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Research Article

Leveraging human mobility data to assess recreational activity across the United States' most visited National Forest

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ABSTRACT

Increasing participation in outdoor recreation is driving elevated levels of human presence in wildlands. If properly managed, outdoor recreation can benefit conservation goals while providing the public with numerous benefits. However, balancing increased demand for recreation opportunities and maintaining ecological integrity can pose difficult tradeoffs for managers. As such, there is a need for additional data-driven resources to help inform land management decisions. Traditional approaches of measuring recreational use, such as trail counters, are costly, labor intensive, and lack the ability to efficiently scale up across large areas. Human mobility data (HMD) offers a detailed, dynamic representation of the human footprint and can provide essential information for the management of human activity at a fine resolution across broad scales. HMD is relatively low-cost and can be analyzed to discern different types of recreation behaviors (e.g., snowmobiling, hiking). Our objective was to explore how HMD can be used to better understand recreation patterns and behaviors within the White River National Forest in Colorado, the nation's most visited National Forest. We leveraged 233 million smartphone locations over 4 years to 1) discern spatial visitor use patterns by creating interactive maps of human use intensity across the WRNF, 2) classify recreation behaviors and summarize user types, 3) quantify overlap between recreation and wildlife habitat.

Management Implications

Our results demonstrate how HMD can provide managers with a relatively cost-effective and efficient means of visualizing, quantifying, and understanding human space use across broad spatial scales with fine resolution. HMD excels at discerning movement patterns which can be analyzed to address management needs – such as distinctions between on-trail and off-trail use, recreation user types, temporal patterns of use, and can also be integrated into area-specific information to derive metrics such as the overlap of recreation within critical wildlife habitat. We caution there are several potential pitfalls in estimating abundance of use with HMD, especially without indexing HMD counts to traditional means of counting recreation users, such as trail counters. However, HMD provided a data-driven approach to inform management of recreation across the most visited National Forest and can serve as a framework for other public land managers.

1. Introduction

Outdoor recreation has steadily increased in popularity, with an estimated eight billion global visits to protected areas occurring annually (Winter et al., 2019). By 2060, an estimated 340 million Americans will be participating in outdoor recreation, nearly double the current

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total (Bowker & Askew, 2012). Increased recreational activities, both motorized and nonmotorized, have been recognized as threats to protected areas (Dertien et al., 2021; Larson et al., 2016; Schulze et al., 2018). These impacts range from disturbance to vegetation and soil (Cole & Landres, 1995, chap. 11) to behavior modification and loss of habitat access for some wildlife species (Reed & Merenlender, 2008; Taylor & Knight, 2003). Furthermore, excessive recreational use and overcrowding can denude the experience of visitors to natural areas (Ferguson et al., 2024; Weinzimmer et al., 2014). Even low levels of recreation have been associated with several changes in wildlife habitat use (Sytsma et al., 2022). Further, noise from recreation activities can permeate far beyond the source and elicit similar wildlife behavioral changes as actual human presence (Zeller et al., 2024) and reduce the benefits of visiting natural areas for tourists (Ferguson et al., 2024). However, with proper management, outdoor recreation can be managed in conjunction with conservation goals. Nature-based recreation has been linked with direct benefits for conservation goals such as donations of time and funds and increased environmental stewardship (Miller et al., 2020, p. 226). Additionally, both consumptive (e.g., hunting licenses) and nonconsumptive (e.g., wildlife viewing tours) recreation can generate revenues that support habitat management (Heflinger et al., 2013; Macdonald et al., 2017).

Developing an effective management plan that balances ecological integrity, wildlife habitat, and recreation opportunities and experience, requires a thorough understanding of the recreational footprint. This includes what types of recreational uses are present, when use occurs, and where use takes place. Unfortunately, collecting this information at the spatial and temporal scales necessary for informed management of large public lands can be both costly and labor-intensive. For U.S. National Forests, which have free entry and numerous access points, it can be especially difficult to understand and map the types of recreation occurring, as well as where, when, and how often they take place. The US Forest Service (USFS) conducts a National Visitor Use Monitoring (NVUM) to inventory use of the National Forest System every few years. However, for a single forest, this effort requires many hundreds of days of sampling (English et al., 2020) and is often not as frequent or detailed as desired for informing management actions at the forest level. Other techniques, such as trail cameras or counters, can provide finer scale information, but require regular servicing which can make them impractical to deploy over large areas. As such, there is a need for more cost-efficient, scalable, data driven methods for quantifying recreation at broad scales with a fine resolution.

Human mobility data (HMD) has the potential to provide reliable, cost-efficient information across large scales. HMD offers a detailed, dynamic representation of how humans move through space and time by capturing location information, often from mobile devices utilizing global positioning system technology (Barbosa et al., 2018; Hu et al., 2021). HMD has been used to map and measure the dynamic human footprint at spatial and temporal scales not previously possible (Barbosa et al., 2018; Ellis-Soto et al, 2023). HMD is considered a powerful tool for conservation planning (Oliver et al., 2024), understanding wildlife behavior in response to human presence (Abernathy et al., 2025b), and for wildlife management applications (Abernathy et al., 2025a). HMD offers a relatively low-cost approach to measuring human activity (Isaacman et al., 2012), and because it relies on GPS locations instead of cellular coverage, it can provide human movement information where cellular service isn't available– a feature critical for recreation management. Indeed, numerous studies have leveraged HMD to assess the distribution of users and measure counts of visitor use across broad scales (Fisher et al., 2019; Liang et al., 2022; Monz et al., 2019; Tsai et al., 2023; Whitney et al., 2023).

In this study we sought to detail and explore the potential for extending the use of HMD to help improve understanding of recreationist behavioral patterns and types of recreation occurring within the White River National Forest (WRNF) in Colorado. The US Forest Service National Visitor Use Monitoring data shows that visitation within the WRNF is the highest in the National Forest System and visitation across the WRNF grew from 13,767,000 site visits in 2017 to 18,437,500 site visits in 2022; a 34 % increase. Our objectives were to: 1) better understand where recreation is taking place and identify concentration zones of high, medium, and low recreation, 2) classify specific types of recreation, and 3) quantify overlap between recreation and critical wildlife habitat. This study exemplifies the potential of how human mobility data could provide a more accurate and cost-efficient approach for informing large-scale recreation management. Results can be used to inform future management decisions on the WRNF and can provide a potential framework for other National Parks and Forests interested in leveraging this type of data to address specific questions about visitor behaviors and general spatial trends in relative use.

2. Methods

2.1. Study area

The White River National Forest is located within the Rocky Mountains of Colorado, USA, and spans approximately 2.3 million acres (Briggs, 2000). The WRNF is the busiest National Forest in the United States with over 18.4 million visits in 2022 (National Visitation Monitoring Program data) and contributes ~$1.6 billion annually to the gross domestic product (USDA, 2019). The eastern edge of the forest begins less than 60 miles from Denver, CO, a metropolitan area of nearly 3 million people. The WRNF includes 12 world-class ski resorts, 8 Congressionally designated Wilderness areas, over 3000 miles of trail, and hundreds of high-alpine lakes provide numerous recreational opportunities including skiing, hiking, biking, motorized sports, hunting, fishing, camping, climbing, caving, snowmobiling, rafting, sailing, and more. Unlike many National Parks and smaller publicly managed natural areas, there are no designated entry points to the forest which makes managing recreational uses difficult. The WRNF also maintains habitat for a wide range of wildlife species including large mammals such as elk (*Cervus canadensis*), bighorn sheep (*Ovis canadensis*) and the federally threatened Canada lynx (*Lynx canadensis*).

2.2. Human mobility data acquisition & description

We purchased human mobility data (HMD) from Unacast, Inc. (formerly Gravy Analytics). The data covered the entire White River National Forest from May 1, 2019 through October 31, 2023 (Table S1; Fig. S1). The locations included were based on GPS locations gathered from mobile applications of anonymous, consenting users in accordance with the California Consumer Privacy Act and European General Data Protection Regulation.

The HMD represents approximately 10–15 % of all cellphone users and relies on GPS locations and not cellular service. This distinction is important because many areas of the forest lack cell phone service. Each record in the HMD contained coordinates, date, time, fix quality flags, and an anonymized device ID. Connecting locations associated with the same anonymous device ID enabled us to calculate movement speed for each user with more than one location.

2.2.1. Data processing

The goal of the data processing tasks was to identify the subset of data that represented only recreational use on the WRNF. We extracted all locations that fell within the administrative boundary of the WRNF and cleaned the data by removing any locations attributed with quality flags provided by Unacast, such as locations associated with a cell tower overload and low accuracy locations. We also calculated and examined movement speeds of users and removed any locations associated with speeds greater than 128 km/h to avoid the inclusion of air traffic and erroneous locations. Next, we visually identified areas of potential cell tower overload by looking for solitary groups of high use amid low use and then confirming the indicative circular pattern or same location drop. These points were then manually removed.

Next, we utilized highway data from the Colorado Department of Transportation to remove all points that occurred within 50 m of state highways. A 50 m buffer was selected to remove highway traffic while retaining points associated with trails and trailheads that are in close proximity of the highway. We also removed points that were associated with use inside buildings by determining which locations fell within a 3 m buffer of building footprints (Microsoft, 2018), removing all indoor locations (including visitor centers) with the exception of locations that fell within ski resorts which were identified separately using the operational boundaries of the resorts (provided by WRNF managers), allowing us to map and analyze use with and without ski areas.

As lands within the administrative boundary may have a variety of ownership, we then worked to identify any remaining points located within private land. We opted to tag these points as private rather than remove them to retain the ability to ask questions about movement between land ownerships. We utilized land ownership data from the Colorado Ownership, Management, and Protection database (CoMap) to attribute any point as private that occurred within any aggregated private land area greater than or equal to 80 acres. The 80-acre threshold was selected so that data points from small private land inholdings surrounded by National Forest, such as mining claim parcels, were included.

2.2.2. *Case study 1 – mapping recreation use on the WRNF*

Our first objective was to map recreational use on the White River National Forest and identify areas of high, medium, and low use. For this exercise we utilized only points that overlapped public land. We created heatmaps using a tessellation of hexagonal polygons that covered the entire forest. We did this at two different resolutions: 500 m for examining forest-wide trends and 100 m for examining trends at finer scales. The 500 m^2 cells were used to provide a better visual representation of visitation at the broader forest-wide scale while the 100 m^2 cells provided a more accurate depiction of use intensity when zoomed into specific areas. The resolution represents the distance between opposite edges of the hexagonal cell.

We used WRNF's travel management dates for defining summer and winter seasons. The summer travel season was defined as May 21st through November 22nd and the winter travel season from November 23rd through May 20th. We calculated the number of locations that occurred within each cell for every season and year (2019–2023). We created maps of counts with and without the inclusion of ski area points. If there were no locations in a cell, it was assigned a value of zero.

To create an easy way to contextualize relative levels of recreational use we delineated areas as high, medium, and low recreational use. This was accomplished by calculating the number of smartphone locations within each hexagonal cell and then categorizing the cells. Cells with counts in the top 1/3rd of all nonzero pixels were labeled as high ($\geq$ the 66th percentile = high), those in the middle 1/3rd were labeled as medium (between the 33rd – 66th percentile = medium), and the remaining were classified as low (<33rd percentile). Due to known high concentrations of use at ski areas, we replicated this process with and without locations within ski area boundaries. We delineated concentration zones using all smartphone locations obtained to provide a comprehensive assessment of the spatial footprint associated with recreation on the WRNF. We report number of locations as well as unique user-days (defined as one unique smartphone ID per day) where the focus is on counts of visitors instead of a spatial distribution of use or types of recreation use.

2.2.3. *Case study 2 – identifying types of recreation on the WRNF*

Our second objective was to identify various forms of recreation occurring on the WRNF, including overnight use, off-road/off-trail use, motorized, and nonmotorized recreation. To identify off-road/off-trail use, we combined the National Forest System Roads and System Trails datasets and buffered roads and trails by 100 m. We also buffered recreation sites within the forest (provided by WRNF managers) by 100 m. Points within the buffer were classified as on-trail/on-road use ($\leq$100 m = on-trail/on-road). Points within water bodies (lakes and reservoirs) were classified as water. Lakes and reservoirs were identified using the Colorado lakes GIS layer from the State of Colorado (2018). Those that fell outside of the buffer around roads, trails and recreation sites and were outside of water bodies were classified as off-trail/off-road use.

Overnight use was classified using the timestamp associated with each location. Locations with a timestamp between 22:00 and 04:00 were classified as overnight use. The hour of 22:00 was selected to filter out any late-evening departures and 04:00 was selected in order filter out any early morning arrivals—leaving only true overnight use.

To identify recreation user types during the summer travel season, we began by classifying smartphone movement rates by calculating the speed between successive locations from the same anonymized ID's locations. To remove any uncharacteristically fast or errant locations, we removed any locations with a speed or distance greater than five times the mean speed or distance of that user. We then removed the top 1 % (greater than the 99th percentile) of locations based on speed, to remove any additional outliers. We then calculated the mean and maximum speed and the variance of the movement rates for the entirety of each set of locations that excluded the outliers. We began by testing our approach within the Wildernest area, including the Salt Lick and Mesa Cortina trail systems using locations collected during the WRNF summer travel season (May 21st – November 22nd). This is a fully nonmotorized area and so we sought to look at different nonmotorized use types. Our aim was to distinguish nonmotorized slow or intermediate travel (i.e. walking, jogging respectively) from nonmotorized fast travel (i.e. mountain biking). We considered users with a maximum speed of 6.4 km/h or less as nonmotorized slow travel (walking; Miller & Stamford, 1987; Wood et al., 2023), a maximum speed of 6.4–16 km/h as nonmotorized intermediate travel (jogging; Miller & Stamford, 1987; Gazendam & Hof, 2007), a maximum speed above 9.6 km/h with high variance (>20) or a maximum speed between 16 km/h and 32 km/h as nonmotorized fast (biking; Selesnic & Kodsi, 2016); speeds above 32 km/h were classified as motorized recreation (any potential users not removed through road buffers or cleaning). We next selected an area in the northwest section of WRNF, on the Blanco District, an area that sees a variety of motorized use (e.g., ATVs and dirt bikes), as well as nonmotorized use. We used locations from the start of the summer travel period (May 22nd) through August of each year, when we were confident there should be no snow cover and distinguished nonmotorized slow travel from fast motorized use using the same methodology applied to the Wildernest area. We then scaled up our approach to classify summer recreation across the entirety of the WRNF considering the same categories of recreation with the addition of a "water" category, describing locations that were collected on lakes and reservoirs within the WRNF.

To identify types of recreation occurring during the winter, we selected a study area within the WRNF's Vail Pass Winter Recreation Area, a 55,000-acre fee area that is intensively managed to separate snowmobile use from skiing to test our ability to distinguish between winter motorized and nonmotorized use. This location was selected because of the forest's intensive management of the area and distinct motorized and nonmotorized areas, and high levels of on-the-ground manager knowledge. We used locations from January–March for all available years, as these dates guaranteed over-snow use. We utilized the same methodology for calculating speed and distances, but as downhill skiing and snowmobilers likely have overlapping maximum speeds (Greenwald et al., 2017), we also assigned points as either uphill or downhill travel. To do this, we assigned each point an elevation using the 30 m resolution 3DEP digital elevation model (DEM) from the US Geologic Survey. Uphill points had a higher or equal elevation than the previous point, downhill points had a lower elevation than the previous point. We then calculated the track's maximum uphill and downhill speed (the maximum speed achieved across all points with an elevation gain and all points with an elevation decrease). We considered any maximum uphill speeds greater than 6.4 km/h as motorized recreation (Miller & Stamford, 1987; Praz et al., 2016; Wood et al., 2023). If the maximum downhill speed within these backcountry areas was greater than 32 km/h, the track was classified as motorized use (Schmitt et al., 2011), though this threshold will overlap with downhill skiers. The remaining locations were classified as nonmotorized winter recreation. Finally, we conducted a visual validation of the classification using maps and management knowledge of use patterns within the Vail Pass Winter Recreation Area. We then used the same methodology to classify winter recreation across the entirety of the WRNF.

2.2.4. Case study 3 – quantifying overlap between recreation and critical wildlife habitat

Our third objective was to quantify the overlap of recreation with critical wildlife habitat on the White River National Forest. For this exercise we looked at habitat for three species: Canada lynx, elk, and bighorn sheep. For elk and bighorn sheep, we looked at two separate types of critical habitat, winter range and production areas. For Canada lynx, we used areas of proposed critical habitat. These publicly available polygons were defined by the Colorado Parks and Wildlife (2024). For each species, polygons of critical habitat were clipped to the forest boundary.

We utilized the same methodology for identifying high, medium, and

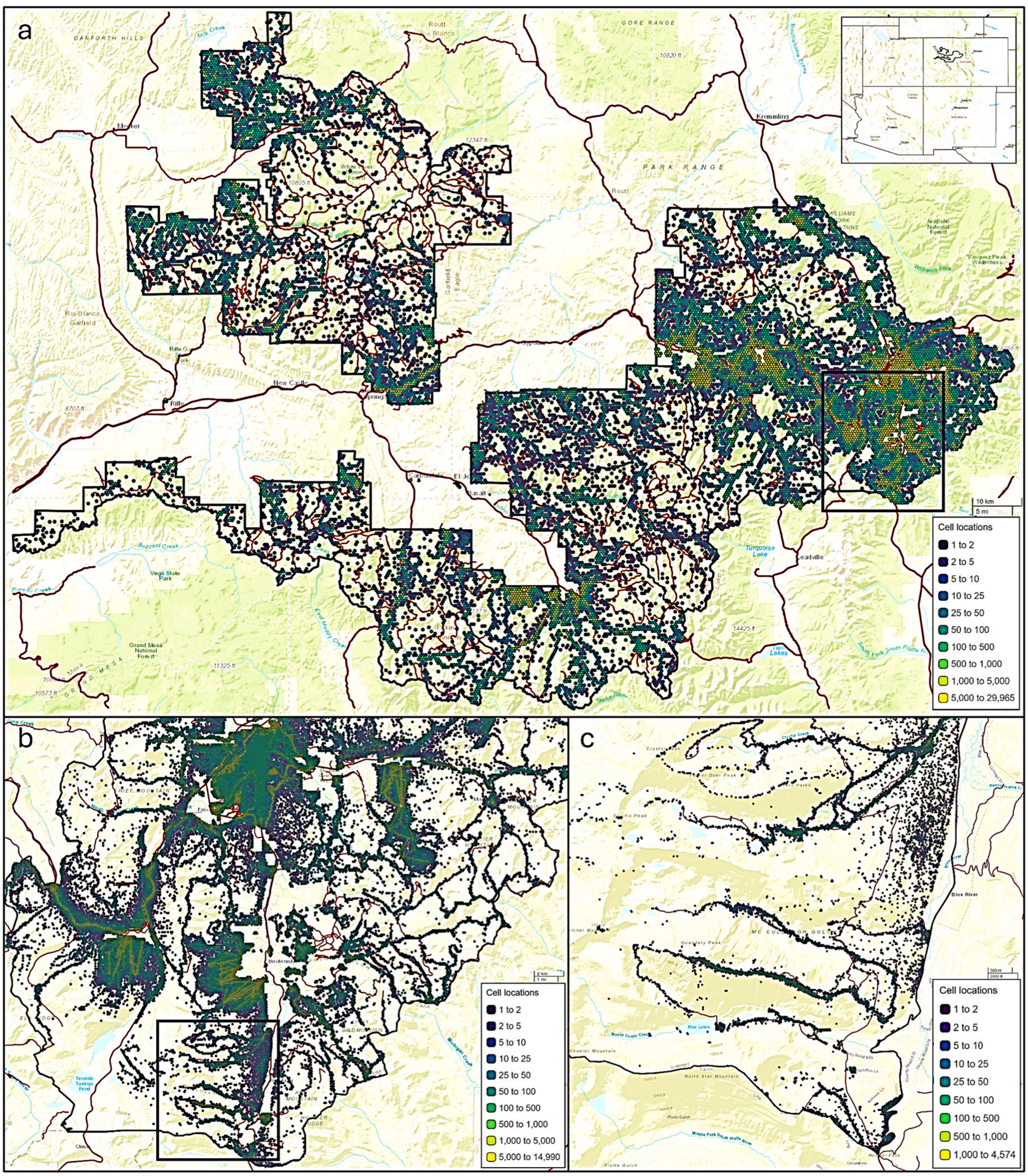

Fig. 1. Distribution of recreation across the White River National Forest, CO, USA during the 2023 summer travel season at the forest scale (panel a), the district scale (panel b; depicting a portion of the Dillon Ranger District, to improve visibility) and site-specific scale (panel c). Recreation was mapped using human mobility data and aggregated in hexagonal pixels. Black boxes represent areas magnified in subsequent panels. Red lines denote roads and trails, black lines represent management boundaries.

low use recreation areas as described in Case 1 except that instead of utilizing travel management dates, we utilized the appropriate occupancy dates for each species and habitat type. For example, in elk production areas we considered locations that occurred from May 15th – June 30th a period covering elk calving within the area. For areas corresponding with winter range of elk, we used HMD locations collected from December 1st – April 14th. In bighorn production areas, we considered HMD locations from April 15th – June 30th and locations from November 15th – April 15th for winter range of bighorn. For wintering range of lynx, we considered locations that fell within the WRNF winter travel season, November 23rd – May 20th. We then calculated the proportion of overlap between areas of low (<33rd percentile), medium (between 33rd and 66th percentile) and high recreation (>66th percentile) within each critical wildlife habitat polygon in order to calculate the percent overlap between concentration zones of recreation and each critical habitat area occurring on public land within the WRNF using the 'sf' package in R (Pebesma, 2018). This was repeated for each available year of data (2019–2023) to examine trends in overlap across years. For visualization purposes, we also delineated 50 % and 95 % kernel density estimates (KDEs) of recreation using the 'st_kde' function in the 'eks' package in program R (Duong, 2024).

3. Results

3.1. Case study 1 – mapping recreation use on the WRNF

We collected a total of 233,645,931 HMD locations on the White River National Forest from May 1st, 2019 through October 30th, 2023. Locations per month ranged from 467,879 to 25,841,302 with an average of 4,768,284 (Table S1). These locations reflected a total of 10,357,249 user-days, which is defined as one individual visiting one day. Monthly user-days ranged from 46,773 to 495,250 with an average of 211,372 user-days per month (Fig. S1).

Forest-wide heatmaps of HMD locations were created for each year and travel season (Fig. 1a.) and for each ranger district. We also occasionally mapped use at the project level scale (Fig. 1c.). These heatmaps were able to help confirm manager perceptions of relative high use areas. These areas included popular destinations such as waterfalls, mountain peaks, and water bodies. We also observed areas of higher use near population centers, at sites easily accessible from Interstate 70, and near ski area operational boundaries (Fig. 1a). Additionally, heatmaps highlighted potential newer growing areas of visitation on the western side of the WRNF near Rifle and New Castle, Colorado, which can serve for future planning and monitoring purposes.

3.2. Case study 2 – identifying types of recreation on the WRNF

We used HMD to identify different user groups (e.g., overnight, off-road/off-trail) and types of recreation (e.g., mountain biking, motorized use) occurring throughout the WRNF using spatial and temporal characteristics of the HMD. We visualized overnight use during the summer travel season for all available years of data by creating a map of aggregate locations. The map of overnight use highlighted popular campgrounds and backcountry camping locations and can be used to inform management of overnight use not associated with designated camping areas on the WRNF. We created two off-road/off-trail maps for both summer and winter travel seasons across all available years. Throughout the year, the proportion of locations classified as off-road/off-trail varied by month, with an annual average of 60.07 % off-road/off-trail locations and 33.69 % occurring near a road, trail or recreational site and an additional 6.21 % of locations collected on water bodies (Table 1). While these proportions may seem surprising, these values exclude locations on ski resort boundaries as these are known developed areas and were considered on-road/on-trail use. Off-road/off-trail use in the winter was concentrated near ski resorts, highlighting popular areas for backcountry skiing while maps of off-road/off-trail use in the summer showed backcountry use across the forest, particularly at the edges of wilderness areas, near lakes and reservoirs, and in known popular hiking areas. Maps of off-road/off-trail use can be used to inform management decisions such as development of new trail systems or seasonal closures.

Table 1
Proportion of human mobility data on the White River National Forest, CO, USA classified as occurring either on roads/trails or as off-road/off-trail (>100 m from a road or trail or recreation site) or water if the location fell within a lake or reservoir during 2022, excluding locations at ski resorts. Locations on ski resorts were removed as known developed areas; however, as a large number of locations are collected on ski resort boundaries, the off-road/off-trail locations reported are a larger proportion than would be if all locations were included. Locations on highways within the forest were removed while National Forest System Roads were retained. Off-road/off-trail locations include all locations that fell outside of the 100 m buffer around roads, trails and recreation sites and outside of water bodies.

	On Roads/Trails	Off-road/off-trail	Water
January	0.346	0.596	0.059
February	0.365	0.575	0.060
March	0.302	0.632	0.066
April	0.259	0.676	0.064
May	0.275	0.658	0.066
June	0.290	0.645	0.064
July	0.280	0.651	0.068
August	0.318	0.617	0.065
September	0.339	0.597	0.064
October	0.358	0.581	0.060
November	0.395	0.536	0.070
December	0.516	0.444	0.039

When classifying winter recreation within the Vail Pass Winter Recreation Area, we observed a total of 1535 user-days across three winters, with 53.75 % engaged in motorized recreation (ex. snowmobiling) and 46.25 % engaged in nonmotorized recreation (ex. skiing). Visual inspection of classified locations showed extensive backcountry skiing and confirmed snowmobile use in areas that allowed snowmobile access and a small subset of locations classified as snowmobiles in areas that prohibit snowmobile use. For winter recreation across the WRNF, the 2021/2022 winter season (Nov 23, 2021–May 20, 2022) included 717,190 unique user-days. We classified 83.65 % of user-days as engaged in nonmotorized recreation, 15.28 % as motorized recreation off-road, and 1.06 % were classified as motorized-on road, with locations occurring only on non-highway roads within the forest. When classifying recreation types during the summer travel season, we identified a total of 83,686 user-days across five summers within the Wildernest area, of which 88.65 % engaged in nonmotorized slow (ex. walking/hiking) or intermediate recreation (ex. running), and 4.50 % engaged in nonmotorized fast recreation (ex. mountain biking). The remaining 6.95 % of user-days were associated with motorized use – these were likely driver locations that may have fallen outside of the road buffers created. Within the Blanco District, we observed a total of 1157 user-days across five summers, of which 41.40 % engaged in nonmotorized slow and intermediate recreation, 15.21 % in nonmotorized fast recreation, and 43.39 % in motorized recreation (Fig. 2).

Forest-wide summer recreation across the entirety of the WRNF resulted in a total of 532,401 unique user days. We estimated 13.59 % of users were associated with motorized recreation, 5.65 % with nonmotorized fast recreation, 6.81 % with nonmotorized intermediate recreation, 69.55 % with nonmotorized slow recreation, and the remaining 4.40 % engaged in water related recreation.

3.3. Case study 3 – quantifying overlap between recreation and critical wildlife habitat

We leveraged the HMD to map and quantify the extent of overlap between recreation occurring within habitat for three large mammal

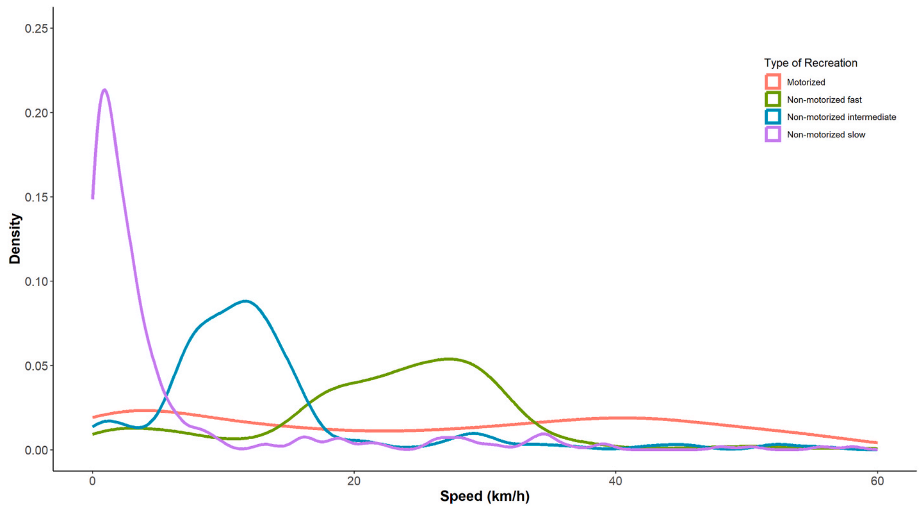

Fig. 2. Density distribution of human mobility data classified by type of recreation during the summer travel season on the White River National Forest, CO, USA from 2019 to 2023 within the Blanco Ranger District. Type of recreation was assigned based on several movement attributes associated with each user's trajectory.

species with designated habitat on the WRNF: lynx habitat, bighorn sheep production and wintering areas and elk production and wintering areas across the forest (Fig. 3). Overall, overlap between concentration zones of recreation and critical wildlife habitat was less than 5 % for all species (Table 2). The greatest total overlap occurred during the COVID-19 pandemic (summer 2020; Table 2). Individually, the highest overlaps were seen between low recreation and elk winter range (3.89 %), lynx habitat and low recreation (3.31 %), and lynx habitat and high recreation (3.89 %). The lowest overlap across years was observed between production areas of elk and bighorn with high use recreation zones (0.24 % and 0.54 % respectively). The lowest average overlap, across all levels of recreation intensity, was between summer production areas for bighorn (2.39 %) and elk (1.58 %). All three species showed higher overlap with recreation during the winter season (lynx 9.80 %) or winter ranges (elk 6.59 % and bighorn sheep 4.51 %).

4. Discussion

Natural areas are experiencing ever-increasing visitation levels, necessitating management of wild lands for both human recreation and ecosystem health and function. The National Forest System spans over 193 million acres – roughly 10 % of the acreage of the continental United States, and provides numerous recreational opportunities, without entrance fees and without monitored entrances, making

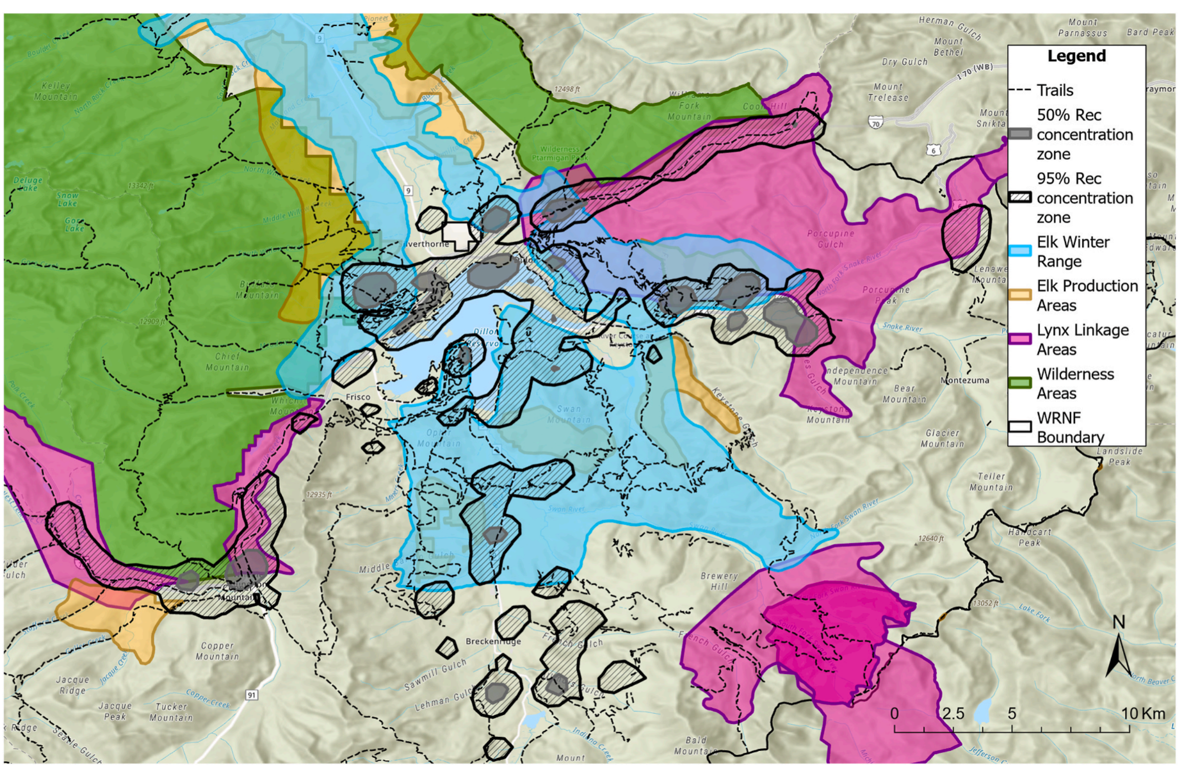

Fig. 3. Overlap of concentration zones of recreation and critical wildlife habitat on the Dillon Ranger District of the White River National Forest, CO, USA. Recreation concentration zones in map were delineated using a 50 % and 95 % kernel density estimate. Critical wildlife habitat includes winter range and production zones for elk, lynx habitat areas and designated wilderness areas.

Table 2
Overlap between low, medium and high concentration zones of recreation, developed by counting the number of anonymous smartphone locations at a 100 m^2 resolution, with wildlife habitat for elk (*Cervus canadensis*), bighorn sheep (*Ovis canadensis*) and Canada lynx (*Lynx canadensis*) on the White River National Forest, CO, USA. Wildlife habitat was provided by Colorado Parks and Wildlife. Values are expressed as percentage overlap. Values with a "-" indicate periods not fully covered by the HMD.

Habitat	Recreation Level	Summer 2019	Summer 2020	Summer 2021	Summer 2022	Summer 2023	Average Overlap
Elk Production	Low	1.16 %	1.47 %	0.36 %	0.29 %	1.11 %	0.88 %
	Medium	0.75 %	0.55 %	0.18 %	0.21 %	0.60 %	0.46 %
	High	0.22 %	0.42 %	0.11 %	0.12 %	0.32 %	0.24 %
	Total (all)	2.13 %	2.44 %	0.65 %	0.62 %	2.03 %	1.58 %
Bighorn Production	Low	–	2.18 %	0.85 %	0.34 %	–	1.12 %
	Medium	–	1.04 %	0.75 %	0.40 %	–	0.73 %
	High	–	1.00 %	0.37 %	0.25 %	–	0.54 %
	Total (all)		4.22 %	1.97 %	0.99 %		2.39 %
			Winter '19 -'20	Winter '20 -'21	Winter '21 -'22		Average Overlap
Elk Winter Range	Low		3.93 %	2.78 %	2.57 %		3.09 %
	Medium		2.17 %	2.27 %	1.94 %		2.13 %
	High		1.73 %	1.24 %	1.14 %		1.37 %
	Total (all)		7.83 %	6.29 %	5.65 %		6.59 %
Bighorn Winter Range	Low		3.23 %	2.06 %	1.44 %		2.24 %
	Medium		1.41 %	1.31 %	1.04 %		1.25 %
	High		1.38 %	0.93 %	0.75 %		1.02 %
	Total (all)		6.02 %	4.30 %	3.23 %		4.51 %
Lynx Habitat	Low		4.58 %	3.03 %	2.32 %		3.31 %
	Medium		2.70 %	2.74 %	2.39 %		2.61 %
	High		4.72 %	3.91 %	3.03 %		3.89 %
	Total (all)		12.00 %	9.68 %	7.74 %		9.80 %

recreation management extremely challenging. Our three case studies explored the potential to leverage human mobility data to quantify recreation in natural areas by examining human activity in the United States' most visited National Forest. We leveraged human mobility data to provide a more cost and labor efficient method for estimating visitation intensity and displaying spatial patterns of use and recreation activity types. Prior to the availability of HMD, such information would have been incredibly costly to obtain and in some cases nearly impossible, for example, quantifying the percentage of off-trail use.

While data on human mobility has most commonly been applied to urban areas (Wang et al., 2019; Zhao et al., 2016), we illustrate some of the many potential applications to recreation management in natural areas. HMD has the potential to restructure decision making for recreation managers by providing an efficient, data driven approach to understanding the patterns of human recreation. The application of human mobility data provided an in-depth assessment of recreation use and patterns at multiple spatial scales and time frames, offering new insights that could be used to help inform large-scale, forest-wide planning efforts such as forest plan revisions and programmatic recreation management strategies. HMD provided the ability for us to classify behaviors based on spatial and temporal characteristics. As such, we were able to map out when and where specific types of recreation were occurring on the WRNF. Such information can be used to understand the relative breakdown of activities on the WRNF, identify key areas for specific recreation types and inform decisions on when and where to manage for various activities. While identifying these behaviors was strongly dependent on our set of assumptions, these data nevertheless provide a comprehensive estimate of the recreation occurring on the WRNF and was conducted in a much more time and cost-effective manner than previous methods, such as visitor surveys.

HMD provided the ability to quantify the footprint of human recreation in sensitive habitats which can assist targeted management actions such as education/outreach or seasonal closures. For example, Abernathy et al. (2025b) used HMD to assess the use of voluntary and nonvoluntary closures for bighorn sheep winter habitat in Grand Teton National Park. They identified which closures were frequently still being recreated within and the locations of the entrants with precision which can inform the placement of better signage and outreach. We found nearly 10 % overlap between the mapped recreation footprint and lynx winter habitat. This estimate does not factor in noise associated with recreational activities which can extend far beyond the recreation site and into surrounding habitat and impact wildlife (Francis & Barber, 2013; Zeller et al., 2024). This higher level of overlap between lynx habitat and human recreation, particularly overlap with high-use areas of recreation, may be concerning as visitation numbers are likely to continue to increase. Lynx habitat likely overlapped with recreation to a greater extent than the other species due to the proximity of critical habitat to ski areas. In contrast, overlap was generally low between recreation and sensitive habitat for bighorn and elk, which suggests existing management strategies, such as seasonal closures and other forest plan management direction, may be effective in balancing recreation with adequate wildlife habitat. Although most overlap between recreation and habitat for elk and bighorn was low when aggregated across the forest, certain areas may experience higher levels of activity that could result in localized disturbances to wildlife that may not be apparent at a forest-wide level.

While human mobility data provides a wealth of information on human activity, there are some important limitations to consider as well. Perhaps the greatest limitation to the human mobility dataset is that only a sample of smartphone users (10–15 %) are represented. Some studies investigating the correlations between on-the-ground counts and HMD-derived estimates have found high positive correlations (e.g., Liang et al., 2022 in Yellowstone National Park) or variable results depending on the site (e.g., Tsai et al., 2023 across U.S. National Parks), while others have found relatively low correlations without combining additional data streams (e.g., Winder et al., 2025 in U.S. National Wildlife Refuges). As such, without additional analyses and validation work within WRNF, any conclusions must be drawn only in relation to relative use and relative change as we cannot quantify absolute values of visitation; however, these issues likely persist with most visitor surveys as well. Here, by comparing relative concentration zones, we were still able to compare large differences across years. Another limitation of the data is the potential influence of poor cell reception and natural features on cell phone use and GPS performance. While GPS does not require cellular service, the accuracy can be diminished in areas such as canyons and under tree canopy (Hanson et al., 2025, p. 46). One final limitation pertains to our second case study, in assuming threshold values for various types of recreation and lack of data availability for validation. While the thresholds for classifying recreation were supported by values in prior studies, these were based on expert judgement and literature review and were not validated with any data on the ground. As such, individuals near threshold values may be misclassified or individuals moving slower than average speeds could be assigned a slower form of recreation in error. For example, our estimates for the percentages of annual "off-trail/off-road" use surprised WRNF managers (average of 60 %) and may require additional information and validation data to improve the classification assumptions and ensure accuracy of the estimates. We suspect a fair amount of this proportion could have resulted in how we handled ski area use (removed since it is considered "developed") and we lacked the actual footprints of other developed sites, such as campgrounds and parking lots, which would improve our classification further. Despite these limitations, HMD provided a data-driven look into the behaviors and types of recreation occurring on the WRNF at broad scales with a fine resolution while offering cross boundary comparisons as well (e.g., among National Forests and Parks).

Our use of human mobility data illustrates an ongoing shift in recreation management from relying on professional judgement and anecdotal evidence about the distribution of recreational use to data-driven information about use across broad scales. As big data continues to redefine a variety of disciplines, recreation management can benefit from this by capitalizing on HMD as a means of efficiently identifying patterns of recreation use. We provide the results of several applications of HMD to questions of recreation management and provide a guideline for other public lands. A reliance on traditional methods for measuring recreation intensity on the WRNF, such as with trail cameras or counters, would neglect the use of roughly 2/3rd of visitor use that occurred beyond 100 m of a road or trail. Managing for the many uses of natural areas, for both humans and wildlife, requires a detailed understanding of the distribution of recreation, where it is concentrated, and how it overlaps with areas of sensitive habitat. Human mobility data has the potential to help answer these questions along with a suite of other possible applications in a fraction of the cost and time it may otherwise require. We recommend, when possible, managers consider the application of human mobility data to help inform their understanding of the human footprint when developing management plans for natural areas.

CRediT authorship contribution statement

Maksim Sergeyev: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis. **Mark A. Ditmer:** Writing – review & editing, Writing – original draft, Supervision, Resources, Project administration, Methodology, Funding acquisition, Data curation, Conceptualization. **Kira Z. Deming:** Writing – review & editing, Writing – original draft, Supervision, Resources, Investigation, Conceptualization. **Natasha Goedert:** Writing – review & editing, Validation, Supervision, Project administration. **Michael K. Schwartz:** Writing – review & editing, Funding acquisition, Conceptualization. **Sam Massman:** Writing – review & editing, Writing – original draft, Validation, Project administration, Methodology, Conceptualization. **George Wittemyer:** Writing – review & editing, Supervision, Project administration, Data curation, Conceptualization.

Declaration of competing interest

Authors have no competing interests to declare.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jort.2025.100973.

Data availability

The data used in this study are confidential.

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