). Even approaches using remotely sensed artificial light as a proxy for human presence have limitations, as they only capture night-time activity and may miss human use in areas without infrastructure (Ditmer et al., 2021).

The need for more precise and dynamic metrics to measure human impacts has grown as conservation challenges become more complex. Advances in large-scale approaches, such as fitness-tracking apps and social media data, have provided spatiotemporal insights into human activity but may introduce biases related to user demographics or behaviour (Monkman et al., 2018; Saad et al., 2019; Venter et al., 2023). During the COVID-19 pandemic, the potential of GPS smartphone data—human mobility data (HMD)—emerged as a valuable tool for studying wildlife responses to human activities (Rutz et al., 2020). By leveraging anonymized data from consenting users across multiple mobile applications, HMD offers detailed, fine-scale insights into human movement patterns (Ellis-Soto et al., 2023; Oliver et al., 2024; Unacast, 2024; Supporting Information S1). Moreover, HMD addresses many of the limitations of traditional methods by incorporating dynamic, fine-scale human activity data with comprehensive spatial coverage while overcoming the biases associated with fitness apps and social media. For example, Strava users tend to be overrepresented by cyclists, with an 8% higher proportion than observed, and males, who are 15.7% more prevalent. Additionally, individuals aged 35–54 are 20.4% more represented than other age groups (Venter et al., 2023). In contrast, HMD draws from GPS smartphone users across various applications, not just fitness applications like Strava (Unacast, 2024). This approach provides broader spatial coverage and captures diverse human behaviours, making it a more comprehensive and accurate means of monitoring human activity in landscapes free of human infrastructure (Figure 1).

The ecological research community has been slow to integrate HMD, potentially due to its high initial purchasing costs and computational requirements, despite its adoption in other fields, such as urban planning and public health (Demšar et al., 2021). Here, we illustrate how HMD can inform management strategies to mitigate human impacts and support conservation goals through thematic sections demonstrating its applications in applied ecology. In the first two sections, we present wildlife management case studies investigating human activity in areas where wildlife is more sensitive to human recreation and human-wildlife interactions. In these sections, we discuss how HMD can broadly improve understanding and intervention related to these thematic topics. Our third section examines the future directions of HMD by discussing its application in conservation and connectivity. Our final section describes the important ways in which HMD can contribute to applied ecology as well as its limitations. The HMD used throughout is fully described in Supporting Information S1.

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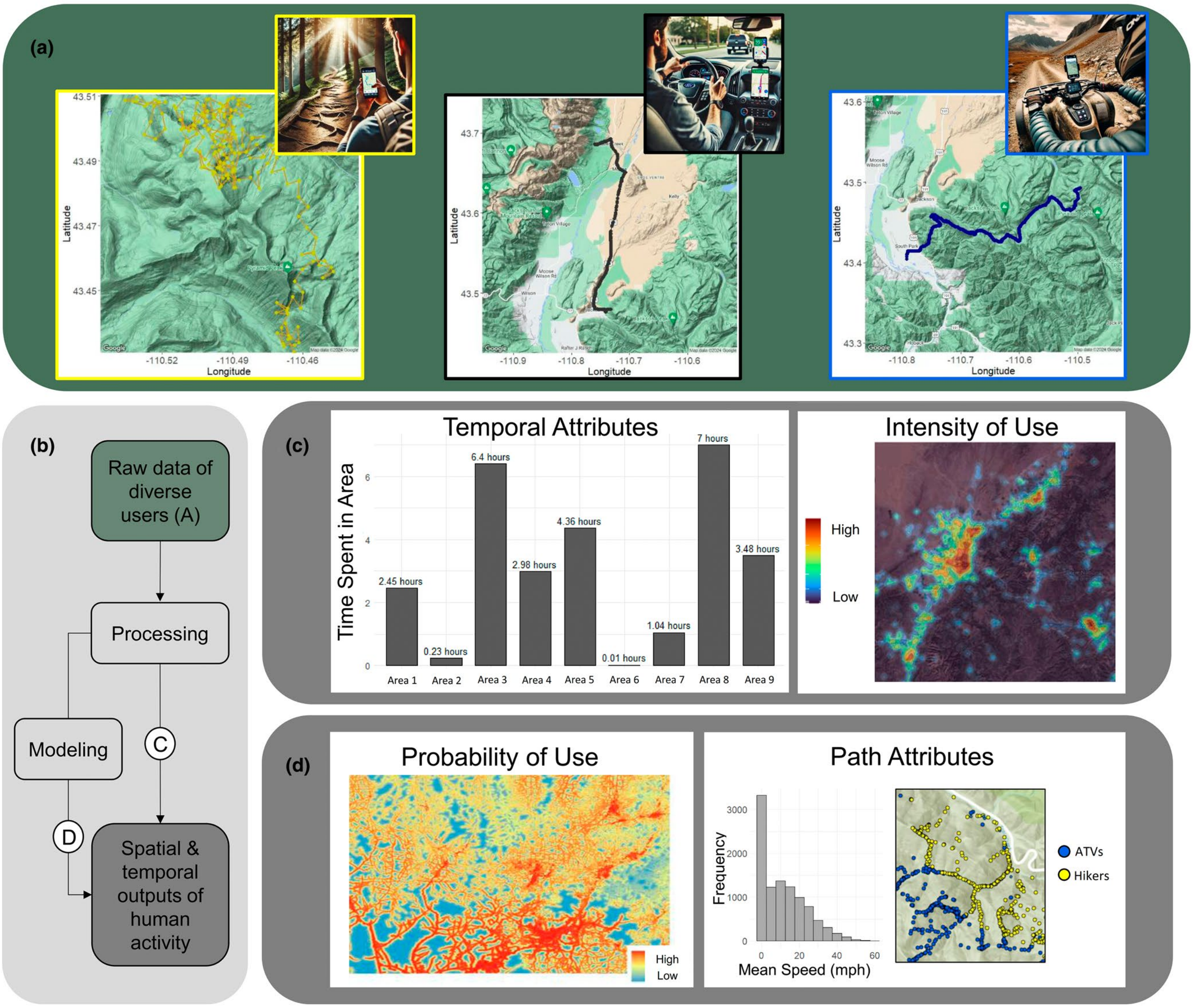

FIGURE 1 A conceptual framework illustrating how raw human mobility data (HMD) represents spatiotemporal human activity. (a) HMD, derived from GPS smartphone apps, captures various user behaviours, such as slow movement in backcountry areas (e.g. hiking, hunting, skiing; yellow), high-speed highway travel (e.g. vehicular traffic; black) and intermediate speeds across mixed terrains (e.g. all-terrain vehicles, snowmobiles; blue). (b) HMD is processed for quality after extraction, and summary statistics (c) or modelled products (d) are generated to quantify human activity in space and time. (c) Representative examples of summary statistics or unmodelled products from processed HMD. For example, temporal products, such as time spent in an area (left) and the intensity of use within an area (right), can be quantified. (d) Representative examples of modelled data products from processed HMD. For example, the probability of human use surfaces (Abernathy, Ditmer, Stoner, et al., 2025) can be derived from resource selection models (left), and movement speeds fed into clustering algorithms can group users by activity type (e.g. hikers vs. ATV users; right). We generated the pictures of smartphone users in (a) using DALL-E (2024).

2 | HUMAN USE OF ECOLOGICALLY SENSITIVE HABITATS

Wildlife may use certain areas or have phenological periods during which they are more sensitive to human activity (e.g. offspring dependency, periods of low resources; Olson et al., 2017; hereafter sensitive habitats). Managing human activity in sensitive habitats is challenging, especially in landscapes with dispersed recreation. This issue is escalating in mountainous systems worldwide, as recreational activities in sensitive habitats continue to rise (North America: Miller et al., 2022; Asia: Jones et al., 2021; Europe: Trišić et al., 2022). To ensure public access and reduce detrimental impacts on wildlife, it is critical to understand and predict visitor use patterns in sensitive habitats.

We assessed human use in an ecologically sensitive habitat—bighorn sheep (*Ovis canadensis*) winter ranges in the Teton Mountain Range, USA. This area contains mandatory and voluntary closure areas (i.e. winter zones; areas: 4.15 km^2 mandatory and 7.94 km^2 voluntary). Voluntary winter zones discourage access but do not legally enforce restrictions. Signage designates them as bighorn sheep winter range and requests that visitors avoid entry unless necessary. Winter zones are implemented on winter range to buffer the negative impacts of recreation during the harsh months when forage is scarce and movement through snow—such as to avoid human recreationists, for example—compounds energetic requirements for survival (Harris et al., 2014; Parker et al., 1984). We used HMD to assess visitor compliance with winter zones (hereafter zones) across two winter implementation periods: (1) December 2020 through April 2021 and (2) December 2021 through April 2022. Mandatory closures ran both years, while voluntary ones ran only during the second year. HMD data consisted of GPS locations and timestamps of unique anonymized users sourced from smartphones (Supporting Information S1). Such data allowed us to track the use of zones (frequency of total smartphone detections and unique smartphones) and residency times (time spent within each zone by smartphone user) and identify entry points.

Across both sampling years, we identified an average of one smartphone detection (ranging from 0 to 2) in one mandatory closure zone. During only one year of implementation, we recorded an average of four smartphone detections (ranging from 0 to 21) across nine distinct smartphones in five voluntary zones, resulting in an average of 4.2 detections monthly. Residency time was zero in mandatory closures, while smartphones averaged 2.57 min (ranging from 0 to 14.7 min) across 12 smartphone tracks in voluntary closures. We report that 680 smartphone detections occurred within 500 m of zone edges (i.e. grey user points, Figure 2) in mandatory ($n = 2$) and voluntary ($n = 645$) zones, suggesting excellent compliance. We report 15 detections across six smartphones after voluntary restrictions were lifted.

HMD revealed that compliance was excellent. We report that voluntary closures were used more than mandatory closures, potentially impacting bighorn sheep energetics and stress in those areas (Harris et al., 2014; Parker et al., 1984). Identifying relatively higher human activity near zone boundaries underscored the need to consider closure size, placement, and enforcement to mitigate potential impacts (e.g. implement targeted signage, collaborate with neighbouring properties). Furthermore, human use intensity increased by over 250% (4.2 smartphones/month to 15 smartphones/month) in the month following the end of voluntary restrictions, underscoring the importance of aligning closure periods with the ecological needs of the target species. HMD also revealed diverse spatial patterns of human use (e.g. Figure 2b versus 2c), highlighting differences between activity concentrated around zone boundaries and more dispersed activity, which can help managers refine mitigation strategies.

Beyond this case study, HMD has significant potential for assessing human use of sensitive habitats across diverse ecosystems. For example, it could inform conservation strategies for disturbance-sensitive carnivores such as wolverines (*Gulo gulo*) and lynx (*Lynx canadensis*), whose habitat selection and fitness can be negatively

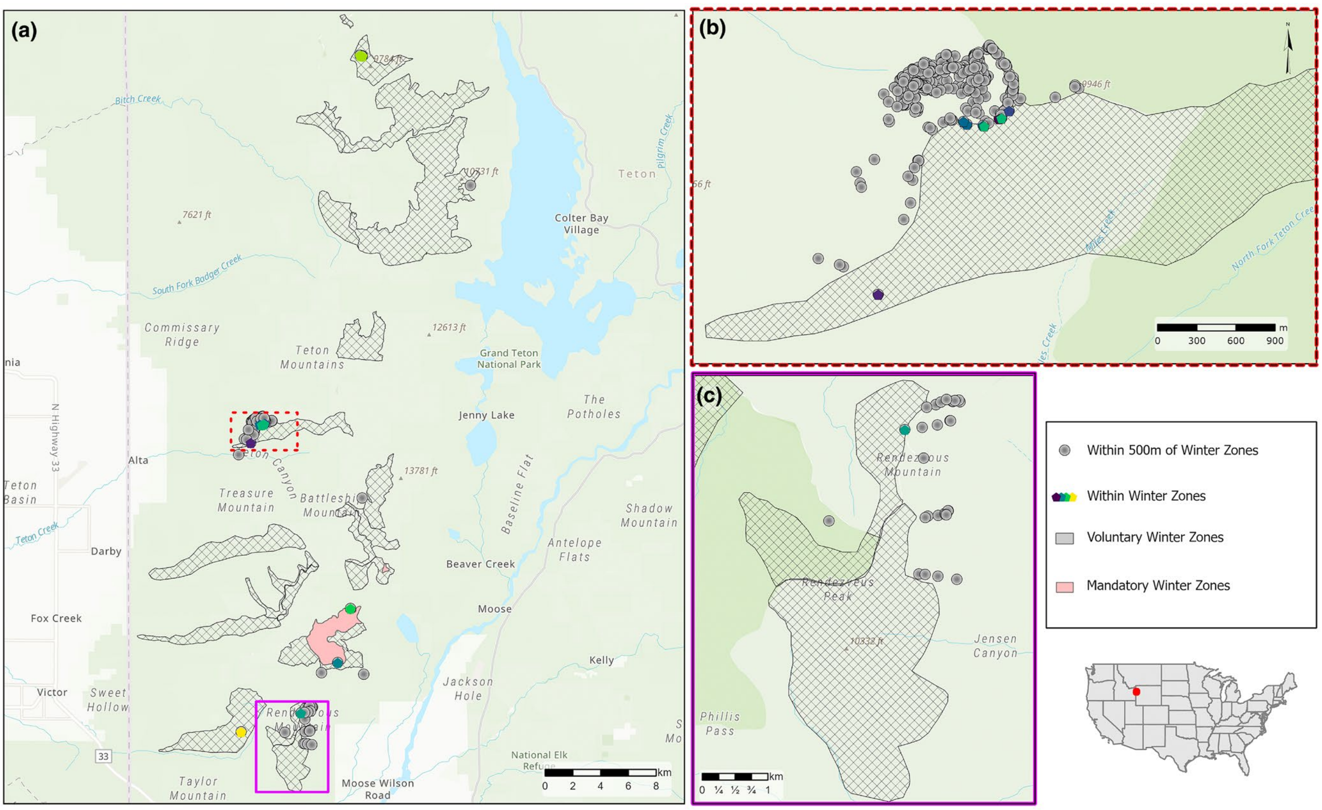

FIGURE 2 Human activity relative to bighorn sheep (BHS) winter zones in the Teton Range (a). Humans are displayed as points, where each detection indicates a unique smartphone relative to winter zones for BHS. The subset maps display a local ski resort (b, hashed red border) and Rendezvous Peak (c, solid purple border), highlighting areas where humans entered winter zones (multicolor) and those that stayed within 500 m of closure edges (grey points).

impacted by human recreation (Heinemeyer et al., 2019; Squires et al., 2019). HMD could be used to assess human activity on nesting beaches for species like sea turtles (Cheloniidae family), refining seasonal closures, as turtles can alter their behaviour based on anthropogenic noise alone (Díaz et al., 2024). Monitoring and enforcing closures in sensitive habitats can also increase local community awareness and participation, fostering a conservation culture where stakeholders recognize the value of healthy ecosystems (Pournara et al., 2023). By identifying where and when human activity overlaps with sensitive habitats, HMD can help managers develop data-driven conservation strategies that balance species protection with sustainable public access.

3 | PROACTIVE CONFLICT MANAGEMENT AND MITIGATION

Increasing human populations, infrastructure development, and recreational opportunities are expanding the human footprint, increasing the potential for human-wildlife interactions (Wittemyer et al., 2008). This risk is expected to increase as climate change alters resource availability and phenology, prompting wildlife to seek resources—whether human subsidies (e.g. garbage or year-round gardens) or natural (e.g. prey)—in human-dominated areas. This shift leads to novel interactions within or near developed regions (Abrahms et al., 2023; Pecl et al., 2017). Elsewhere, species reintroductions and improved management have resulted in wildlife expanding into human-dominated areas (Banasiak et al., 2021). Understanding when and where human-wildlife interactions occur, especially with sensitive and conflict-prone species, is crucial for conservation, management and safety.

We assessed cougars' (*Puma concolor*) proximity to humans (via HMD; Supporting Information S1) in California's eastern Sierra Nevada mountains, an area of high-use recreation, to provide temporal and spatial information on where human–wildlife interactions are more likely to occur. We identified potential human–cougar interactions using GPS collar data from mountain lions ($n=8$; 3-h GPS intervals; data derived from a California Department of Fish and Wildlife study) and smartphone locations of humans represented in the HMD (Figure 3). Capture and handling were conducted in accordance with California Department of Fish and Wildlife Animal Welfare Policy (2018–02) and capture protocols (Mountain Lion Capture Plan 2006-10–2024-10) were approved annually. Potential interactions (hereafter, 'interactions') were defined as cougar and smartphone locations within 300 m and 2 h but further classified by probability (hereafter, 'interaction probability'): high (≤75 m & ≤30 min), medium (≤150 m & ≤60 min) or low (≤300 m & ≤120 min but outside medium or high criteria). See Supporting Information S1 for more information.

In total, across the year, we identified 13,556 potential human-cougar interactions (i.e. proximity within 300 m and 2 h) between 10,233 GPS-collared cougar locations (monthly mean = 853; range = 697–988) and human smartphone users during 2021 in the Sierra Nevada mountains (Figure 4). Of these, 71.6% involved driving/road use (9707 locations), 20% were within buildings (2709 locations) and 8.4% involved outdoor/offroad users (1140 locations; Figure 4). Interaction probabilities varied: road interactions were consistent across categories (high: 76.3%, medium: 71.2%, low: 71.6%), while interactions near buildings decreased as probability increased (high: 0.0%, medium: 13.7%, low: 20.2%). Conversely, outdoor/off-road user interactions increased with higher probabilities (high: 23.7%, medium: 15.2%, low: 8.2%; Figure 4).

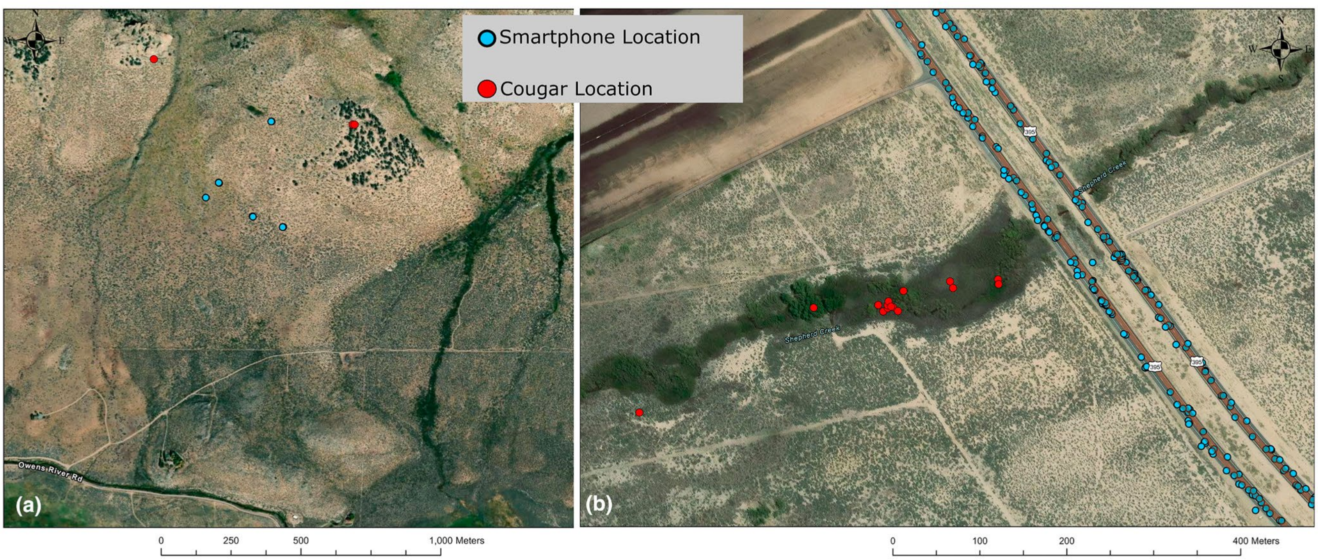

FIGURE 3 Spatial proximity of GPS-collared cougars and smartphones in the eastern Sierra Nevada mountains. (a) Example of a smartphone user, likely a recreationist, near a recent cougar location. (b) Example of a cougar's multiple approaches to a busy highway (US-395) but returning to its original trajectory after encountering the road each time.

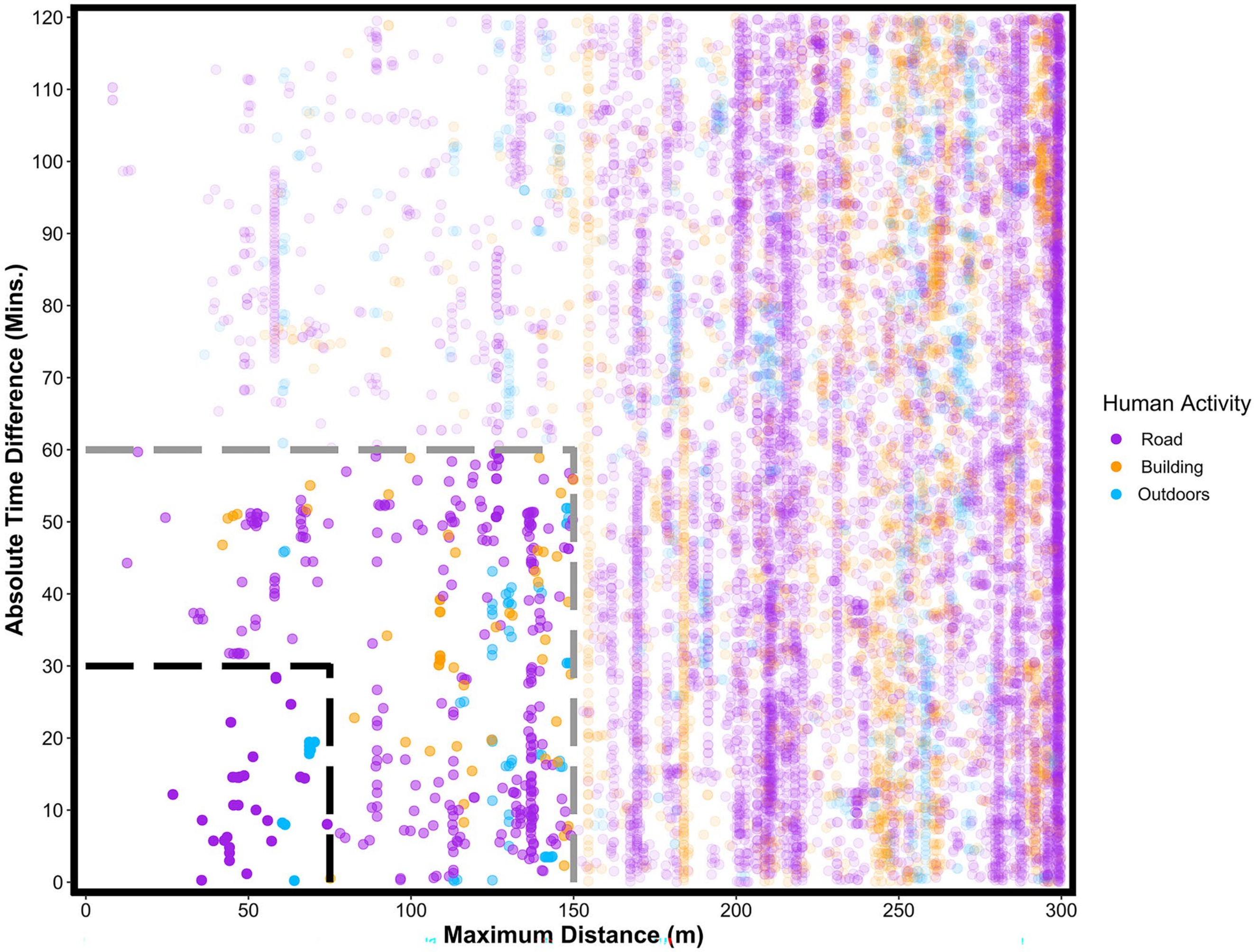

FIGURE 4 Scatterplot showing the maximum distance (meters, *x*-axis) and time difference (minutes, *y*-axis) between GPS locations of eight collared cougars and smartphone users in the eastern Sierra Nevada mountains during 2021. A threshold of 300 and 120 min was used to identify 13,556 potential interactions. Smartphone locations were classified by activity type based on proximity to roads and buildings or distance from both for outdoor/off-road users. Possible interactions with the lowest probability of direct interaction are represented with the most transparency. Interactions with medium probability are within the dashed grey box, while those with the highest probability, based on proximity and time difference, are found in the dashed black box. The figure illustrates that proximity interactions were relatively rare, at least given the GPS fix schedule, and predominantly linked to human vehicle use, with some outdoor/off-road users. The limited number of potential interactions with humans inside buildings highlights the role of human infrastructure in shaping human-wildlife proximity.

August had the most potential interactions overall (4048; Figure 5a), with interactions more frequent in late fall and early winter (October–December). Outdoor/off-road user proximity peaked in July (n=310) and November (n=485), with July interactions occurring throughout the day (Figure 5b), while November interactions were mainly in the afternoon (hours of the day 13–15; Figure 5c). Our results also revealed the cougars' individuality and helped discern which individuals were more likely to interact with humans. Overall, interactions were highly individual-specific, with 97.4% of observed interactions involving just two of the nine cougars considered in this analysis, while one had no interactions. For these two frequently interacting cougars, 5.3% and 13.1% of their GPS fixes were linked to at least one interaction event. These data highlight potential habituation or individual-level differences in tolerance toward human proximity, even within a subset of this population.

While direct conflicts between humans and cougars are rare, HMD enabled us to quantify the frequency of cougars' proximity to humans in natural settings and the timing of these interactions. This case study underscores HMD's potential as a valuable tool for understanding human-wildlife interactions' timing, location, and nature. For example, cougars typically avoided human proximity near buildings but showed higher interaction probabilities in outdoor recreation areas, likely due to the unpredictable presence of recreationists (Figure 4). In addition, this case study underscores how HMD can provide insights into wildlife mortality risks and connectivity bottlenecks. Areas with large numbers of cougar–vehicle interactions highlight the potential for road barriers and the placement of crossing structures or signage to reduce wildlife mortality (Figure 3b).

HMD's flexibility allows practitioners to assess spatiotemporal overlap between humans and wildlife at ecologically and

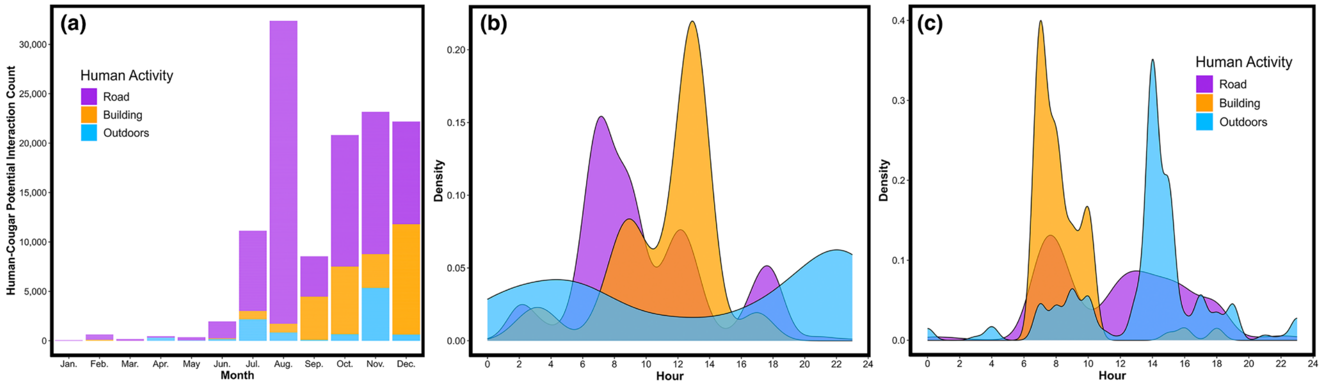

FIGURE 5 Count of potential interactions between GPS-collared cougars and smartphone users in the Sierra Nevada mountains during 2021 by month (a). The other panels show density plots of the timing of the interactions, broken down by human activity type of the smartphone user, for all hours of the day during (b) July and (c) November. The figure shows that potential human-cougar interactions peaked in late summer and fall, with distinct temporal patterns based on activity type: Road-related interactions were more evenly distributed throughout the day. In contrast, building and outdoor recreation interactions exhibited clear peaks during midday and early afternoon hours, highlighting the variability in interaction timing across activity types and seasons.

management-relevant scales. Despite representing a sample of smartphone users, the extensive spatial scale (e.g. nationwide; Unacast, 2024) of HMD enables predictive mapping of potential human–wildlife interactions beyond areas with GPS-collared animals. Integrating HMD data with conflict records can prioritize areas with higher conflict risks, offering a proactive approach to wildlife management interventions that can reduce risks to animals and humans. For example, in many densely populated countries in Europe, brown bear (*Ursus arctos*) conflicts arise both near protected areas (Sıkdokur et al., 2024) and in new regions where their geographic range expands (Cimatti et al., 2021). Integrating HMD with known conflict data could be used to develop predictive conflict maps. Similarly, GPS data from conflict-prone individuals may be combined with HMD to intervene before conflict occurs (Bombieri et al., 2021).

4 | FUTURE RESEARCH: OPPORTUNITIES FOR HMD TO IMPROVE CONNECTIVITY AND CONSERVATION EFFORTS

Habitat fragmentation disrupts wildlife movement, migration and gene flow, increasing species' vulnerability to local extinction and environmental events (Fahrig, 2003; Tucker et al., 2018). Conservation efforts have traditionally focused on maintaining connectivity to mitigate these effects. Connectivity models estimate landscape resistance using animal movement data and genetic relationships, primarily interfacing with static landscape features like roads, buildings and land cover. However, these models fail to capture the dynamic nature of human activity, including seasonal, interannual, and intra-daily variability (Zeller et al., 2020).

Incorporating HMD into connectivity modelling allows practitioners to understand relative human use within commonly mapped features like roads, hiking trails and impermeable surfaces by capturing real-time human presence across landscapes (e.g. relative densities; Figure 1). For example, HMD from the outdoor recreation application Strava outperformed traditional proxies like infrastructure and land use in brown bears (*Ursus arctos*) habitat models in Italy, offering a more accurate reflection of human disturbance (Corradini et al., 2021). Similarly, HMD captures human activities in areas and across spatial extents relevant to wildlife that may be difficult to monitor with traditional methods like camera traps or trail cameras, such as trails and backcountry regions. For example, Strava data provided a multi-scale proxy for outdoor recreation intensity, revealing that Eurasian lynx (*Lynx lynx*) avoided high-recreation areas within their home ranges, without modifying their overall home range location (landscape-scale; Thorsen et al., 2022).

HMD captures temporal fluctuations in human activity, allowing practitioners to quantify bottlenecks better and prioritize fragmentation interventions (e.g. Figure 6). For instance, HMD can measure road traffic volumes and, when integrated with wildlife movement data, help predict areas with high wildlife-vehicle mortality (van Langevelde & Jaarsma, 2005). Elevated traffic levels—which HMD can measure—are avoided by larger migrating mammals, which further fragment populations and disrupt established migratory routes (Jacobson et al., 2016; Nojoumi et al., 2022). Indeed, the awareness of vehicles and the risk of collisions appears to deter many species from crossing busy roads, often leading to prolonged isolation of habitats which, in turn, can result in reduced genetic diversity and population viability (i.e. population bottlenecks; Chen et al., 2021; Seidler et al., 2015).

HMD is a critical tool for disentangling the effects of structural human features from actual human presence, generating a more accurate measure of cumulative human impact on wildlife movement. For example, by incorporating HMD into resistance and connectivity models, we can identify critical thresholds of human presence beyond which movement or gene flow is impaired or becomes a complete barrier. This includes factors such as road traffic at various periods throughout the day or week (or during seasonal

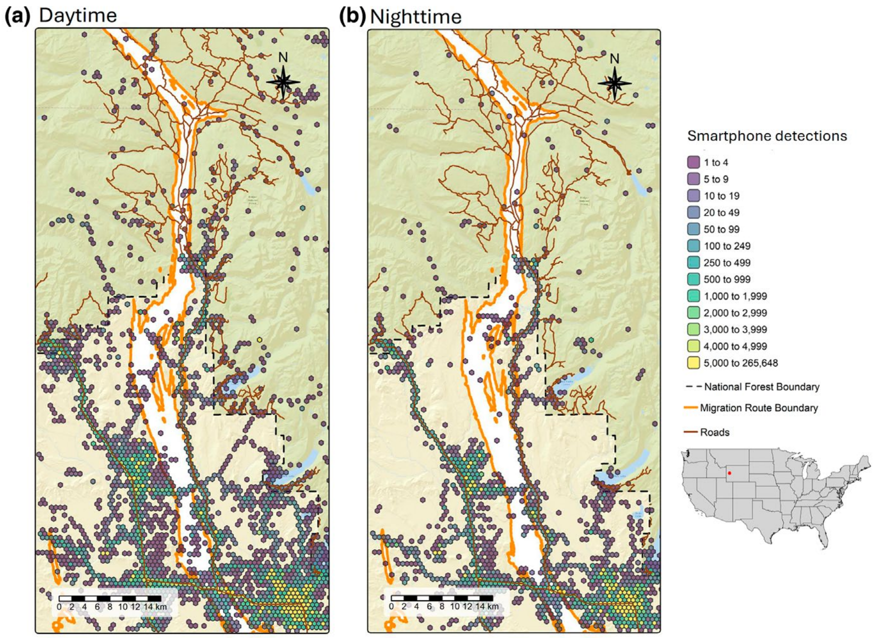

FIGURE 6 The spring migration corridor (orange polygon) of pronghorn (*Antilocapra americana*) in western Wyoming (Kauffman et al., 2022). Overlaid on the migration route are total smartphone detections from 2020 to 2022 during the migration period (March 1 to April 30). This corridor connects public lands (National Forest) to adjacent private land use areas. Integrating the HMD over this migration route reveals traffic and human activity fluctuations during daytime (a) compared to night-time (b), particularly on public lands. It is important to note that significant investments have already been made in this area to construct wildlife overpasses and underpasses aimed at reducing wildlife–vehicle collisions, improving connectivity, and facilitating animal movements.

migration periods; Figure 6) or the frequency of recreation trail use. Conversely, a road or trail that might have been identified as a highly resistant feature in previous static models could have a much lower resistance when incorporating HMD data if those features have very little human traffic (e.g. Figure 6). As was shown in studies emerging after the COVID-19 shutdowns, reduced human mobility led to a 'release from the landscape of fear' in cougars (Benson et al., 2021; Wilmers et al., 2021), despite the persistence of the structural human footprint. This highlights that structural features alone do not capture the full impacts of human presence on wildlife movement and connectivity.

HMD can also be critical in identifying effective management options for maintaining or restoring connectivity. For example, HMD can identify high-use trails or roads intersecting key wildlife corridors, which previously were difficult to detect at large scales (Figure 6). This dynamic information helps refine connectivity models by capturing the cumulative impacts of human presence, not just the structural footprint. HMD not only refines our understanding of wildlife connectivity but also enhances our ability to manage landscapes as human activities intensify, making it an invaluable tool for large-scale conservation efforts in a changing world.

5 | CONCLUSIONS

The case studies presented here highlight HMD's advantages compared to traditional methods such as land use change or infrastructure (Gaynor et al., 2018; Seto et al., 2012; Tucker et al., 2018; Williams et al., 2020). By measuring the dynamic nature of human activity, HMD can provide a more accurate, near real-time representation of human activity, even in remote areas without infrastructure. As the use of HMD becomes more widespread, it holds significant promise for research and management across spatial and temporal scales. In addition to uses highlighted by our case studies, HMD can support restoration and reintroduction efforts globally for conflict-prone species like the brown bears and wolves (*Canis lupus*) in North America and Europe (Sıkdokur et al., 2024; Smith & Peterson, 2021), ungulates and elephants (*Elephantidae*) in agricultural regions across the world (Krishna et al., 2016; Naha et al., 2019), or species sensitive to human disturbance, like the wolverine (*Gulo gulo*) in Colorado and California (Heinemeyer et al., 2019). Furthermore, HMD can inform recreation management by identifying likely types of activities (e.g. hiking, motorized use) based on speed and spatial data derived from anonymized user tracks. With minimal processing, HMD can identify access points and residency times in protected areas, potentially indicating unauthorized human presence related to activities such as poaching, logging or mining (Figure 1). While HMD alone cannot confirm illegal activity, its insights into human movement patterns can support natural resource management efforts by guiding targeted monitoring and enforcement strategies, like its applications in law enforcement.

Despite the advantages of HMD, there are several challenges and limitations to consider. Working with HMD requires expertise in handling large datasets, as the raw information often spans terabytes and must be processed and cleaned before use in analyses. While HMD excels in capturing relative patterns of human space use, variability in smartphone user sampling over time complicates the estimation of raw abundance patterns through time without high-quality validation data (e.g. traditional counts throughout areas of interest). Further, although HMD data does not rely on cellular coverage, sampling biases may occur, as smartphones tend to take more frequent location fixes in areas with strong coverage. Importantly, HMD is derived from numerous smartphone applications, which should overcome the limitations of reliance on a single application (e.g. Strava, social media; Monkman et al., 2018; Saad et al., 2019) and can include individuals across various smartphone applications. However, HMD is still limited to individuals using applications that track locations, albeit with a more even population sampling. Moreover, while privacy concerns may impede the adoption of HMD for some agencies and institutions, many of these issues can be mitigated by aggregating raw GPS locations (Oliver et al., 2024). Finally, difficulties associated with this data may arise in countries with contrasting privacy laws regarding its purchase and use, which may complicate cross-boundary work, and in such cases, coarse metrics are the best option (e.g. Tucker et al., 2018; Williams et al., 2020).

HMD offers a critical opportunity to enhance wildlife ecology and conservation efforts in a world with an increasingly pervasive human footprint. By unlocking HMD's potential, wildlife managers and researchers can gain more accurate insights into human-wildlife interactions and develop more effective strategies for balancing human activities with conservation goals. As HMD technology advances, it will play an increasingly vital role in informing management decisions and ensuring the long-term sustainability of both wildlife populations and human use of natural landscapes.

AUTHOR CONTRIBUTIONS

Heather Abernathy conceptualized the manuscript, wrote most of the text, created Figures 1 and 6, led drafting and revisions, and coordinated the overall project. Mark Ditmer conceptualized the manuscript, contributed substantial text, created Figures 3–5, significantly contributed to editing and revisions, assisted with project coordination and provided funding for the project. Seth Hibbard contributed to the writing, created Figure 2 and assisted with editing. Jason Lombardi provided data and contributed to editing and revisions. Thomas Stephenson provided data and contributed to editing and revisions. John Squires contributed to editing and revisions. Jennifer Newton provided data and contributed to editing and revisions. Sarah Dewey provided data and contributed to editing and revisions. Katherine Zeller contributed to the manuscript's conceptual framework, writing and editing. Michael Schwartz contributed to the manuscript's conceptual framework, writing and editing. George Wittemyer contributed to the manuscript's conceptual framework, provided funding for the project, contributed multiple rounds of edits, and offered substantial feedback throughout the manuscript's development.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest related to this work.

DATA AVAILABILITY STATEMENT

Publicly shareable data are available at https://doi.org/10.5061/dryad.sqv9s4nfb (Abernathy, Ditmer, Hibbard, et al., 2025). This dataset includes the anonymized cougar data used in the cougar–human interaction analysis. Due to the sensitive nature of wildlife GPS data, particularly for large carnivores like cougars in California, location information has been modified to protect individual animals and conservation efforts. Human mobility data (HMD) used in the analysis are proprietary and cannot be shared due to legally binding data-sharing agreements with a commercial provider (Supporting Information S1). As such, we cannot release the raw HMD underlying the analysis. However, we provide derived variables from the HMD, including spatial and temporal differences between cougar and human locations, and the distance from the nearest anthropogenic features (e.g. buildings, roads) as used in the interaction modelling in case study two. Other raw datasets, including winter closure zone data provided by Grand Teton National Park, are similarly restricted from public release due to their sensitive nature.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

Data S1: Detailed description of the human mobility data (HMD).

Data S2: Additional information for 'Proactive conflict management and mitigation' section.

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