Innovative New Ways to Count Outdoor Recreation:
Using data from cell phones, fitness trackers, social media, and other novel data sources

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About Headwaters Economics
Headwaters Economics is an independent, nonprofit research group whose mission is to improve community development and land management decisions. https://headwaterseconomics.org/

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1. Executive Summary

We know that outdoor recreation is a large and growing part of our economy, as described by the Bureau of Economic Analysis[1] and the Outdoor Industry Association[2] and evidenced by the many state offices of recreation. But what we *don't* know is: how much recreation is happening, and where is it happening? Traditional methods used to measure recreation, especially dispersed activities on trails, are expensive and time-consuming and as a result are too often imprecise or inconsistent.

Trail-based recreation tends to be dispersed across the landscape with many access points that make counting difficult. Unlike traditional revenue-producing activities on public lands such as timber harvesting, livestock grazing, and oil and gas production, the impacts of recreation cannot be measured in board feet, animal units, or barrels of oil. Because trail-based recreation happens in many locations with many access points and without a central permitting office, it is more difficult to measure. Some trail managers resort to indirect measures of use such as rolls of toilet paper replaced at pit toilets, or number of dog waste bags replaced at trailheads, to determine whether trail use is increasing or decreasing. We can and should do better.

Federal agencies and many state and local groups sometimes have strategies in place to count recreation, but these efforts generally are limited by the high cost of on-site counting methods (such as infrared cameras) and the inability to capture snapshots of recreation across numerous trailheads and types of uses. At the same time, those who manage recreation are challenged with growing demand and declining budgets for recreation. For example, from 2010 to 2018 the Bureau of Land Management reports that their recreation budget declined by $14 million, or 18%.[3] During the same years the recreation budget for the Forest Service declined by $49 million, or 16%.[4] As the demands for recreation increase and new types of use emerge, the entities managing the lands and trails need robust, modern strategies to capture dispersed recreation across large tracts of land.

In this report we review the state of knowledge on how best to count recreation, exploring novel data sources and methods to supplement traditional, on-site counts. New data are available via social media, fitness tracking applications, cell phones, and other novel sources. The original purpose of these "big data" sources was not to count recreation, but researchers have developed methods to extrapolate recreational use. We test some of these sources and methods in a case study to identify opportunities and limitations for different approaches.

While all the methods described in this report require calibration with traditional on-site user counts, the novel methods have the potential to allow land managers to develop a more complete and timely picture of how people are recreating in their jurisdiction. The novel data methods also have the potential to standardize and centralize the bulk of data collection and analysis for large federal agencies, removing some of the burden from the managers of individual units.

Highlights from our review of existing research and our case study conclude:

- Novel data can successfully be used to estimate trail use, with limited on-site calibration.
- The more users, the more accurate the trail use estimates. The most accurate predictions are at monthly or annual scales.
- There remains a need to improve methods to ensure the use of novel data sources accurately represent trail users' demographics (e.g., race, income, and age).
- From our case study and other research, we see strong potential to expand these models nationally, and expand the models to estimate economic impacts.

The novel data sources and techniques described in this report also can improve trail management and allow managers to proactively anticipate needs rather than simply react when parking lots and pit toilets are overflowing. With detailed information on use across all trailheads, those managing recreation can better understand trail use across the entire system, identify unsanctioned routes, spot new trends in types of use such as e-bikes, and identify when and where trail use is highest to help mitigate user conflicts.

Based on this research, we propose five policy recommendations. These recommendations are intended to help agencies, recreation managers, and advocates incorporate novel data into planning and resources allocation, with the goal of helping communities and agencies take advantage of the economic potential of outdoor recreation.

1. Build a regional or national model to calculate trail use on federal lands.
2. Mandate and fund improved recreation counts to improve recreation management.
3. Incorporate improved recreation counts into funding allocations.
4. Build partnerships between app companies, agencies, and nonprofits.
5. Estimate economic impacts using novel data sources.

2. Traditional methods to count recreation are inadequate

We know that outdoor recreation is a large and growing part of our economy, as described by the Bureau of Economic Analysis[5] and the Outdoor Industry Association[6] and evidenced by the many state offices of recreation. But what we *don't* know is: how much recreation is happening, and where is it happening? Traditional methods used to measure recreation, especially dispersed activities on trails, are expensive and time-consuming and as a result are too often imprecise or inconsistent.

In this report we review the state of knowledge on how best to count recreation, exploring novel data sources and methods to supplement traditional, on-site counts. New data are available via social media, fitness tracking applications, cell phones, and other novel sources whose original purpose was not to count recreation, but from which researchers have developed methods to extrapolate recreational use. We test some of these sources and methods in a case study to identify opportunities and limitations for different approaches.

In this report we focus on trail-based recreation, such as hiking, horseback riding, ATVing, and mountain-biking. Trail-based recreation tends to be dispersed across the landscape with many access points that make counting difficult. Recreation on trails also requires infrastructure (e.g., parking areas and bathrooms at trailheads) and maintenance that increase as use increases. It is important for agencies to have information on recreation use so they can proactively anticipate needs rather than simply react when parking lots and pit toilets are overflowing. We are interested primarily in estimating more accurately the total volume of trail use, but several of the methods described in this report can be used also to better understand the mix of uses.

Those who manage recreation, particularly on federal lands, are challenged with growing demand and declining budgets for recreation. For example, from 2010 to 2018 the Bureau of Land Management reports that their recreation budget declined by $14 million, or 18%.[7] During the same years the recreation budget for the Forest Service declined by $49 million, or 16%.[8]

But what do we know about recreation use on BLM and Forest Service lands? Not enough. The BLM estimates that from 2010 to 2018 recreation use has gone up by more than 8.5 million visits, or 14%.[9] The Forest Service, whose lands likely should see similar trends, estimates something very different. They only provide information for two time periods: FY2007 to FY2011 and FY2012 to FY2016. During those two time periods they estimate recreation increased by only 3 million visits, or 2%.[10] It is not credible that these two agencies with similar recreation opportunities could have such divergent visitation trends. These wildly differing numbers tell us that it is most likely that neither agency has very accurate estimates of total recreation use on lands they manage. Accurate measures for individual sites and over shorter time periods are particularly challenging.

Unlike traditional revenue-producing activities on public lands such as timber harvesting, livestock grazing, and oil and gas production, the impacts of recreation cannot be measured in board feet, animal units, or barrels of oil. Recreation also is not a commodity that is sold, which makes it hard to track the way one would track, for example, timber sales from Forest Service lands.[11] Because trail-based recreation happens in many locations with many access points and without a central permitting office, it is more difficult to measure. Some trail managers resort to indirect measures of use such as rolls of toilet paper replaced at pit toilets, or number of dog waste bags replaced at trailheads, to determine whether trail use is increasing or decreasing. We can and should do better.

Federal agencies and many state and local groups sometimes have strategies in place to count recreation, but these efforts generally are limited by the high cost of on-site counting methods (such as infrared cameras) and the inability to capture snapshots of recreation across numerous trailheads and types of uses. As the demands for recreation increase and new types of use emerge, the entities managing the lands and trails need robust, modern strategies to capture dispersed recreation across large tracts of land.

Accurate recreation counting is important at the national and local levels

The need to count recreation more accurately has implications at the national and local levels.

At the national scale, more accurate counts of recreation use will help make the administration of federal programs more efficient by directing resources where they are most needed. Counts will more accurately highlight the demand for recreation and associated infrastructure to inform public agencies' budgets. The Great American Outdoors Act will provide $1.9 billion to address the maintenance backlog on public lands and $900 million for conservation and recreation projects.[12] These funds can be more effectively distributed to places where funding has been inadequate to meet the demand.

While outdoor recreation on federal lands can provide an economic boon for nearby communities, at the local scale it also puts pressure on roads, sewer, and emergency services. The federal Payments in Lieu of Taxes (PILT) program provides funding to communities to compensate for the tax-exempt status of federal lands. PILT funds support essential services in the community such roads and emergency services that are used by residents and visitors alike. In rural recreation destinations with low population but high visitation, the PILT funds may not adequately compensate local governments for recreation impacts (e.g., the costs of road and trail maintenance and search and rescue operations). Reforms to the PILT payment formula that incorporate more accurate estimates of recreation on federal lands, and that result in proportionally larger payments for counties with large numbers of recreationists on federal lands, would help local governments better manage the impacts of visitation. A reform to the PILT formula has been proposed, but for a formula that incorporates recreation to work best, more accurate measures of recreation use are needed.

Accurate trail use counts help local land managers understand how the public is using trails and the relative importance trails and recreation play in a community. The COVID-19 pandemic has highlighted the importance of recreation opportunities close to home as parks and trailheads have seen a large jump in use.[13] An accurate picture of the community's demand for trails, trailheads, maps, and restrooms can help justify new or ongoing funding allocated to infrastructure development and maintenance.

The novel data sources and techniques described in this report also can improve trail management and allow managers to be proactive rather than reactive. With detailed information on use across all trailheads, those managing recreation can better understand trail use across the entire system, identify unsanctioned routes, spot new trends in types of use such as e-bikes, and identify when and where trail use is highest to help mitigate user conflicts.

This report synthesizes the state of knowledge related to novel data sources, describing the most common sources, their applications, and their challenges. The report concludes with a case study to evaluate some of the data sources accessible to recreation managers and advocates who do not have the capacity to process "big data." While all the methods described in this report require calibration with traditional on-site user counts, the novel methods have the potential to allow land managers to develop a more complete and more timely picture of how people are recreating in their jurisdiction. The novel data methods also have the potential to standardize and centralize the bulk of data collection and analysis for the large federal agencies, removing some of the burden from the managers of individual units. There is an opportunity for agency staff at the national and local level to collaborate with academic researchers, nonprofits, and private companies to collect and analyze these data.

3. Novel data sources and methods are used to count recreation

Why we need new strategies to count recreation

Traditionally, land managers have relied on stationary trail counters and in-person surveys to estimate recreational use, but these methods have several significant limitations. First, in areas with numerous entry points, it is usually cost-prohibitive to set up enough counters (or in-person surveyors) to capture all use. Second, because traditional methods require prior understanding of where use occurs, it is difficult to capture unexpected "hot spots" where recreationists might congregate or use unsanctioned, user-created trails. Third, some in-person surveys are designed to estimate use for a specific purpose, and it might not be feasible to apply those estimates to another purpose. For example, the National Visitor Use Monitoring (NVUM) survey administered by the U.S. Forest Service is designed to generate estimates for an entire Forest Service unit (e.g., the Gallatin-Custer National Forest), not an individual location such as a trail.

Finally, trail counter technology itself is imperfect. The counters do not capture all use, as some users veer off-path, take shortcuts, or create unsanctioned trails. Some sensors are unable to differentiate between individuals within a group and count a group as one person, underestimating actual use. Also, the accuracy and ease of use varies across technology types.[14]

The promise of "novel data"

To address the challenges of traditional counting methods, researchers have developed creative ways to measure visitation using novel data sources. "Novel data" refers to data sources whose original purpose was not to count recreation, but from which researchers have developed methods to extrapolate recreational use. Examples of novel data sources include applications (apps) such as Instagram and Strava, websites such as Google and Flickr, and cell phone GPS locations.

Novel data sources often start with a person who uses technology on their phone. For example, a person might search for details about a trail using Google, go for a hike and bring a cell phone and then use the phone to track the hike on Strava, take a photo and upload it to Instagram, or write an impression of the experience on Twitter. Millions of people do at least one of these activities every day. The cell phone and app companies store these data, and after removing individual details to protect users' privacy, some companies make them available to researchers, land managers, and other app developers.

All novel data sources share three attributes. The data:

- can be pinpointed to a specific physical location ("geolocation"),
- represent many individuals aggregated together, and
- are made available by companies to the public.

Glossary of terms

API: "Application programming interface," allowing researchers to download large, detailed datasets from websites.

Calibration: Adjusting estimates of total use to account for how much use is represented by people included in the novel data source.

Cell phone tracking data: The information created when cell phone GPS features ("location services") are turned on.

Fitness tracking data: The data generated from apps like Strava and MapMyFitness allow users to track the location, distance, and speed of workouts.

Geolocation: The specific latitude and longitude where novel data are generated. This information allows researchers to identify where users were when they used Strava, Twitter, or other apps.

Novel data: A new data source whose original purpose was not to count recreation, but from which researchers have developed methods to extrapolate recreational use. It includes data from apps, websites, and cell phones.

Socially-generated data: Data generated from social media platforms like Twitter and Instagram.

Social media posts: The photos, tweets, or other details users add to social media apps.

Trail counters: Traditional technology used to count the number of people using a trail.

User tracking data: Data sources that track users' interests (e.g., Google searches) or movements (cell phone tracking).

Voluntary app-based data: Any data users choose to upload to apps, including social media, fitness tracking, and photo sharing. This does *not* include cell phone data tracking.

The data are made available using interactive dashboards that summarize data, or through an "application programming interface" (API) that allows programmers to access raw data to allow for customized analysis.

Beginning in 2013, researchers began validating novel data sources against traditional counting methods, such as those obtained from infrared trail counters. Particular emphasis was placed at first on data obtained from photo-sharing websites like Flickr because they had an API available to download photos' geolocation. Researchers first used these data to evaluate their accuracy when compared to standard data that existed on visitation in parks and protected areas. The results were promising, showing that estimating recreation use from Flicker data closely matched the recreation use trends recorded via the standard, more expensive, and time-consuming, methods.[15,16] Since then, research has expanded to include other novel data sources like socially-generated data (e.g., Instagram and Twitter), fitness tracking apps (e.g., Strava and MapMyFitness), Google search trends, and cell phone tracking data.

Calibrating novel data sources

Novel data sources still require some on-site, traditional counting to calibrate the trail use because novel data sources represent only some of the total number of users. All novel data sources discussed in this report need to be calibrated.

"Calibration" refers to a process by which researchers adjust the estimates of total use to account for how much actual use is represented by people included in the novel data source. For example, if researchers use data from an app to estimate that 10 people per day use a trail, and then compare this to the 100 people per day determined from a trail counter, they know that the app represents about 10% of actual trail use. They can then apply this 10% to estimates of trail use on other days or in other locations where trail counters are not installed. Calibration can be a simple ratio as described above, or a statistical relationship as demonstrated in the case study.

Because novel data sources depend on some on-site counting, they cannot fully replace traditional trail counters and surveys. However, novel data sources can allow trail managers to estimate trail use where counters are not available, better understand where users are going, and proactively manage for changing trends in use.

The following sections describe the most commonly used data sources, followed by a brief case study in which we compare estimates from traditional counting methods to novel data sources.

Specific novel data sources

Novel data sources that count recreation generally fall into two categories: voluntary app-based data and user tracking data.

With voluntary app-based data such as Flickr, Instagram, Strava, and Twitter, users choose to share data on a social media or other sharing platform. These data have geolocation information attached that identifies the user's location, which the app companies then anonymize and make available to researchers. The second category can be described as user tracking, whether through cell phone GPS locations or the number of Google searches. Like app-based data, private companies provide user tracking data that has been anonymized or aggregated for researchers.

Access to these data depends on the specific company: some, like Strava, are free to qualified partners working on specific transportation planning projects. Other sources, like the photo-sharing site Flickr, are available to any developer, subject to terms

Novel data sources reviewed

Voluntary app-based data

Social media and photo-sharing apps

* Flickr (photo-sharing)
* Instagram (social media & photo-sharing)
* Twitter (social media)

Fitness tracking apps

* Strava

User tracking data

* Cell phone tracking data
* Google Trends (search engine trends)

of use. With all apps and websites, the terms of use and data made available are continually evolving along with developers' needs and regulations and concerns about users' privacy.

All novel data sources are potentially biased and not fully representative of the actual people using a trail or visiting a park. Many app users tend to be younger, more highly educated, and more affluent than the general population.[17] Inferences related to recreational use trends and patterns must consider the underlying biases of the data sources. This could be best accomplished using on-site surveys to determine the actual users' socioeconomic profiles and weighting the estimates from novel data accordingly. The technical methods to accomplish socioeconomic weighting have not yet been applied to novel data for counting recreation, to our knowledge, and need to be a priority research area. The following section provides more details on bias concerns for specific apps.

This section walks through the most commonly used data sources, the situations when they work best, and the challenges associated with implementing them.

Social media and photo-sharing apps

How the social media and photo-sharing apps are used

Several platforms allow users to upload and share photos, which are then tagged with the location where the photo was taken. When someone posts a photo online, (s)he is also making available information on where the photo was taken, and there is now a record that one person stood on a particular location at a specific date. They are "geolocated." When millions of people do this every day, large aggregate data sets are created that show where people visit and when. The photos themselves are not of interest and are not shared. However, the location and date information are made available to researchers in a way that is aggregated and anonymous. Users can opt out of this geolocation.

Instagram and Flickr are the most common photo-sharing apps used to count visitation. Twitter posts also have their users' locations attached.

When researchers aggregate many of these photos and posts, they can identify the locations people visit most frequently. When they aggregate the posts over time, researchers can identify trends in visitation. When researchers use geolocated photos and tweets in conjunction with on-site visitor counts, they can estimate total visitation.

Researchers also can identify common and emerging types of uses[18] and, in the case of Instagram and Twitter which support captions or commentary, assess the quality of visitors' experiences. Researchers access these data using APIs which, at the time this report was written, are free. After researchers download data attached to social media posts, they use the post's date, location, and anonymous user ID to estimate the number of unique users active on a given day, defined as "photo user days" or "Twitter user days."[15]

Early research using social media apps focused on whether there was a reliable relationship between social media data and traditional counting methods. In general, researchers have found that photo-sharing apps do have a strong relationship to actual use, with correlation coefficients ranging from 0.5 to 0.9.[16] In other words, the relationship is moderately to very strong, and when actual visitation increases so do the number of photos and tweets posted. Correlations allow researchers to show trends in visitation but are difficult to use to count actual visitation.

More recent studies build statistical models rather than rely on correlations, allowing researchers to estimate visitation given a particular number of social media posts. These models incorporate time of year, unique site and regional characteristics, special events or holidays, and weather.[19,20] One paper combined social media and on-site visitor counts from recreation sites in Washington State to create a statistical model predicting visitation. The researchers used the model parameters to also predict visitation for recreation sites in New Mexico, and found they were able to predict actual visitation within 91% accuracy. The findings suggest that robust statistical models created in one area may be applied in other areas to predict visits.

The paper also notes that the strongest models calibrate social media data with data obtained from on-site visitation measures (such as infrared cameras and other trail counting techniques). Robust statistical models developed in one location can then be used by researchers to predict visitation in other locations without on-site counts or social media data, although one of the two is needed.[19]

Specific social media and photo-sharing apps for research

The apps used most for research are not always the apps used most by visitors. App popularity with researchers is a function of the availability of consistent, long-term, and automatically geotagged posts. In one meta-analysis of research, Flickr was used in 60% of the 58 published studies using social media to measure visitation,[16] but represented only 0.1-0.2% of actual visitors in another study.[19] Twitter was used in 17% of published studies and represented 0.1-0.4% of actual visitors. Instagram was the third most popular app for research but by far the most popular app used by actual visitors: it was used in 14% of published studies and represented 3% of actual visitors. This discrepancy raises important concerns regarding the representativeness of novel data sources, and must be acknowledged in research conclusions. On-site surveys that collect data on trail users' socioeconomic characteristics could be used to weight trail use estimates derived from apps, although this has not yet been applied in trail use counting estimates, to our knowledge.

Researchers who use app data to count recreation must adapt to changes in popularity of platforms, changes in the way they are used by visitors, and changes in the data provided by the platforms themselves. Flickr, for example, is declining in popularity,[16] yet it contains billions of geolocated images going back to 2004.[21] Instagram, while much more popular with visitors, has been increasingly restrictive with the data it provides researchers and, to protect user's privacy, no longer provides precise geolocation data. Researchers using Instagram data now must manually connect users' tags to recreation areas. For example, rather than having the precise latitude and longitude automatically assigned to a post, researchers now have the location name such as "Yellowstone National Park" if the user chooses to assign a location name to the photo.

Researchers have found that models that combine data from multiple sources have the strongest predictive power.[19] Interestingly, they find little correlation in posts across platforms, suggesting that different platforms represent different types of users who post in different ways.[19]

Situations when social media and photo-sharing apps work the best

The relationship between social media posts and actual visitation is strongest in places with a relatively high number of visits, and when social media is used to estimate visitation at the scale of months to years; daily visits are more difficult to predict.[22] In general, places with high and medium visitation levels have the strongest correlation between photo user days and traditional visitation statistics. The nature of photo-sharing means that people are more likely to share novel locations, events, and activities, making these apps a good way to spot emerging trends.[23]

The higher the concentration of posts, the more accurately photo/Twitter user days predict visitation. Researchers found the highest social media post concentrations in places with high per capita GDP, and decreasing photo concentrations the farther away from a city of at least 100,000 residents.[24]

Researchers have found a strong relationship between photos uploaded and visitation in national parks in the United States,[21] Australia,[25] Spain,[26] Finland,[27,22] and South Africa.[22] A study of all U.S. national park units found a strong correlation with the number of user days calculated using Flickr and the visitor statistics published by the National Park Service. The researchers found that a 1% increase in photo user days corresponds with a 0.65% increase in visitation.[28]

A study of all national parks, national forests, and state park lands in Utah found that photo user days had the strongest predictive power for national forests, explaining 79% of variation in traditional visitation estimates. The predictive power for national parks followed closely behind (72% of variation explained). Photos explained only 29% of visitation estimates for state parks.[21]

Challenges of using social media and photo-sharing apps

The greatest challenge of using social media apps is that users are not necessarily representative of the population using an area. In general, users of these apps tend to be younger, wealthier, and highly educated.[23] Flickr users have a particularly high share of white and Asian people, and a high share of users with advanced degrees in management, business, science, and the arts.[29] Flickr users also skew toward females and younger users.[20] Twitter users are more likely to have advanced degrees, relatively high incomes, and work in management, business, science, and the arts.[29] Each platform has its own unique socioeconomic profile,[17] and careful analyses must consider the implication of any biases in the platform.

Nonrepresentative social media users are a problem when the people who are less represented in the social media apps visit more, visit less, engage in different activities, or visit different destinations. Their needs would not be represented in management decisions based on visitation estimates.

For example, social media posts skew toward visitors rather than local residents: researchers find a stronger correlation between out-of-state visitors relative to in-state visitors[30] or at other tourist attractions.[29] In other words, people on vacation tend to take, and post, more photos. Without accounting for this bias, the ways in which local residents use trails or visit landmarks might receive less weight. Places popular on social media can become vulnerable to a powerful feedback loop when locations are particularly popular and frequently identified on social media, which then begets more visitation and more social media posts, leading to overuse. Land managers can monitor social media posts to anticipate vulnerable hot spots.

A study of urban parks in New York City found that Twitter and Flickr posts related to parks was negatively correlated with a larger share of minorities in the neighborhood. This could indicate that parks in these neighborhoods are not used as much, or instead could show that people in the surrounding neighborhoods do not post on social media as much about time spent in parks.[31] On-site counts in a representative sample of parks can help to calibrate social media posts to actual visitation.

The seasonality of visitation may not be well represented, either. Many apps skew toward younger users, therefore parks with activities for younger people may have a higher relative number of posts, and times when schools are not in session will be overrepresented. Additionally, fewer photos are taken during colder months or inclement weather.[22]

Additionally, sudden or unique events like an eclipse, super bloom, or celebrity sighting can increase the relative number of photos.

Finally, researchers must consider that users posting to a social media app are not necessarily behaving naturally. In other words, a user might not post a picture of an uneventful walk in the woods but may be more inclined to post a picture of a particularly scenic or exciting outing.[32]

These challenges are not insurmountable but reinforce the need to pair app data with traditional on-site counting and surveying methods.

Fitness tracking apps

How fitness tracking apps are used

Several platforms that allow users to track their workout, hike, walk, and bike ride have APIs that enable developers to download anonymized samples of users' routes. When these routes are aggregated, researchers can get a sense for most popular routes and trails.

Like early social media app research, early fitness tracking app research calculated correlations between traditional on-site counts and fitness tracking apps to identify popular areas and estimate use when trail counters were not available. Researchers overlay routes from numerous users to identify the most popular routes and likely congestion areas.[33]

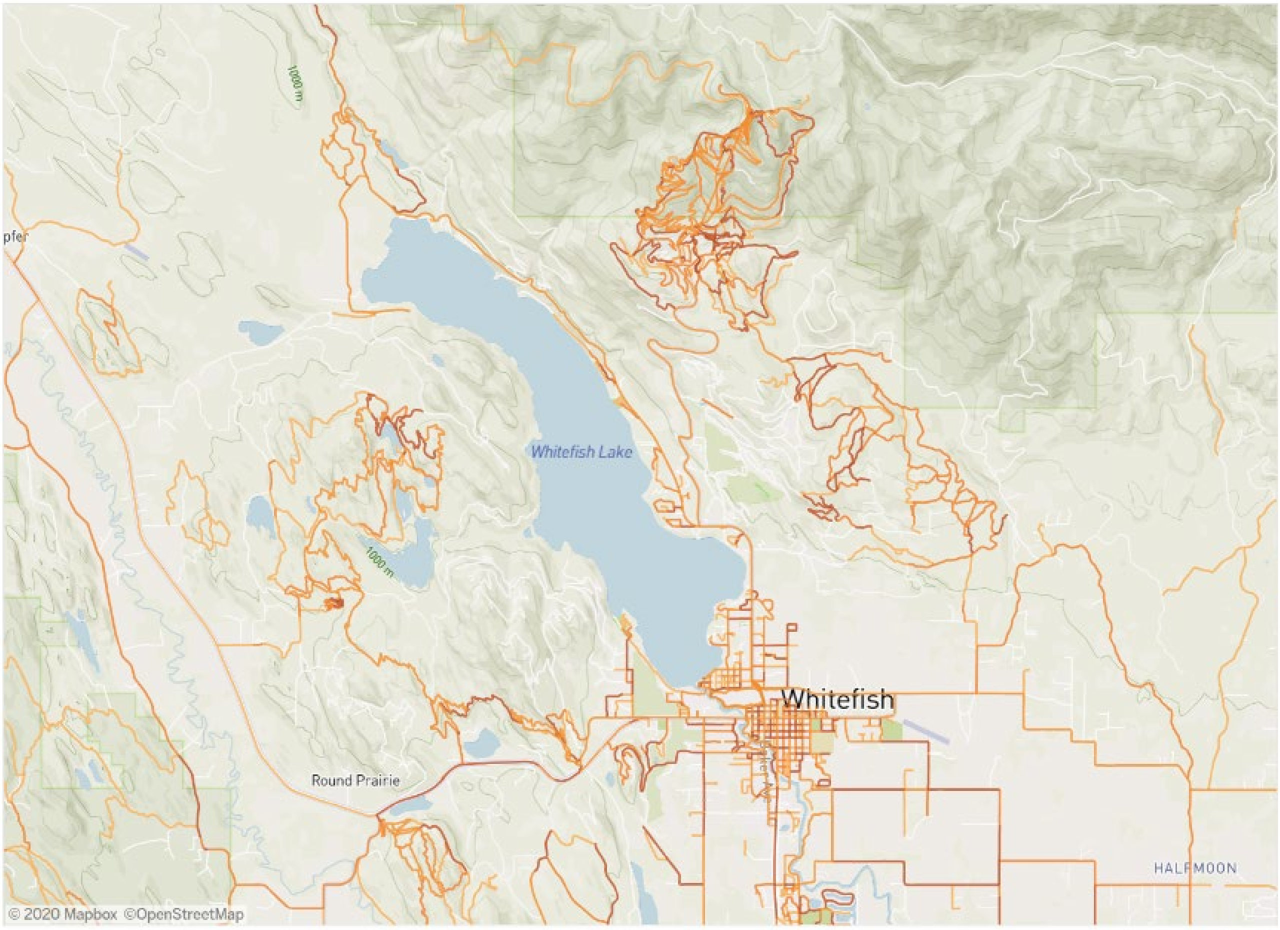
Figure 1 shows a "heat map" created from Strava data, showing relative trail use in Whitefish, Montana. Darker colors correspond with more popular routes. For this project, we (researchers at Headwaters Economics) were interested in trail use across a large area. Based on trail use counts from infrared counters positioned at four trailheads, we determined that Strava users made up between 1% and 5% of total trail use, depending on the trailhead. For example, at the Lion Mountain trailhead, Strava trips represented 4% of total trips, so we multiplied the number of Strava trips by 25 times to estimate total use. Using this relationship, we estimated trail use at dispersed sites across the community. We relied on local expertise to determine which trailheads were more likely to have a lower share of Strava users, and which trailheads were likely have a higher share of Strava users. This undoubtedly introduced some error into our total estimates and could be improved upon with more on-site surveys at additional trailheads.[34]

Although we only had infrared trail counters placed on four trails, by using Strava data and calibrating the data with information from our four locations, we were able to estimate trail use across the community and many other trails for which we did not have trail counters.

As the science has evolved, researchers have gone past simple correlations and used routes from fitness tracking apps to predict use and popular routes using statistical models that incorporate physical characteristics like slope, the presence of bike lanes, population density, and other characteristics.[35, 36]

In Austin, Texas, researchers built a statistical model to predict the most popular cycling routes using route data from Strava, combined with data on residential and employment density, land use types, the presence of bike lanes or paths, and terrain characteristics. They use this statistical model to predict the areas best suited for cycling use, information that can be used by city planners to identify the most suitable areas to invest in bike and pedestrian infrastructure.[35] Similar research in Victoria, British Columbia, also incorporated physical characteristics and Strava data into a statistical model predicting use by cyclists. The researchers found they were able to predict 62% of the variation in manual counts using these models.[36] For this type of model, 62% is moderately high.

Fig. 1. Sample "heat map" created by combining infrared counter data and Strava data to show areas of more intensive use (darker lines) near Whitefish, Montana.



Specific fitness tracking apps for research

The apps that researchers have used most often to estimate visitation in parks and protected areas are Strava, Wikiloc, MapMyFitness, and GPSies.[16] Some platforms provide information as to whether the user was a pedestrian or cycling, and whether they were recreating or commuting. As with social media apps, the app companies make anonymized data available through an API. Ongoing data availability and types of data available are at the app companies' discretion.

At the time this was written, Strava is unique among social media and fitness tracking apps in having an arm of its organization dedicated to research, called Strava Metro. Strava Metro provides approved partners doing transportation planning, such as city staff and advocates, with access to a free dashboard that distills trends in bike and pedestrian use in their area. The dashboard distinguishes between "trips" and "people." Trips refer to an outing taken by a person; "people" refers to individual Strava users. Users will likely take many trips in a year: in Flathead County, 6,938 people took 63,913 trips, or about 9 trips per person. These include any time people used Strava to record their outing: trips for recreation and commuting purposes, and trips on roads, pathways, and trails.

The dashboard provided by Strava Metro eliminates the significant technical and analytical hurdles required to process the raw data downloaded via APIs.[37] Currently the dashboards provide data at a county level. Researchers who want data for specific trails can access processed Strava usage statistics via a dashboard provided by the trail mapping website TrailForks. Researchers can access statistics from https://www.trailforks.com/statistics/. Researchers have used data from this website to verify on-site trail counters as well as estimate trail use at sites without trail counters.[38]

Situations when fitness tracking apps works the best

Like social media apps, fitness tracking apps have better predictive power the more users there are in an area. Mid- to large-sized cities and places where recreational and commuter routes overlap have the most users and routes to provide robust data.[36] Less-populated areas with a high concentration of fitness or outdoor enthusiasts also can generate robust trail use estimates using fitness tracking data.[34,38] Unlike social media apps, data from fitness tracking apps can help researchers distinguish between cyclists and pedestrians.

Challenges of using fitness tracking apps

Fitness tracking apps share similar challenges to social media apps. Specific app popularity, the rate of technology adoption, and how the technology is used is constantly evolving. Apart from Strava's new dashboard, available to approved partners, data accessed via API are computationally intensive. Fitness tracking app users are not necessarily representative of the average trail user. They tend to be more avid, which means they may use different routes, travel farther distances, or recreate more frequently.

A 2016 study compared commuting data from Strava with data on active commuting rates from the nationally representative American Community Survey in four U.S. cities: Austin, Texas; Denver, Colorado; Nashville Tennessee; and San Francisco, California. The researchers found correlations ranging from 0.28 (a weak but positive relationship) in Nashville to 0.58 (a moderately strong positive relationship) in San Francisco, reflecting differences in technology adoption.[39] In other words, the relationship between app use and actual use is strongest where more people are using the app. Before researchers purchase data or invest in expensive analyses, app companies like Strava can provide researchers with an approximate number of users in the area.

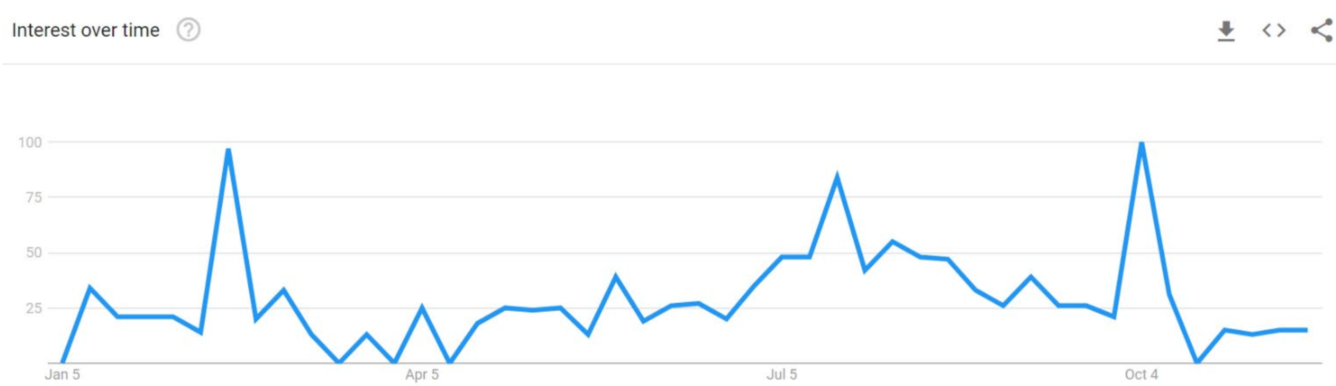
Like analyses using social media app data, fitness tracking app data need to be verified using traditional on-site counting methods. They also may benefit from surveys to better understand the avidity of fitness tracking app users so researchers can adjust estimates accordingly. The Stava dashboard has the added benefit of providing researchers with an age breakdown of users, which researchers can compare to demographic data for the area.

Search engine data

How search engine data are used

Some researchers have used the frequency at which search terms are entered into Google as a proxy for the number of visitors to an area, with the potential of using search frequency to forecast future visitation. While relatively unproven for recreational visits (at the time this report was written we knew of only one U.S study), they have been used with relative success to predict tourism in the Caribbean,[40] South Korea,[41] and Beijing.[29] Google provides these data for free using a simple dashboard called Google Trends; Figure 2 shows an example of the frequency with which the "Whitefish Trail" search term was used (see Figure 2).

Fig. 2. Searches for "Whitefish Trail" in Flathead County, Montana, 2020 from Google Trends.



One study used Google Trends data to predict visitation to 58 national parks in the United States using a statistical model built around the frequency with which the park was named in a Google search. Across all national park units combined, the model explains nearly 98% of variation in actual annual park visitation numbers. For individual national park units, however, the Google Trends model performed worse than the statistical model that is used by the National Park Service to predict future visitation using historic visitation during the previous five years.[42] While it sometimes predicted visitation much better (up to 27% more accurate) or worse (up to 13% less accurate), for most of the parks the Google Trends model performed worse. The Google Trends model showed the greatest improvement for Great Smoky Mountains, Yosemite, and Yellowstone National Parks.[43]

Situations when search engine data works the best

Google Trends is best used to forecast changes in use, and they may be able to improve on traditional models that rely on historic, observed visitation when a unique event will occur like a race or super bloom. The researchers for the National Park Service study found no evidence that Google Trends data performed better in places visited more frequently by people who did not live in the area.[43]

Challenges of using search engine data

An important technical concern relates to the format Google Trends uses to present data. The frequency of searches is not reported as an absolute number, but instead on a scale from 1 to 100 relative to the maximum number of searches in the selected time range. This makes it necessary to consider data for any one point in time in context with other data points in the range, complicating longer-term analyses.[43]

Like social media and fitness tracking apps, data from Google Trends must be analyzed alongside traditional counting techniques to calibrate the results for a specific location. Because Google Trends are reported on a 1 to 100 scale, calibration to total use must be applied as percentage changes as well. For example, if the Google Trends score is 50 and actual use is 5,000, we know that the Google Trends score represents 1% of actual use and a multiplier of 100 must be applied to Google Trends scores on other days. Then for a day with a Google Trends score of 100, we would multiply the 100 Google Trends score by the 100 multiplier, estimating 10,000 users. This simple approach assumes that Google Trends always represents 1% of total use, when the relationship is likely nonlinear. The simple approach will overestimate for the lowest Google Trends scores and underestimate for the highest Google Trends scores. More sophisticated methods could improve Google Trends' predictive power.

The predictive power of Google Trends varies significantly across national park units for reasons that are not yet known. The data have not been tested in published papers for other types of locations such as specific trails, national forests, or state parks.

Google Trends data may also perform worse in locations that receive many visitors from other countries where Google might not be the dominant search engine.

Cell phone data

How cell phone data are used

Cell phones with GPS capabilities create very detailed data about the habits and travels of their owners. Several private companies (AirSage, StreetLight, and Cubeiq are a few) sell anonymized GPS data from a sample of about 30% of U.S. cell phone users. These data are aggregated to the site level so they do not contain individually identifiable data. These data have many commercial applications and are just beginning to be used to estimate visitation to parks and protected areas.

One study of water recreation at 500 sites in New England developed statistical models predicting visitation based on cell data counts and controlling for site and weather characteristics. The researchers found that even without controlling for site and weather characteristics, cell data predicts about 86% of the variation in on-site counts. However, the researchers found that cell data overestimates on-site counts by as much as four-fold. The larger, busier sites overestimated the most. This error could arise if: 1) on-site counting methods at the busiest sites are flawed (in this case large beaches with numerous access points), or 2) the sample of users provided by the commercial data provider are not representative of the population visiting the site.[44]

Research in Lake Tahoe, California, assessed public transportation needs for the area, but the findings were able to highlight two insights relevant to recreation counting research. First, as with the New England study, the cell data generated visitation estimates about four times higher than on-site counts. Second, the hot spots where visitors congregate differed from planners' expectations.[45]

A study in Orange County, California, used cell phone data combined with traffic counters to estimate use nature reserve sites across the county. Researchers found that cell phone data estimated about 6% lower visitation than observed vehicle counts, but the day-to-day differences were not statistically significant, indicating the cell phone data were relatively accurate measures of daily visits.[46]

Situations when cell phone data works the best

The cell phone data are promising because they provide an incredible level of detail and are likely more representative than social media or fitness tracking apps. The detailed data allow researchers to learn visitors' origins, facilitating more sophisticated analyses of economic impacts and travel costs that are used to determine what visitors are willing to pay to visit an area.

In the New England and Lake Tahoe studies—very busy locations with many access points—the cell data yielded estimates about four times that of traditional on-site counts. Traditional methods to count visitors at large, busy locations without "choke points" where visitors can be counted easily rely on sampling techniques that are likely inaccurate. The most useful application for cell phone data is likely in places with inaccurate counts due to many visitors over a dispersed area.

Challenges of using cell phone data

Cell data provide tremendous detail for many users, and their analysis requires expertise in "big data" analysis. Some companies, such as AirSage, provide a more aggregated, dashboard-style data presentation for a higher fee.

These data are provided by commercial companies and are costly to obtain. In general, the costs are based on the number of cell users and the length of time requested and are likely to cost well into the tens of thousands of dollars. Data at a finer geographic scale could be somewhat less expensive, but cell data may provide the most valuable insights for the busiest locations.

While cell phone data likely represent most trail users, they will not include those without phones with GPS capability. This likely will overlook the youngest, oldest, and lowest-income trail users. As with other novel data sources, on-site surveys to elicit information about the share of trail users carrying GPS-enabled cell phones can provide researchers with an estimate of the share of trail users missing from cell phone data.

Finally, as with other novel data sources, it is unclear whether these data are, as the providers claim, representative. The algorithms they use are proprietary and may change over time. Researchers may be able to request demographic profiles of the aggregated users represented in their cell data sample to be sure they reflect the demographics in on-site user surveys.

Other novel data sources used to estimate recreation

Researchers have used other data sources to estimate recreational use, including neighborhood-level socioeconomic data. A study in Minneapolis, Minnesota, and Columbus, Ohio, used socioeconomic variables like age, median income, racial diversity, population density, employment diversity to predict trail use. Researchers were able to predict 64% of use in Minneapolis and 58% of use in Columbus. The denser the area, the better the model's predictive power.[47] This approach is best suited for estimating trail use across neighborhoods in dense urban areas. It has the advantage of relying on data that are readily available across the United States.

Top takeaways on using novel data sources to count recreation

Despite the drawbacks associated with socially generated data, novel data sources are a big step forward compared to many current on-site recreation counts, which may only be useful at large scales such as entire national forests, are intermittently available, or are not available at all. Novel data sources provide an opportunity to supplement or limit the need for traditional data sources and improve estimates for individual sites. Novel data sources must be calibrated to on-site counts, making it unlikely that novel data sources can completely replace traditional counting methods. Table 1 summarizes the primary takeaways from research that has used novel data sources to count recreation.

Table 1. Advantages and limitations of using novel data sources to count recreation.

Advantages	Limitations
Understanding users and types of uses	
• The more users, the more accurate the predictive power. • Help identify “emerging activities” like kitesurfing, snow scootering, fat biking.	• Social media and fitness tracking app users are not representative of the broader population. Many apps favor younger, higher-income, and more educated people. • Socially-generated data tend to favor particularly noteworthy, unique, or photogenic recreation; commuting and neighborhood park uses are difficult to estimate. • The data provided by apps and cell phone data for research is a subset of the total data generated by users. The methods used to sample the full dataset are proprietary, so it is uncertain whether the subset represents the larger population. • App users may not behave “naturally” if they are recreating to post on social media, skewing results toward types of activities or destinations likely to be popular.
Identifying locations	
• Useful for identifying most popular locations and uses • Work best for locations closer to population centers. • Work better for areas with greater protection, like national parks.	• Can be difficult to identify less popular or less photogenic destinations and activities.
Measuring timing of use	
• Can estimate use in almost “real time”	• Apps have data available over different time frames and may not be available for the full time series researchers want. • The accuracy is highest for annual or monthly counts, rather than weekly or daily.
Level of analysis required	
• Require fewer people on-site. • Opportunity to centralize and standardize analysis across large agencies.	• Can be computationally intensive, requiring expertise in analysis of “big data.” • The correlation between traditional counters and novel data sources will vary over time as the number of users change and the way people use the platforms changes. • The data that apps and websites make available will continue to shift in response to changing developer needs, app companies’ interest in monetizing user data, and user privacy concerns. This will make it difficult to have consistent methods over time.

4. Case study: Whitefish, Montana

Our synthesis of the scientific literature demonstrates that novel data sources could be well-suited to provide counts of trail-based recreation in many different settings. We wanted to evaluate some of these sources from the perspective of a land manager, district ranger, and recreation advocate to determine how well novel data sources can help people with limited on-site counting capacity make well-informed, proactive management decisions.

Our goals for this case study are to evaluate the feasibility of combining traditional on-site counting methods and novel data sources to: 1) predict trail use where on-site counters are not available, and 2) forecast future trail use. If we can successfully predict trail use where on-site counters are not available, it will reduce the need for local calibration data. For example, a single trail counter in the region could be used to calibrate novel data over the entire region, reducing the need for costly and maintenance-intensive stationary counters. If we can successfully forecast future trail use, it could help trail managers anticipate budgetary needs for maintenance and site improvements, as well as help identify when trail capacity may be exceeded and additional trail access points are needed. We evaluate these two goals keeping in mind these methods' accessibility for land and trail managers, not necessarily researchers with extensive computer programming capacity. This is a small case study for one trail system but could be done at a larger scale.

In this case study we evaluate Strava and Google Trends data because they are easier to process than other sources like Flickr and thus have the potential to be used by land managers and trail advocates without computer programming expertise. Additionally, these sources have not yet been rigorously evaluated in the more recent literature using statistical modeling to predict trail use, and this analysis provides an opportunity to explore their usefulness.

Methods overview

This case study measures trail use on the Whitefish Trail, a 43-mile, nonmotorized trail system in Whitefish, Montana. The trail is a popular destination for both local residents and visitors and currently has 14 trailheads, making it cost-prohibitive to install long-term trail counters at each site.

The analytical strategy for this case study leans heavily on Woods et al, 2020, in which researchers developed a statistical model in one location and used it to predict use in another. [19]

We developed a statistical model to predict the count of weekly trail use at one trailhead, Lion Mountain in Whitefish, and use this model to predict use at two other trailheads, Beaver Lakes in Whitefish and the Gallagator in Bozeman, Montana. We chose these sites because they have data from trail counters, Strava, and Google Trends for at least one year. The data from the trail counters is useful and important, as it allows us to build a statistical model where the novel data sources are calibrated by on-site trail counter data.

In addition to the Strava and Google Trends data, the final model includes weekly total precipitation and a set of calendar variables controls for weeks of the year. This serves as a proxy for seasonal temperature patterns and holidays. We include a time trend to allow for any broader trends of increased (or decreased) use, as well as to enable us to forecast future use.

Full details of the model specifications are provided in Appendix A.

Results

Individual variables

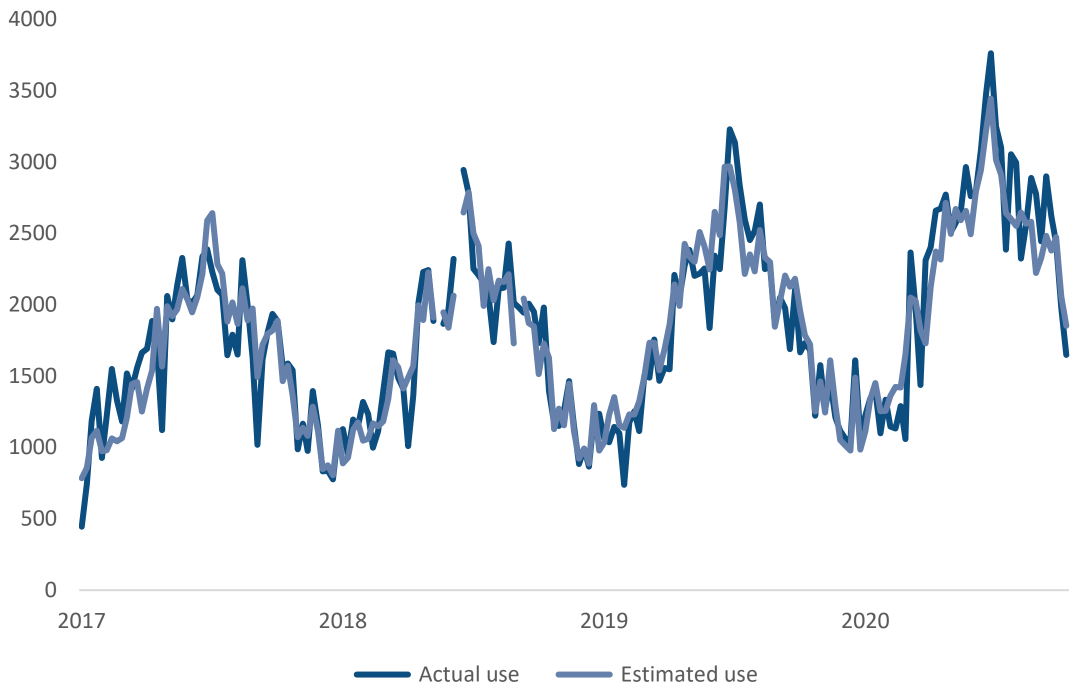
We find that for every 10% increase in trips recorded on the Strava app, trail use increases by 0.3%. We do not find a statistically significant relationship between Google Trends search frequency and total use. We find that trail use increased an average of 8.7% per year. The relationship between trail use and weekly precipitation is not statistically significant.

Model's predictive accuracy

The model predicts 87% of the total variation in trail use (R^2), meaning only 13% of the week-to-week differences in trail use is explained by factors *other than* the variables in the model.

Figure 3 shows estimated and actual trail use at the Lion Mountain trail from January 2017 through October 2020. When compared to use data for this trail from traditional trail counters ("observed data"), the model predicts within 10% of observed trail use for the estimation sample, on average.

Fig. 3. Actual (dark blue) versus estimated (light blue) weekly trail use at Lion Mountain.



We estimated use at the weekly level. When we aggregate the estimated results to a longer time scale, the model's accuracy improves. Table 2 summarizes how model accuracy improves as the time scale increases. The model estimates weekly trail use within 10% of actual use, monthly totals within 6%, and annual totals within 2%.

Table 2. Model accuracy over weekly, monthly, and annual time scales.

Time scale	Average % difference between actual and estimated use
Weekly	10%
Monthly	6%
Annual	2%

Case study goal #1: Using the model to estimate use at places without counters

The first objective of this case study is to see how well the model, specified using actual data at one site, estimates use at other sites. At three sites where we have long-term trail counter data, we compare the estimates from our model to observed use from trail counter data and build and test a statistical model. We evaluate the model's accuracy at two very different types of sites:

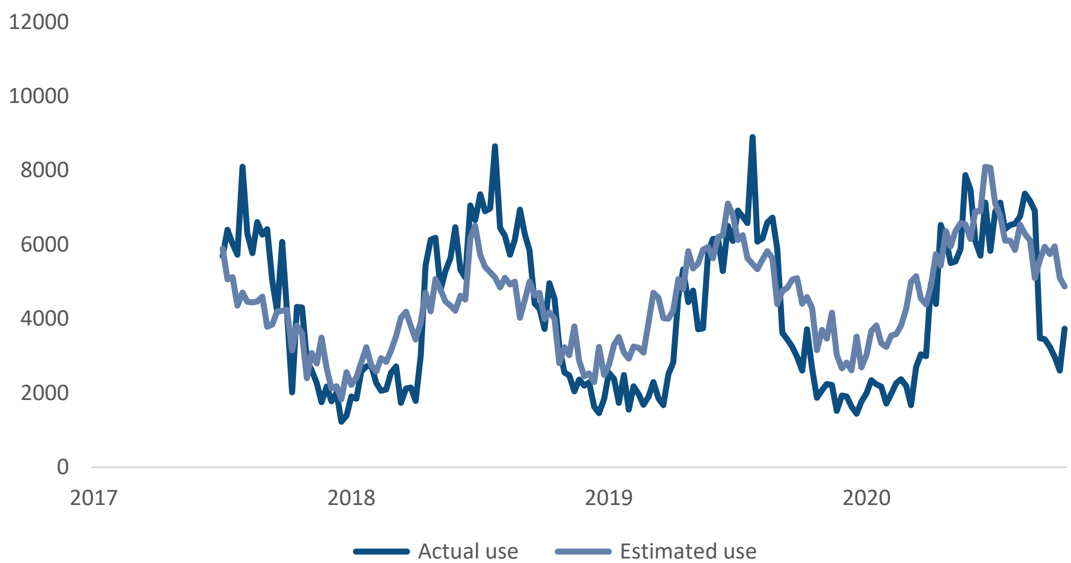
- *Beaver Lakes Trailhead in Whitefish, Montana:* This trailhead is another access point to the Whitefish Trail System. It is 9 miles from Whitefish and has 132 average weekly trail users.
- *Gallagator Trail in Bozeman, Montana:* This town trail runs through residential areas and connects the town's library and Montana State University, as well as other parts of the town's trail system. It has 2,072 average weekly trail users.

For comparison, Lion Mountain is 2.4 miles from the center of Whitefish and averages 908 weekly trail users.

Figure 4 summarizes actual trail use from the infrared trail counters at each trailhead and estimated trail use from the model.

Fig. 4. Actual (dark blue) versus estimated (light blue) weekly trail use for two trailheads: (a) Gallagator Trail in Bozeman, Montana, and (b) Beaver Lakes in Whitefish, Montana.

a) Gallagator Trail in Bozeman, Montana (high commuting and recreational use, in town)



b) Beaver Lakes trailhead in Whitefish, Montana (low recreation use, farther from town)

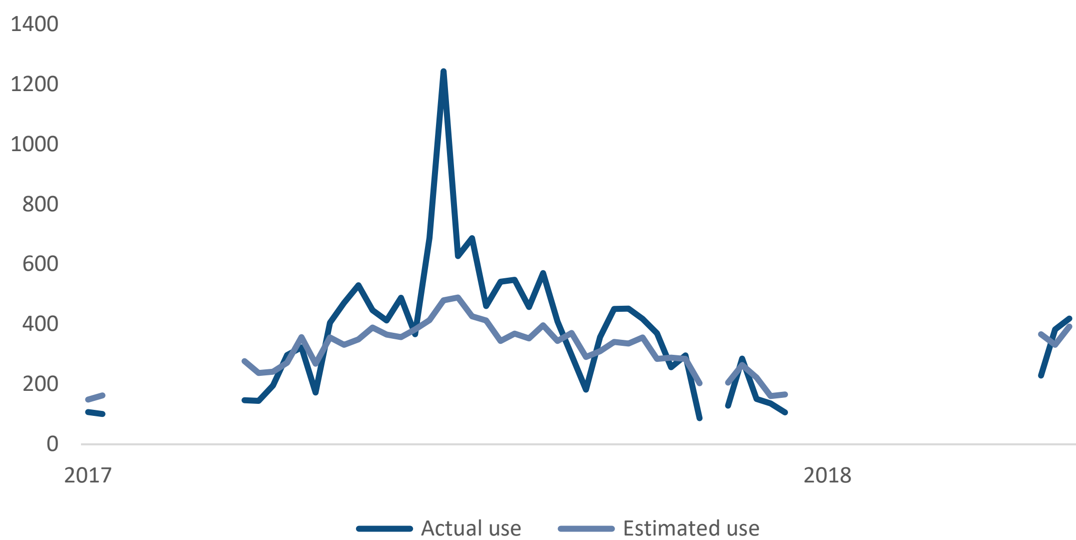


Figure 4 demonstrates there is substantial variation of the accuracy of the two model predictions, with the trail with the most accurate estimates is the trail with the most use, despite its location in a different community. The estimates for the Gallagator were least accurate in the latter half of 2019 and into 2020. In 2017 and 2018, weekly estimated use was within 29% of actual use, on average. In 2019 and 2020, estimated use was within 45%. This gap likely developed because trail use in Whitefish was increasing by 8.7% per year, while trail use on the Gallagator has been flat or even declined in 2020.[1]

Table 3. Model accuracy over weekly, monthly, and annual time scales at three trailheads .

Time scale	Average % difference between actual and estimated use		
	Lion Mountain	Beaver Lakes	Gallagator
Weekly	10%	43%	38%
Monthly	6%	37%	31%
Annual	2%	19%	15%

At Beaver Lakes, gaps in Strava data limited our ability to estimate use. In total, we had only about 47 weeks of data, which may not be sufficient to accurately estimate trips at trailheads with low use. A large outlier in use in July 2017 may have hampered our ability to predict trail use accurately over time. However, replacing this outlier with the mean only improved the model's accuracy by about one percentage point.

At both sites, the model's predictive power increased as we aggregated to longer time scales, as is summarized in Table 3. At Beaver Lakes, accuracy improved from 43% different from actual use at a weekly scale to 19% different at an annual scale. At the Gallagator, accuracy improved from 38% different at the weekly scale to 15% different at the annual scale. If we look only at 2017 and 2018 estimates, the model predicts within 9% of actual totals on the Gallagator.

Case study goal #2: Using the model to forecast future use

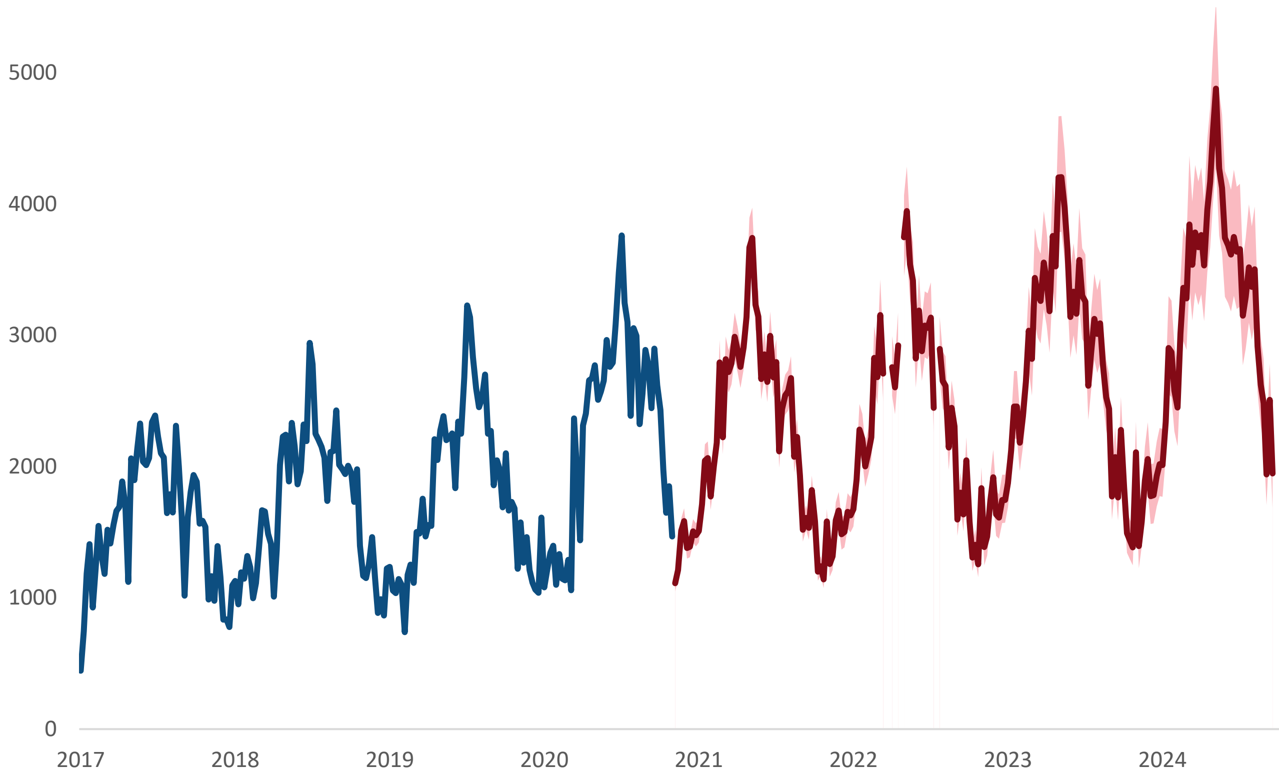
The model estimates that use at Lion Mountain increased by 8.7% per year between 2017 and 2020. We use this relationship to forecast use for 2021-2024. The model forecasts that peak trail use in 2024 will be 4,881 and will occur the week of July 4th, a 30% increase above the peak of 3,762 the same week in 2020. By incorporating confidence intervals for the estimates, we can be 95% certain the range that week will be between 4,295 and 5,545 trail users. As expected, the farther into the future we forecast trail use, the wider the range of likely estimates (Figure 5).

Given the model specification, we find that forecasting trail use is relatively simple. It relies on the assumption that basic patterns of use will not change (e.g., no new trailheads opened or closed nearby, no new uses allowed). Aggregating trail use forecasts to the monthly or annual level could also improve confidence in the forecasts. Confidence intervals help to provide a likely range of trail use rather than relying on a single point estimate. The likely range increases the farther in the future one predicts, communicating to the reader the uncertainty behind the underlying model.

Trail use forecasts would be valuable for those managing and funding trails, to better plan and fundraise for future maintenance and infrastructure such as parking lot capacity at trailheads.

[1] The decline in trail use on the Gallagator in 2020 is likely due largely to a decline in commuters due to COVID-19 restrictions.

Fig. 5. Actual (blue) and forecasted (red) trail use at Lion Mountain trailhead, with 95% confidence bounds around the forecast.



Case study conclusions

Our first goal—to estimate use at sites without trail counters by calibrating with data from trail counters at other sites—shows promise but needs additional work. The model estimates use most accurately on busier trails and on longer time scales (e.g., annually rather than weekly). The shortcomings seen in this exercise may be overcome by including a more representative set of original sites to calculate the model, including a range of use volumes (high, medium, low) and types of uses (commuting, casual recreation, more intensive recreation), and mode (pedestrian, bike, equestrian, motorized, combined). Increasing the total number of sites used to create the statistical model likely also would improve its predictive power, as in Woods et al. (2020), who used data from 29 sites to develop a statistical model with strong predictive power in other locations.

Our second goal—to forecast future trail use by combining on-site trail counter and novel data sources—is attainable with current methods, and is a potentially valuable application to allow recreation managers to anticipate future infrastructure and maintenance needs.

We find a small but strong statistical relationship between Strava use and actual use. However, there are some gaps in the data (as at Beaver Lakes) and not all routes can be easily downloaded from the Strava Metro website. This would be particularly limiting for those managing newer trails. Including Strava trips in the model limits the analysis to trails with predominantly bicycle and pedestrian uses; the model would not accurately estimate use on trails frequented by equestrian and motorized users.

We find that the Google Trends score adds little to the model. Google Trends could be useful to include when modeling use at high-profile sites with name recognition, but these few sites also could be prioritized for on-site counters.

The next research steps would identify the ideal length of time for on-site counters needed to develop an accurate model, given the level of trail use. This insight would allow trail managers to develop a plan for how long trail counters need to be deployed across a system to gather sufficient data. Additionally, developing and applying methods to integrate socioeconomic metrics of trail users from on-site surveys with socioeconomic profiles of users from the novel data sources is an important future step to ensure the data are socioeconomically representative of the actual people using the trail.

5. Conclusions

While we know outdoor recreation is a big and growing part of the U.S. economy, we know much less about how many people are participating and where. Consequently, those trying to manage rapidly growing recreation demands often are stuck reacting to, rather than anticipating, overcrowding, new hotspots, and new kinds of uses only when they start to pose a management problem. They rely on ad hoc measures like rolls of toilet paper used at trailhead bathrooms. This is particularly true on federal lands where use has skyrocketed while recreation budgets have been cut. The expense of traditional on-site counting methods (through counters and in-person surveys) has made counts of trail-based recreation inaccurate, limited, or inconsistent.

Extensive academic research has demonstrated that app-based data and user tracking data can generate statistically valid estimates of recreational visits to an area. The use estimates from novel data sources are strongest when they are calibrated with traditional on-site counting methods; therefore, both the novel methods and traditional methods are strongest when paired together.

> *"While social media do not fully substitute for on-site data, they are a powerful component of recreation research and visitor management." Woods et al, 2020*

Novel data sources will not replace traditional on-site counting methods but will add geographic and special breadth and specificity to recreation counts. These methods have been used successfully to estimate recreational use across diverse landscapes in the United States and abroad,[16] identify unexpected visitation hot spots,[45] and detect emerging kinds of uses.

The analytical science continues to evolve, with the most recent studies showing that statistical models can be developed using data in one area and generalized to predict use in other areas.[19] This development would help to reduce the substantial analytical burden associated with most of the novel data sources. It also shows the potential to target the limited resources for in-person counts to locations without much available social media data. App-based data can help land managers target their resources for on-site counting efforts more efficiently, deploying more traditional on-site counters where there is little or no app-based data, and using fewer on-site counters where abundant app-based data provide a detailed picture of use.

Novel data sources come with significant though not insurmountable challenges. First, novel data sources are not usually representative of the general population, tending to skew toward younger, more educated, higher-income users. Traditional on-site survey methods can be used to determine the actual socioeconomic profile of users, and researchers can then weight app-based data sources appropriately. App-based data must be used to reduce inequities in access and resources, not reinforce them because different groups use particular platforms differently.[18] Second, as the technology is evolving, researchers must also regularly refresh their methods to keep pace. Third, novel data sources generally require analysts with "big data" processing expertise and significant computing and analytical capacity. Finally, because novel data need to be calibrated using some traditional on-site counting methods, they will not completely replace traditional on-site methods.

Specific units within federal agencies, like the Mt. Baker-Snoqualmie National Forest, have led the development of methods to use novel data sources.[19] There has not yet been a coordinated effort to incorporate these methods across units and agencies. As the methods and data have evolved, there is now an exciting opportunity to use these sources to improve how we manage recreation across the United States.

Five policy recommendations

Based on our review of the technical literature and our case study evaluating the potential to use novel data sources for forecasting future use and estimating use at other sites, we provide the following policy recommendations. These recommendations are intended to help agencies, recreation managers, and advocates incorporate novel data into planning and resources allocation, with the goal of helping communities and agencies take advantage of the economic potential of outdoor recreation.

1. *Build a regional or national model to calculate trail use on federal lands.* The assortment of data from traditional on-site counters needs to be aggregated and combined with novel data sources at the regional or national scale. As shown in our case study, statistical models can accurately estimate trail use where stationary counters are not available. Large-scale aggregation will allow researchers to refine a robust model that can be used to estimate recreational use at sites across the country. A prototype could be developed for a model that includes a wider range of trail types and geographies. The next generation of these models also would incorporate weighting techniques to ensure the novel data sources used are representative of actual trail users.

2. *Mandate and fund improved recreation counts to improve recreation management.* Federal agencies currently have systems to count recreation, but they are inadequate to managers coping with growing infrastructure and maintenance needs. Specific enabling legislation, funding, and direction from Congress that requires agencies to count recreational use would ensure these counts can be used to allocate funding appropriately and managers can adapt to changing needs.

3. *Incorporate improved recreation counts into funding allocations.* Currently, federal programs such as the Land and Water Conservation Fund, Great American Outdoors Act, and Payment in Lieu of Taxes do not consider the impact that recreationists have on local infrastructure and emergency services. Incorporate results from the agency-wide recreational use counts to ensure that state and federal funding allocations reflect the demand placed on local services.

4. *Build partnerships between app companies, agencies, and nonprofits.* Novel and traditional data need to be aggregated across numerous sites and their analysis centralized and standardized. Formal agreements between these entities can help agencies and researchers adjust their methods as technology advances.

5. *Estimate economic impacts using novel data sources.* Novel data sources like Strava and cell phone data can be used to determine the share of trail users who are visitors, an essential component of economic impact analyses. Paired with limited on-site surveys, researchers can estimate visitor spending and calculate economic impacts. This information can help communities determine the economic potential of outdoor recreation and make well-informed decisions about local economic development plans.

Appendix A: Methods and Data Sources for Case Study

Case Study Objectives

The purpose of this case study is to evaluate statistical methods that use novel data sources to estimate trail use. We evaluate two novel data sources—Strava and Google Trends—which had not yet been tested empirically using statistical models in the published literature at the time of analysis. In addition to evaluating the potential and limitations of these two data sources, we have two policy-relevant goals:

1. *Use the statistical model to estimate trail use at places without counters.* We estimate the model in one location, and then apply the model to predict trail use in two other locations. A robust model that can predict trail use in many locations can reduce the need to use time-consuming and expensive trail counters.
2. *Use the statistical model to forecast future trail use.* Using historical data, we forecast a likely range of future trail use in the same location. The ability to forecast use can help trail managers anticipate demands on infrastructure and plan future maintenance schedules and budgets accordingly.

Data

We use four data sources for our model: trail counters for on-site counts; the number of Strava trips on trail segments where the trail counters are located; the Google Trends score for trails; and total precipitation. We expect trail use declines, on average, on rainy or snowy days. All data are aggregated by week, so the model is specified using total weekly trail use, total weekly Strava trips, Google Trends score for the week, and total weekly precipitation. We chose these three sites because they have trail counter, Strava, and Google Trends data available for at least approximately one year.

Table A-1 provides summary statistics for all variables used in the analysis, by site.

Table A-1. Summary statistics for variables used for modeling, by site.

	N	Mean	Standard Deviation	Minimum	Maximum
Lion Mountain					
Total use	200	1,819	637	445	3,762
Precipitation (in.)	199	0.33	0.38	0	1.93
Strava trips	197	37	43	1	200
Google Trends score	200	0.30	0.19	0	1.00
Beaver Lakes					
Total use	70	264	216	26	1,243
Precipitation (in.)	70	0.37	0.41	0	1.71
Strava trips	47	18	18	1	70
Google Trends score	70	0.28	0.18	0	1.00
Gallagator					
Total use	174	4,155	2,026	1,225	8,901
Precipitation (in.)	174	0.43	0.43	0	1.96
Strava trips	173	141	105	1	435
Google Trends score	174	0.27	0.19	0	1.00

Trail Counter Data

We use data from trail counters at three trailheads: Lion Mountain trailhead in Whitefish, Montana; Beaver Lakes trailhead in Whitefish, Montana; and the Gallagator Trail at East Garfield Street in Bozeman, Montana. All three locations use EcoVisio infrared counters. The trail counters were installed on different dates, therefore we have different but overlapping time series for each one. For all sites we include the sum of trips in both directions, consistent with our treatment of Strava data. The time span for each site is summarized in Table A-2.

Table A-2. Time span for each site.

Trailhead	Begin date	End date
Lion Mountain	Jan. 1, 2017	Oct. 31, 2020
Beaver Lakes	Jan. 1, 2017	April 30, 2018
Gallagator	July 2, 2017	Oct. 31, 2020

Infrared counters do not provide perfectly accurate counts. Where people are travelling side-by-side, the counter may record multiple people as one. Trail counters also can overestimate actual use when they are installed too low and record dogs as well as people. We did not have on-site, manual count verifications at all three sites and therefore we did not adjust any of the trail counter estimates before including them in the model. We anticipate that this introduces little consistent bias to our final results because the trail counters installation location did not change during the study's time period. Therefore, if counters are overestimating or underestimating, it will likely be relatively consistent over time and the relationship between infrared counter estimates, Strava and Google Trends data, and weather data, will not change.

Strava Data

We obtained data on the number of trips recorded on Strava, by week, for individual trail segments that correspond with the location of trail counters. These data were downloaded from the Strava Metro dashboard, to which we gained access via a partnership agreement. The data include trips by bikes and pedestrians, and all locals and visitors. These data have been de-identified and aggregated so researchers cannot identify any individuals from these data. Because we include trail counter trips going both directions on the trail, we also include total Strava trips for "forward" and "reverse."

Strava data are limited in that they can only be downloaded from the Strava Metro dashboard if they overlap with existing routes on Open Street Maps. This means that newer trails, social trails, or trails with low use could not be included in this analysis.

We also found that Strava data were missing for several weeks, particularly for the Beaver Lakes trailhead which was missing about 1/3 of the weeks for which we had trail counter data. Because Strava data are de-identified and aggregated to mitigate user privacy concerns, low-use areas will likely face more frequent gaps in Strava data. The missing data were only a problem in three of 200 weeks at Lion Mountain and 1 out of 174 weeks on the Gallagator. These data gaps limited our ability to estimate trail use at Beaver Lakes but not at the other sites.

Google Trends Data

We downloaded data from Google Trends for January 1, 2017, through October 31, 2020. These data represent the frequency at which people searched for specific terms or phrases and are provided as a score on a 0 to 100 scale. We used "Whitefish Trail" for both the Lion Mountain and Beaver Lakes trailheads, as there was an insufficient number of searches for the specific trailhead names. For the Gallagator we used "Bozeman trails" as the search term because there were insufficient searches for the term "Gallagator."

Weather Data

We downloaded daily precipitation totals for the nearest weather stations to our trail counters from the National Oceanographic and Atmospheric Administration's Climate Data Online using the Search Tool by city.[48] We summed daily precipitation to calculate weekly total precipitation for all sites.

Analytical approach

We parameterize a statistical model using data from one trailhead (Lion Mountain) and use those model parameters to: 1) predict use at other trailheads, and 2) predict future use at Lion Mountain trailhead.

The analytical approach used in this paper is similar to that used by Wood et al. (2020).[19]

Statistical Model

We use a linear regression model to estimate the number of trail uses, specified as follows:

$$\log(T_w) = \beta_0 + \beta_1 \log(Strava_w) + \beta_2 GoogleTrends_w + \beta_3 Precip_w + \beta_4 Year + \gamma_w Week$$

In this model, *T* is the number of trips, *Strava* is the number of weekly trips recorded on Strava, *GoogleTrends* is the score from Google Trends, *Precip* is the weekly precipitation, *Year* is a time trend, *Week* is a vector of indicators for week of the year, and *w* indexes the individual weeks. *Week* captures the effect of both seasonal weather and holidays. We use the natural log of trips to avoid negative predicted number of trips and the natural log of Strava trips to reflect the nonlinear relationship we hypothesize between Strava and total trips.

Throughout the discussion in the report of different types of novel data sources we describe the need to calibrate novel data sources to on-site counts. In our analysis, the statistical model serves as "calibration," estimating the relationship between Strava and Google Trends and on-site use, holding constant other influencing factors like precipitation, seasonality, and holidays.

We measure the model's accuracy using Monte Carlo simulation methods in four steps. First, we divide the dataset into an estimation sample (75% of the data), and a non-estimation sample (25% of the data). This strategy allows us to determine how well the model performs on data it has never "seen." Second, we estimate the model parameters using the estimation sample. Third, we use the model parameters to predict total use for both the estimation sample and the non-estimation sample. Finally, we calculate the percentage difference between observed and predicted use to see how far off the model estimates are from observed use. We replicate this process 10,000 times and take the average of the percent difference between observed and predicted trail use to measure model accuracy.

Methods for Objective #1: Predicting use in other locations

We estimate use at other sites by first parameterizing the model using data from Lion Mountain, then applying those parameter estimates to data at Beaver Lakes and the Gallagator. We adjust predicted use at each site by the use at the new site relative to use at Lion Mountain. Total use at Lion Mountain averages 1,819 trips per week, the Gallagator averages 4,155 trips per week, and Beaver Lakes averages 264 trips per week. We adjust predicted use at the Gallagator by a factor of 2.28 (4,155/1,819). We adjust predicted use at Beaver Lakes by a factor of 0.145 (264/1,819).

Methods for Objective #2: Forecasting future trail use

We predict use at Lion Mountain for the next five years by applying the model parameters for the 2017-2020 data to the years 2021-2024. This approach essentially applies the annual growth rate to the following five years. We calculate 95% confidence intervals for predicted use.

This forecasting method assumes the relationship between trail use and modeled explanatory variables—Strava trips, Google Trends score, and precipitation—do not change over time. This approach also assumes the factors that affect trail use but are *not* explicitly incorporated into the model, such as the presence of other trailheads or general popularity of trail-based activities, also do not change dramatically in the future.

Results

This section summarizes the model estimation results and diagnostics. We discuss the results for predicting use in other locations and forecasting future trail use in detail in the main report.

Table A-3 summarizes the estimation results for four versions of the model: 1) including precipitation, year, and week indicators only; 2) adding in Strava only; 3) adding in Google Trends score only; and 4) adding in both Strava and Google Trends score. We report the p-value for the significance of the coefficients, calculated using robust standard errors.

Table A-3. Model results for four specification strategies (p-values in parentheses).

	(1)	(2)	(3)	(4)
Variables	Calendar & Precipitation	Strava	Google	Strava & Google
ln(Strava trips)		0.0343*** (0.008)		0.0349*** (0.008)
Google Trends score			0.0899 (0.343)	0.102 (0.31)
Weekly precipitation (inches)	-0.0378 (0.313)	-0.0353 (0.320)	-0.0383 (0.305)	-0.0365 (0.30)
Year	0.0948*** (0)	0.0871*** (0)	0.0950*** (0)	0.0871*** (0)
Constant	-184.5*** (0)	-168.9*** (0)	-185.1*** (0)	-168.9*** (0)
Observations	199	196	199	196
R^2	0.862	0.866	0.864	0.868
Root mean square error	0.160	0.159	0.160	0.159
***: significant at 1%; **: significant at 5%; *: significant at 10%				

Strava trips have a positive, small, and statistically significant relationship with total use. For every 10% increase in the number of Strava trips, total use increases by 0.03%, a finding consistent between both Models 2 and 4. In other words, if total use were normally 1,819 (the average at Lion Mountain), and Strava trips increased by 10% (about 4 trips, evaluated at the mean for Lion Mountain), we would expect total use to increase by about 6 trips per week to 1,825. Across both model specifications the parameter estimate is statistically significant and changes little.

Google Trends score does not have a statistically significant relationship with total use. It is likely that the relatively generic search term used (“Whitefish Trail”), which could also refer to other trails in the Whitefish area, is too general to align with individuals’ research before using this specific Whitefish Trail trailhead.

Precipitation is only weakly related to total trail use. Across all model specifications, the coefficient on precipitation is negative, indicating a negative relationship between trail use and precipitation. It is likely that by aggregating trail use to the weekly level we obscure day-to-day differences in trail use due to rain on a particular day. In other words, if it rains on a given day, people may use the trail on the day before or after.

The time trend is statistically significant and positive across all model specifications, showing that trail use increased by between 8.7% to 9.5% per year. The growth rate is largest in the specifications without Strava data (Models 1 and 3), consistent with the growth in Strava use each year. At Lion Mountain, Strava use increased by about 32% per year.

We do not report the individual coefficients for week indicators. Of the 51 indicators estimated, 38 are statistically significant. The coefficients that are not significant occur mostly during the winter months.

We consider R^2 and root mean square error (RMSE) when selecting our most preferred model. Across the four model specifications, we see only slight differences in R^2 and RMSE. R^2 is highest for Model 2 (Strava added to base model) and Model 4 (Strava and Google Trends added to base model). Similarly, RMSE is lowest (better), although only slightly, for Models 2 and 4. Given these model performance metrics, Model 4 is our most preferred model.

The results from the Monte Carlo analysis of our most preferred model's predictive accuracy are summarized in Table A-4. In this analysis we compared the percent difference between predicted and observed trips for the estimation sample (75% of all observations) and the non-estimation sample (25% of all observations) to see how well the model performs on data that were not used to estimate parameters.

Table A-4. Summary statistics of model's predictive accuracy from Monte Carlo analysis.

	% difference between actual and predicted use		R^2
	Estimation sample	Non-estimation sample	
Mean	9.4%	15.9%	0.88
Standard Deviation	2.3%	0.6%	0.01
Minimum	6.9%	8.9%	0.84
Maximum	11.0%	28.0%	0.94

For the estimation sample, the model predicted within 6.9% to 11% of the observed number of trips, with a mean of 9.4%. For the non-estimation sample, the accuracy ranged from 8.9% to 28% with a mean of 15.9%. Across the 10,000 simulations, R^2 ranged from 0.84 to 0.94, averaging 0.88.

Figure A-1 plots actual versus estimated use for Lion Mountain. The solid line reflects a perfectly accurate model; the dashed line shows the trendline modeling the relationship between actual and estimated use. Estimated use is quite close to actual use, although the model underestimates use somewhat at the highest use levels.

Figure A-1. Actual versus estimated use at Lion Mountain.

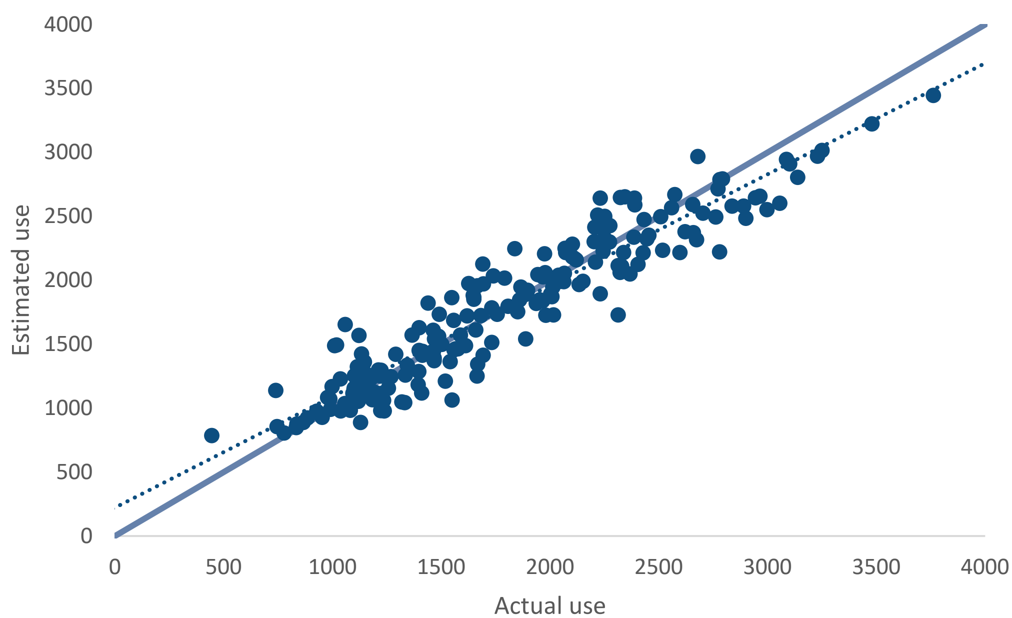
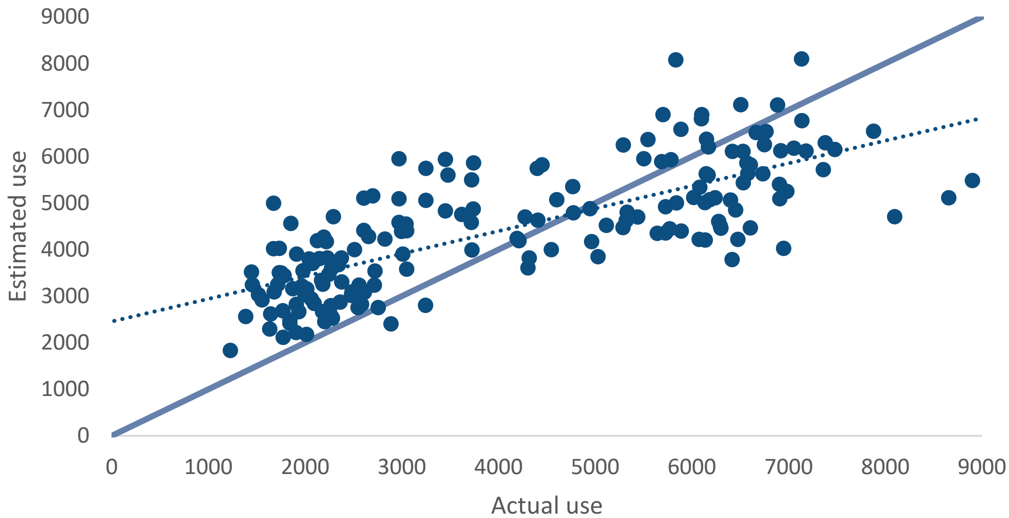
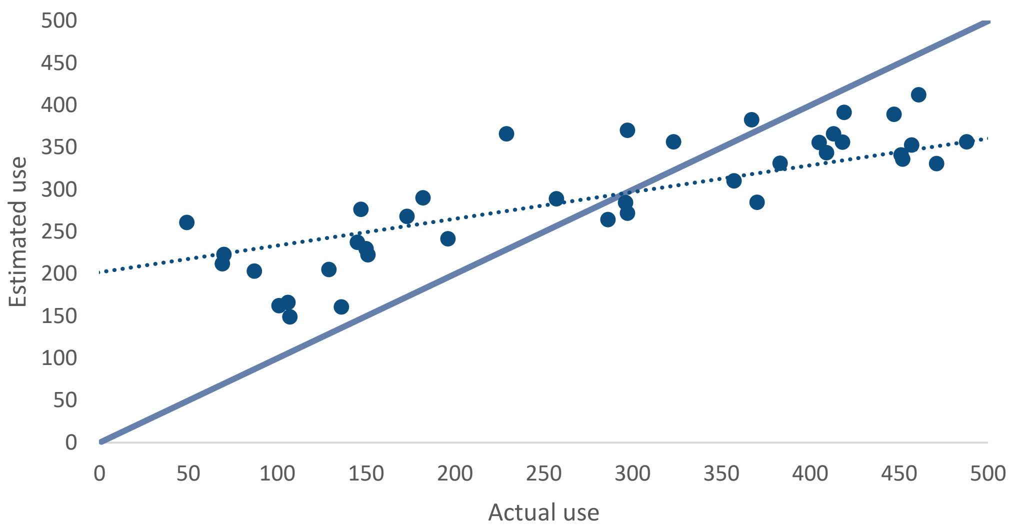


Figure A-2. Actual versus estimated use at the Gallagator (Panel A) and Beaver Lakes (Panel B).

a) Gallagator Trail



b) Beaver Lakes



Diagnostics for Objective #1: Predicting use in other locations

We provide plots of the actual versus estimated use for Beaver Lakes and the Gallagator in Figure A-2. At both sites the model underpredicts at the highest levels of use and underpredicts at the highest levels of use.

Diagnostics for Objective #2: Forecasting future trail use

We forecast future use in 2021-2024 based on model parameters estimated using data from Lion Mountain for 2017-2020. We calculate the 95% confidence intervals around these predictions using Delta-method standard errors for the years 2021-2024.

Future research

Predictive accuracy likely can be improved if the model were estimated with more sites. A larger set of sites for estimation would allow us to develop a more robust model that could account for different types of sites such as high and low use, recreation versus commuting use, and primary types of uses. Including indicators for these categories could improve the model's predictive power at other sites. The model presented here works best at sites with relatively high use. A larger set of diverse types of sites to parameterize the model, including low-use sites, could improve model performance at low-use sites.

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