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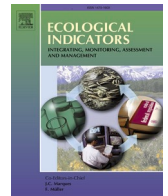
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Using social media data to estimate recreational travel costs: A case study from California

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ABSTRACT

Understanding the economic value of ecosystem services is necessary to facilitate sustainable land use management, and to inform policy and decision making. However, valuing and monetizing ecosystem services remains challenging. Benefit-transfer and non-market valuation methods typically rely on administrative data and surveys, but this is time consuming, limited, and requires much more resources. Social media and other types of big data provide accessible and georeferenced data that can be incorporated into valuation approaches. We use recreation as an example and the Tahoe Central Sierra Initiative (TCSI) project area in California as a case study to explore the usefulness of such data in estimating travel costs that form an integral part of determining the value of recreational ecosystem services through the travel cost model. We estimated 6,951 person user days of recreation from 2,245 visitors who uploaded photographs to the Flickr photo-sharing application between 2005 and 2019. We used metadata from the images to infer visitor origins and estimate trip distance and costs of travel for visitors that took day trips (<500 miles (~800 kms) roundtrip) to the area. Our results show that the most demand for recreational opportunities in the TCSI came from domestic visitors, particularly those from California and Nevada who took day trips. On average, visitors spent \$156 per single day trip. The total cost of travel for recreational visits to the TCSI for the period was \$491,500 (an average of \$32,800 per year). However, when adjusted to align with actual visitation, the travel costs could range from \$1.35 to \$1.84 billion per year. Estimating recreational use and highlighting the travel cost for recreational opportunities illustrates how crowd-sourced data can refine valuation approaches such as the widely used travel cost approach, which may fill in data gaps in valuing ecosystem services.

1. Introduction

Natural landscapes provide numerous benefits to people, including recreational opportunities that are linked to improved physical health as well as psychological and emotional well-being (Bratman et al., 2019; Remme et al., 2021; Wolsko et al., 2019; Russell et al., 2013; Sandifer et al., 2015; Daily, 2021; Daily and Ruckelshaus, 2022). Nature-based recreation, for example, is believed to be the fastest-growing sector of the recreation and tourism industry globally and generates about \$600 billion annually for the global economy (Sonter et al., 2016; Balmford et al., 2015), with increased visits to forested regions during the COVID-19 pandemic (Fagerholm et al., 2021). Illustrating the economic value of

ecosystem services, and recreation in particular, generated by natural areas can provide a powerful incentive for their conservation (Bilmes and Loomis, 2019; Montagnini et al., 2022; Mayer and Woltering, 2018; Shrestha et al., 2007; Gnedenko, 2021; Hale et al., 2019; Quesnel Seipp et al., 2023).

Although studies quantifying ecosystem services are rapidly growing (Wood et al., 2020; Zhang et al., 2021; Paracchini et al., 2014; Mayer and Woltering, 2018; Sinclair et al., 2018; Hermes et al., 2018), valuing and monetizing the recreational benefits of landscapes remains a challenge. This is largely due to a lack of indicators and associated data that approximate the value of recreation benefits (Bowker et al., 2009; Mayer and Woltering, 2018), which poses a challenge in informing

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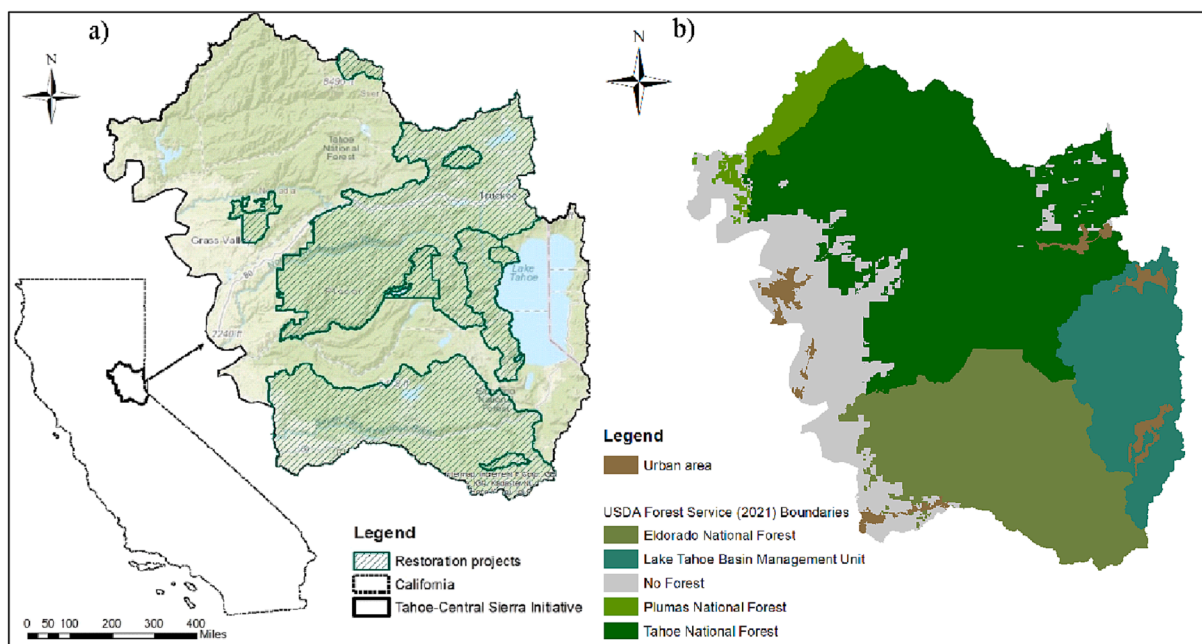


Fig. 1. A) Location of the TCSI within the state of California and forest restoration projects being undertaken in the area, b) the United States Department of Agriculture (USDA) forest service national forest boundaries as well as locations of urban areas in the TCSI.

management or policy actions that would prioritize recreational benefits. Natural recreational resources are environmental goods and services which belong to non-marketed goods and services; thus they do not have actual market prices as they are not traded in normal markets (Bigirwa et al., 2021; Ezebilo; 2016). As such, ascertaining the net economic value of recreation is typically conducted through non-market valuation techniques such as contingent valuation, travel cost, choice experiments, and hedonic pricing (Mäntymaa et al., 2021; Rogers et al., 2019; Sánchez et al., 2021). Typically, for economic valuation, the net economic value or consumer surplus of a good or service, i.e., the difference between the individual's maximum willingness to pay as defined by the individual's underlying demand for the good or service and the total amount that they pay, is used (Bowker et al., 2009). Consumer surplus is inferred from revealed preference data or directly estimated using stated preference data, where people state their maximum net willingness to pay within constructed market conditions via surveys (Rosenberger, 2018; Kubo et al., 2020).

The travel cost method, based on welfare estimates typically from preferences revealed in survey responses, is the most well-established and commonly used method for the valuation of recreational benefits (Parsons, 2003; Bartczak et al., 2008; Sinclair et al., 2020; Sardana et al., 2016; Lankia et al., 2015; Parsons et al., 2021). The method relies on detailed data about trip characteristics and visitation numbers to an area as a measure of the demand for recreation. A key assumption in this method is that the return cost of travel (including associated fees) incurred from a visitor's home to a site is a proxy or shadow price for the value of the recreational experience (Ghermandi and Sinclair, 2019; Teles da Mota and Pickering, 2020; Rashidi et al., 2017; Parsons, 2003). However, traditional administrative data and direct observations commonly relied on, including the amount and character of visitors as well as the spatial and temporal extent of recreational activities (Wood et al., 2020; Oteros-Rozas et al., 2018), are usually site specific, time consuming, expensive, and limited in both spatial coverage and content richness, with fewer travelers captured during surveys.

Technological advancements have created many streams of fine-scale big data (e.g., social media data) as billions of posts, including text, videos, and geotagged images with a wealth of spatial and temporal metadata from millions of users, are uploaded to different platforms

(Richards and Friess, 2015; Hale et al., 2019; Hausmann et al., 2018; Clemente et al., 2019; Lee et al., 2019). This data and techniques, such as machine learning, are increasingly being used in the field of ecology, and in particular, the mapping and modeling of ecosystem services (Manley et al., 2022). Several studies have found georeferenced, publicly accessible social media data to be a good proxy for mapping recreational ecosystem services in natural areas and a useful source of data for predicting the home locations of visitors with good accuracy (Wood et al., 2013; Wood et al., 2020; Sonter et al., 2016; Sinclair et al., 2020). Some studies have demonstrated that estimates relying on Flickr data reasonably compare to primary survey results from other sites (Keeler et al., 2015; Ghermandi, 2018; Sinclair et al., 2018). This provides an opportunity to explore how these techniques and data can be incorporated into the valuation of ecosystem services, for example, with the widely used travel cost method. The travel cost method is a promising approach that could bolster research on recreation and its values, particularly in areas considered too costly or difficult for traditional monitoring. Although there is emerging research utilizing crowdsourced data, including social media and mobile phone data, to value recreation, the inclusion of such data to fill data gaps in valuation approaches is still in its infancy (Sinclair et al., 2018; Sinclair et al., 2020; Ghermandi, 2018).

The objective of this study is to explore the use of social media data in estimating recreational use as well as travel costs, which form an important component in valuing recreational ecosystem services. Using the Tahoe Central Sierra Initiative (TCSI) prototype project area in California as a case study, we illustrate how easily available social media data provides a spatially refined and low-cost data source for estimating use and associated travel costs that can improve data gaps in the travel cost method for valuing recreational services provided by nature. We specifically integrate data extracted from geotagged photographs uploaded to Flickr between 2005 and 2019 in the TCSI to illustrate how crowdsourced data is a powerful tool for overcoming current limitations of ecosystem service valuation approaches, including data availability, uncertainty in valuation, and challenges in connecting the biophysical and social aspects of ecosystem services to value the socio-ecological system as a whole.

2. Materials and methods

2.1. Study area

The TCSI is a pioneering 2.4-million-acre (~9,700 km²) landscape-level forest restoration effort under the Sierra Nevada Watershed Improvement Program (California Tahoe Conservancy, 2019). Fig. 1 illustrates the location of the project, which brings together innovative planning, investment, and management tools for multiple restoration initiatives and collaboratives to improve the health and resilience of the Sierra Nevada (Sierra Nevada Conservancy, 2021). Recent land cover estimates from the California Department of Forestry and Fire Protection (CALFIRE) Fire and Resource Assessment Program (FRAP) (2015) show that the area is predominantly conifer forest (68.2%), with hardwood forests, shrublands, and water accounting for 8.8%, 8.5%, and 6.6%, respectively. The area is also covered by barren (4.1%), herbaceous (2.1%), urban (1.1%), wetland (0.4%), and agricultural (0.2%) lands. The forested landscapes and watersheds of the area provide significant fish and wildlife habitat and are a recreational playground for millions of visitors all year round (Sierra Nevada Conservancy, 2021). For example, an estimated 8 to 14 million annual visitors recreate in the Lake Tahoe region and form the foundation of the Lake Tahoe Basin's \$5 billion economy (Tahoe Regional Planning Agency, 2021; Sierra Nevada Alliance, 2021; The Sierra Nevada Ally, 2021; California Tahoe Conservancy, 2021).

2.2. Data

Despite the limitations of social media data, including restricted access to Application Programming Interfaces (APIs) for some platforms such as Facebook, Twitter, and Instagram, underestimation of actual visitor estimates, assumptions about the motivations for sharing photographs, biases around accessibility to and participation in social media (Wood et al., 2013; Toivonen et al., 2019; Hausmann et al., 2018; Muñoz et al., 2020; Ciesielski and Stereńczak, 2021; Mancini et al., 2018), social media data can be a rapid and readily accessible source of data for ecosystem service research. We wrote Python scripts to connect to Flickr's API and downloaded geotagged photographs taken between 1 January 2005 and 31 December 2019 in the TCSI. We ended our photograph search in 2019 to avoid the effects of COVID-19-related travel restrictions (i.e., stay at home orders, lockdown orders) on recreational visits. We chose Flickr because of easy access to the public content through its API as well as its popularity among nature photographers (Ruiz-Frau et al., 2020) and studies mapping recreation and other ecosystem services (Muñoz et al., 2020; Keeler et al., 2015; Ghermandi, 2018; Sinclair et al., 2018; Wood et al., 2013; Wood et al., 2020; Mancini et al., 2018; Richards and Tunçer, 2018). Based on our query, we downloaded all available public photographs, and metadata including the longitude and latitude, date, and time the photograph was taken, as well as the photographer's origin based on the location listed on their online profiles. We excluded urban areas from the analysis to measure recreation in natural landscapes outside cities. To do this, we filtered the Flickr records using a U.S. Census Bureau (2020) urban area shapefile to discard any record in a location with an urban area. To avoid double-counting of photographs and problems of having users that uploaded many or few images from a single visit being counted differently, we calculated Photo-User Days (PUDs) for the TCSI. One PUD at a location represents one unique photographer who took at least one photo on a specific day within the area based on the date and location where the content was created along with the photographer's unique identifier (Wood et al., 2013).

2.3. Estimating cost of travel to the TCSI

Here, we estimate the travel cost, a key element of the travel cost model, a popular method used to estimate the value of recreational

benefits generated by ecosystems (Ward and Loomis, 1986; Parsons, 2003; Bartczak et al., 2008; Sinclair et al., 2020; Sardana et al., 2016; Lankia et al., 2015; Parsons et al., 2021). The travel cost method is based on the idea that even if there is no explicit price for recreation, an individual visiting a recreation site is willing to pay for traveling to the site and back and forgoes working time that has monetary value (Amoako-Tuffour and Martínez-Españeira, 2012; Bowker et al., 2009; Czajkowski et al., 2019). There are several variants of the travel cost method, including single site models focusing on the valuation of a single recreational site and those that focus on multiple recreational sites using random utility models (Sinclair et al., 2020; Parsons, 2003). Our analysis estimates the return travel cost incurred from a visitor's home to a site, which can then be used in the travel cost model to estimate the net economic value or consumer surplus of the recreational service (Parsons, 2003). As such, the estimated cost of travel to the TCSI was estimated as the return trip cost to visit the TCSI, including the opportunity cost of time. Time costs are a function of travel time and the opportunity cost of time, which is evaluated at one-third of the wage rate (Baarenklau, 2010; Sardana et al., 2016). Smith et al. (1983) highlight that the appropriate valuation of time devoted to recreation trips depends on the nature of the time constraints facing each individual, including the opportunity cost of time, which depends on the types of trips undertaken (e.g., long vacations versus weekend excursions) and on the individual's available leisure time. While most travel cost method estimates are limited in scope because they require user participation and often rely on traditional administrative data and direct observations to obtain data on the amount and characteristics of visitors, here we illustrate how crowdsourced visitor information from Flickr can be used. Previous travel cost method studies, including Sinclair et al. (2018), Sinclair et al. (2020), Parsons (2003), and Sardana et al. (2016), have typically only considered day and single-purpose trips to avoid the multiple destination and multi-purpose trip problem. Multipurpose and multi-destination trips yield a biased estimate of the recreation benefits of a site as some proportion of a person's total trip travel cost and travel time are incurred for other purposes not related to nature-based recreation (Loomis, 2006; Parsons, 2003). Single-purpose trips thus fit the travel cost model, as all travel expenses can be attributed to creating the recreation experience. We estimated the distance traveled to visit the location in the TCSI site for each visitor based on the home location stated on their Flickr profile. The user's first photograph from their first visit to the TCSI was used as the point to which they would travel. We considered day trips and single-purpose trips as those that are under 500 miles (~800 kms) round trip (which predominately originate from California and Nevada) and assumed car to be the preferred mode of transport for these visitors based on estimates from English et al. (2018) who determined the probability of flying versus driving using reported travel mode choices from a national telephone survey. Their results suggest that for driving distances under 500 miles, travelers almost always drive, and for driving distances greater than 1,500 miles (~2,400 kms), travelers fly roughly 85 percent of the time. As such, for visitors whose round-trip distance from their origin to the first location they visited in the TCSI is under 500 miles, we used the most efficient route as identified using the "osrmTable" function in the "osrm" R package (R Core Team, 2022) to calculate travel distance. To estimate the travel cost, we used Eq. (1) adapted from Sardana et al. (2016):

$$\text{Travel Cost} = \text{Distance} \times \text{Cost} + 0.33 \times \frac{\text{Income}}{2000} \times \frac{\text{Distance}}{40\text{mph}} \quad (1)$$

In Eq. (1), *Distance* is the round-trip distance from the visitor's origin to a destination in the TCSI. Using the travel distance, *Cost* was calculated as the average vehicle operating cost (including fuel and maintenance) per mile for a typical sedan-type car for each year as defined by the American Automobile Association (<https://exchange.aaa.com/>). Additionally, the time costs are a function of travel time estimated by dividing the round-trip distance by an average speed of 40mph (~64km/h) (Rosenberger and Loomis, 1999; Sardana et al., 2016).

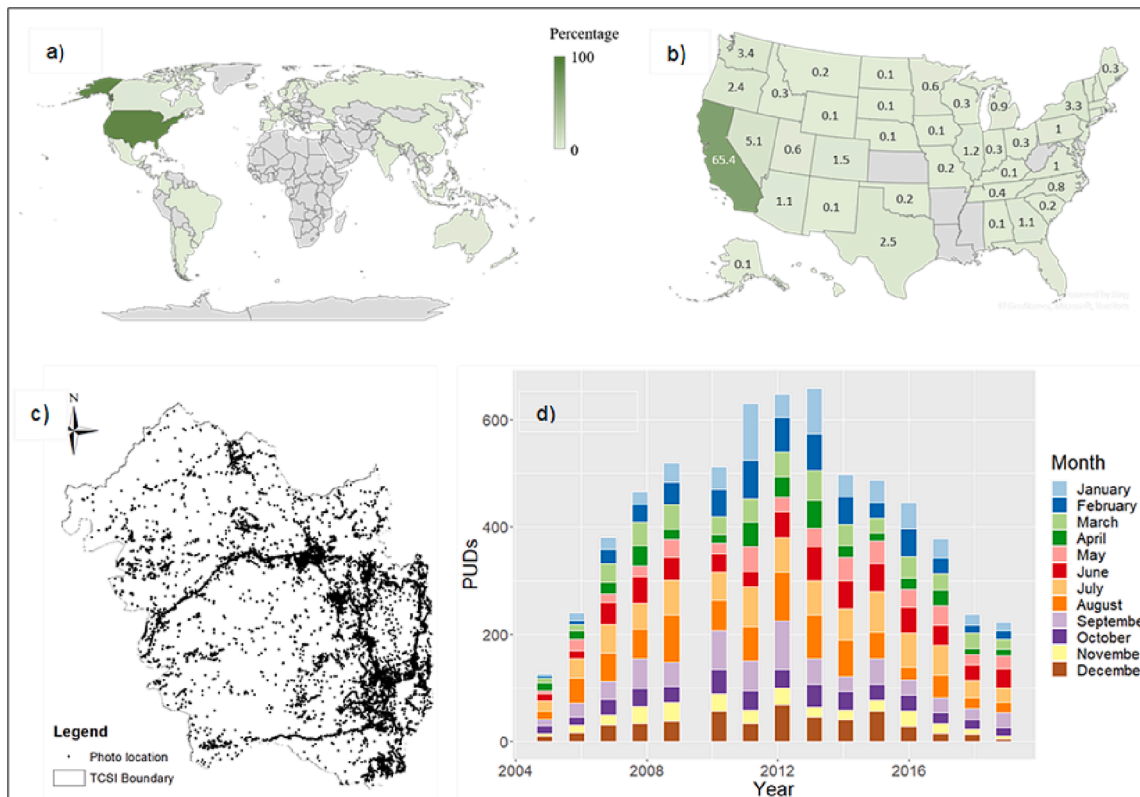


Fig. 2. Spatial and temporal distribution of the Flickr visitation data: a) country origins of the visitors to the TCSI, b) distribution of domestic visitors by state of origin, c) visitor locations within the TCSI, and d) temporal distribution of the PUDs.

Income was estimated as the median income for the place, county, or state of origin and extracted from 2010 U.S. Census Bureau data using the “censusapi” package in the R statistical computing software (R Core Team, 2022). Following Sardana et al. (2016), the wage rate was estimated by dividing the proxy income per annum by 2,000 based on a 40-hour week for 50 weeks in a year. Similarly, the opportunity cost of time was estimated as one-third (0.33) of the wage rate, a commonly used figure in the literature (Sinclair et al., 2018; Sardana et al., 2016). To factor inflation, we adjusted the income to 2019 dollars following the U. S. Census Bureau methodology, which uses the Bureau of Labor Statistics’ (BLS) Consumer Price Index Research Series (CPI-U-RS) to adjust for changes in the cost of living (U.S. Census Bureau, 2021). CPI-U-RS values are available for the period 1947 to 2020 (Appendix 1) and we chose 2019 to coincide with the last year of data collection from our Flickr dataset. For example, the 2010 values were adjusted by a factor of 1.18% to 2019 dollars as follows:

$$\text{Adjusted estimate} = 2010 \text{ estimate} \times \left(\frac{2019 \text{ CPI} - U - RS(376.5)}{2010 \text{ CPI} - U - RS(320.4)} \right) \quad (2)$$

2.4. Improving the recreational travel cost values

Social media data might not capture all recreational visitors, considering that not all visitors will post photographs of their visits online (Hausmann et al., 2018). To overcome this challenge, here we show how the mean recreational visitor estimates derived from the National Visitor Use Monitoring Program (NVUM) for each national forest can be used to adjust social media-based travel cost estimates. Through the NVUM, the USDA Forest Service produces estimates of the volume of recreation visitation to National Forests. Each National Forest Service unit participates in the NVUM on a regular 5-year schedule, and visitation is estimated for the entire unit for the entire year, with roughly

23,000 recreation visitors surveyed (English et al., 2020). The survey data are used to estimate the average spending of visitors, which is combined with NVUM visitation figures to estimate total visitor spending at the forest level. For each National Forest within the TCSI shown in Fig. 1 (Tahoe National Forest, Eldorado National Forest, Plumas National Forest, and the Lake Tahoe Basin Management Unit), we obtained descriptive information about visitation, including trip spending connected to the visits. Depending on the National Forest in the TCSI, the NVUM visitation is available for the years 2005, 2007, 2010, 2012, 2015, 2017, and 2020. Like the Flickr data, we did not consider any NVUM data after 2019 to limit the influence of COVID-19-related travel restrictions on our analysis. As such, we obtained NVUM data for the period 2005–2017 for the TCSI for this analysis and were particularly interested in NVUM estimates of the average number of people that visited the TCSI to recreate annually. Using this information, the annual adjusted travel cost estimates for the TCSI were estimated as the annual total travel cost values based on the Flickr data (Travel cost) scaled by the ratio of the annual visitors to the TCSI from the Flickr data (Flickr visitors, i.e., the actual number of people that posted photographs to Flickr) and the mean annual number of recreational visitors to the TCSI from the NVUM database (NVUM visitors) for the TCSI:

$$\text{NVUM Adjusted travel cost estimate} = \text{Travel cost} \times \frac{\text{NVUM Visitors}}{\text{Flickr Visitors}} \quad (3)$$

3. Results

3.1. Characteristics of visitation

From the Flickr data, we obtained a unique dataset of approximately 81,500 photographs taken in non-urban areas of the TCSI between 2005 and 2019 by 5,000 users. 6,951 PUDs were obtained from 34,737 images

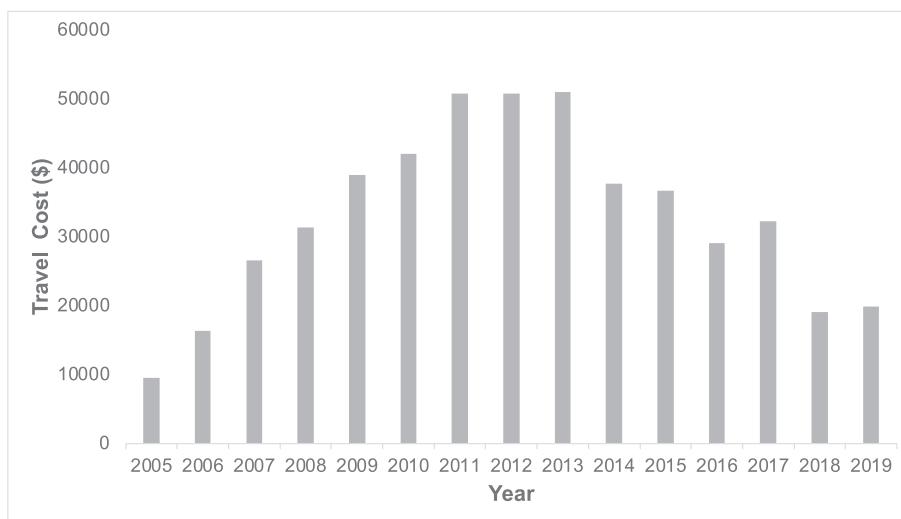


Fig. 3. Annual travel costs to the TCSI.

Table 1

NVUM based recreational visits and trip spending in national forests located within the TCSI.

National Forest	Survey period	Average visitation	Trip spending (\$)	Average party spending (\$)
Eldorado National Forest	2007, 2012, 2017	1,200,000	62,000,000	410
Lake Tahoe Basin Management Unit	2005, 2010, 2015	7,700,000	1,000,000,000	1,450
Plumas National Forest	2005, 2010, 2015	357,000	19,000,000	185
Tahoe National Forest	2005, 2010, 2015	1,600,000	94,000,000	210
Total		10,857,000	1,175,000,000	560

associated with 2,245 visitors whose origin was stated with an accuracy sufficient to designate the city, county, state, or country of residence. Most visitors (88%) originated from the U.S., while international visitors were mostly from the United Kingdom (3%), Canada (1.5%), and Germany (1.2%) (Fig. 2a). Within the U.S., most visitors were from the states of California (65%), Nevada (5%), and Washington (3.4%) (Fig. 2b). The years 2012 and 2013 had the highest number of visitors, accounting for 718 and 755 PUDs, respectively, while the least number of visits were associated with 2005 and 2019 (131 and 235 PUDs, respectively) (Fig. 2c). Most visits were in the months of July and August, with 793 and 771 PUDs, respectively (Fig. 2d). On average, visitors originating within the U.S. traveled 1,266 miles round trip (~2,000 kms) to the TCSI, with most visits (78%) being single day trips. However, most visitors from California and Nevada traveled <400 miles (~640 kms)

round trip. The average length of stay for overnight trips observed was 3 days.

3.2. Estimates from the travel cost analysis

The total travel costs associated with recreational visits to the TCSI, including opportunity costs for travel, for the period 2005–2019 based on the Flickr travel cost analysis for round trips less than 500 miles (obtained from 3,153 PUDs) was \$491,500 (2019 dollars). The average travel cost for these single day trips was \$156 per trip. We observe differences in these values across the different years. For example, 2012 and 2013 have the most amount of travel costs (\$50,700 and \$51,000, respectively) while 2005 and 2006 have the least travel costs (\$9,500 and \$16,300) (Fig. 3).

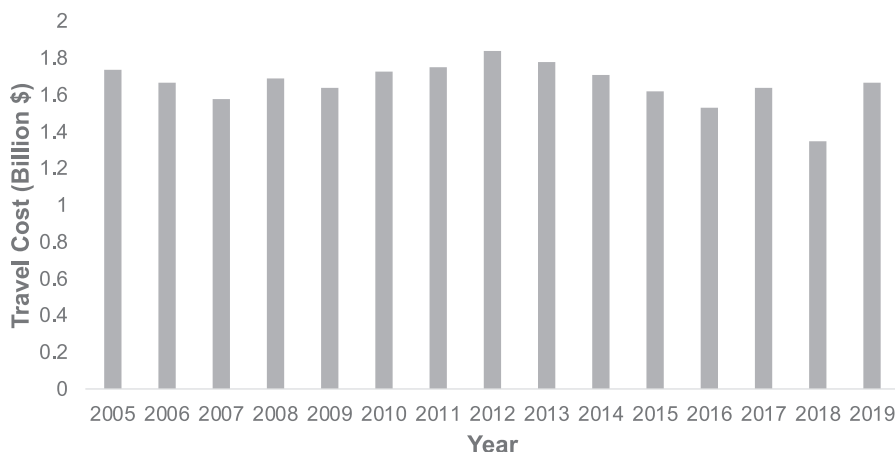


Fig. 4. NVUM adjusted annual travel costs for the TCSI.

3.3. NVUM adjusted travel costs for the TCSI

The travel costs associated with recreation in the study area increased significantly when adjusted using reporting from the NVUM and recreational values from National Forests between 2005 and 2017. During this time, on average, 10.8 million people visited national forests located in the TCSI area (Fig. 1b) to recreate annually. These visitors spent about \$1.18 billion during their trips, with an average spending per party of \$565 (Table 1). Like the visitation data from the Flickr images (Fig. 2c), the Lake Tahoe Management Basin had the highest number of recreational visits in the TCSI.

Scaling the Flickr based travel cost estimates using the average annual NVUM recreational value (Eq. (3)) allows us to improve the limited Flickr visitation data and estimates of the travel costs associated with recreational activities in natural lands of the TCSI shown in Fig. 3. The ratio or difference between the Flickr and NVUM estimates is greatest for the years 2005, 2006, and 2019, which also happen to be the years with the lowest amounts of visitation based on the Flickr data (Fig. 2d), and lower for 2011, 2012, and 2013, where we have higher visitation rates from the Flickr data. Our NVUM adjusted total travel costs across the period of analysis (2005–2019) based on the day trip data are \$25 billion, and Fig. 4 shows the distribution of the adjusted annual travel costs (average = \$1.7 billion per year).

Although the distribution of these adjusted annual values looks different from Fig. 3, 2012 and 2013 still have the highest annual estimates (\$1.84 and \$1.78 billion, respectively), while 2018 has the smallest value of \$1.35 billion.

4. Discussions and conclusions

Informed by the growing body of research focusing on social media data to understand cultural ecosystem services such as recreation, we set out to develop a social media-based approach to estimate travel costs associated with recreational ecosystem services. While several studies have used social media to map recreational services (Manley and Egho, 2022; Wolsko et al., 2019; Wood et al., 2013), not many have used it to fill data gaps that can improve our estimation of the monetary value of those services, for example, using the travel cost method. Non-market valuation approaches such as the travel cost method rely on limited administrative data and surveys (Bowker et al., 2009), but with the emergence of big data, social media offers a rapid and readily accessible indicator of how and where people interact with nature, and a valuable resource for estimating the fine-scale and location-specific travel costs that form an important aspect of how we estimate the recreational values of landscapes. Wood et al. (2013), for example, observed that the number of people who visit a location annually is related to the number of photographs taken in the same area and uploaded to the Flickr database at 836 visitor attractions worldwide. As such, approaches that take advantage of such emerging data sources are critical in filling existing data gaps as they capture a wide variety of information not typically captured in surveys or which could be time consuming to collect. Such data informs economic valuation models that are important for developing efficient land and forest management policies that improve forest health to deliver these recreational services to different beneficiaries (Shrestha et al., 2007).

Social media data has been used increasingly in the mapping and modeling of ecosystem services, but not so much in filling in data gaps in the valuation of these services. In this study, we show that social media data is a powerful tool available for use in ecosystem service research

with the ability to fill data gaps and improve our valuation methods, for example, in estimating travel costs for the travel cost model. Based on information from approximately 81,500 images posted to Flickr between 2005 and 2019 (Fig. 2c), our results show that the total travel costs associated with recreational activities in the TCSI for the period of analysis (2005–2019) could be anywhere between \$491,500 and \$25 billion (annual average = \$32,800–\$1.7 billion). Although this range of values is consistent with findings from the NVUM, which estimated approximately \$1.18 billion a year in trip costs (Table 1), our unadjusted total travel costs from the Flickr data (\$491,500) are way lower than the NVUM estimate of \$1.18 billion a year and the reported multi-billion-dollar economy sustained by recreation in the area (Tahoe Regional Planning Agency, 2021; Sierra Nevada Alliance, 2021; The Sierra Nevada Ally, 2021; California Tahoe Conservancy, 2021). However, this is not surprising considering the low volume of the input data from Flickr used in the analysis when compared to NVUM survey estimates. This limitation of Flickr as well as other social media data has also been documented in prior research findings (Wood et al., 2013; Toivonen et al., 2019; Hausmann et al., 2018; Muñoz et al., 2020; Ciesielski and Stereńczak, 2021; Mancini et al., 2018). For example, Wood et al. (2013) and Toivonen et al. (2019) highlight that while social media data are helpful for predicting visitation with moderate certainty, the number of social media posts is less than the total observed user days on the ground. In their analysis, Wood et al. (2013) found that Instagram accounts for 3–4% of total observed user days, while posts on Twitter and Flickr represent less than 1% of the observed user days. Although Flickr has limited user numbers and lower post frequencies than Instagram and Facebook, it allows easy access to public content through its API, unlike Instagram and Facebook, which have increasingly restricted content access (Ruiz-Frau et al., 2020). Despite this, our average per person per single day trip values from this analysis (\$156) are lower than NVUM trip cost estimates, which range between \$210 and \$1,450 per party in the TCSI. This also suggests that although social media data is helpful to estimate use and travel costs that inform the valuation and management of recreational opportunities, particularly in areas with limited survey data, there is need for further research to understand how visitation estimates based on social media data can be improved. Here, for example, we mean adjusted the annual travel cost estimates based on the Flickr data with NVUM data (Eq. (3)). Doing this increased our total travel costs to the TCSI from \$491,500 to \$25 billion for the period under analysis. These results go to show that while Flickr is useful, it does not account for the dispersion of people recreating across the landscape, and there is still need to refine social media-based visitation estimates that inform valuation methods and provide improved estimates of the recreational value of landscapes.

In addition to estimating travel costs for recreational visits, this analysis also establishes the demand for recreational opportunities in the TCSI and illustrates that the patterns of domestic and international tourists differ. In line with findings from previous studies, including Duane (1996), our results have shown that there is demand for recreational opportunities in the TCSI from visitors originating within the state of California as well as the neighboring states of Nevada and Washington (88%). Additionally, most of these visitors make day trips, and this is particularly important for encouraging local and state officials to ensure access to various areas within the TCSI. According to Loomis and Keske (2012), local residents, or day trippers, provide consistent travel to recreation areas that may remain unchanged even during times of economic recession. Leh et al. (2018) found a significant relationship between the time cost and the number of visitors and that the increase in

visiting time resulted in a reduction in the number of visitors. For locals, it might be easier to access this area at a lower cost than for international visitors, who must fly thousands of miles to come to the area. These results are particularly important in understanding and addressing the value of current intense wildfires on recreational services, as studies (Gellman et al., 2022; Bawa, 2017; Duffield et al., 2013; Kim and Jakus, 2019; White et al., 2020) have shown drops in recreational demand due to smoke and bad air quality from wildfire outbreaks.

Although social media data has been used for ecosystem service research, it is not without limitations (Wood et al., 2013; Toivonen et al., 2019; Hausmann et al., 2018; Muñoz et al., 2020; Ciesielski and Stereńczak, 2021; Mancini et al., 2018), and this affects ecosystem service valuation approaches such as the travel cost method that rely on visitor estimates and travel costs from such data. Firstly, unlike field surveys, social media data is based on inference considering that the motivation for sharing photographs is not known and the initial purpose of social media is not for ecosystem services research. Additionally, approaches such as ours relying on social media data assume that a visit to the area is only for the purpose of recreation and do not account for the people who travel through the area to recreate in other places. Duane (1996), for example, highlights how many foreign visitors appear to travel through the Sierra region as part of more extended holidays originating in either Los Angeles or San Francisco and terminating at the other, often passing through the area as part of a larger trip that will include either Yosemite National Park or the Lake Tahoe region, Death Valley National Park, and Las Vegas, Nevada. Dorwart et al. (2009) also highlight that the occurrence and density of photographs of nature can provide an indicator of public interest in nature in that location, but there is a disconnect between such an indicator and a measure of cultural ecosystem service value. A further limitation of relying on social media data, more specifically a single photograph platform (in our case Flickr), is the assumption that each visitor travels alone, which adds to the fact that the number of observations provided is sometimes too low to adequately represent visitor rates in natural areas. Social media might underestimate the actual visitation as a smaller proportion of people visiting parks and other recreation locations may post images to Flickr (Hausmann et al. 2018). Additionally, there are biases inherent in the social media data due to issues of accessibility to and participation in social media. Most social media platforms are dominated by younger, wealthier, and more highly educated people, and different demographic groups use different platforms (Smith and Anderson, 2018; Oteros-Rozas et al., 2018; Richards and Tunçer, 2018). Oteros-Rozas et al. (2018) also highlight that social media data is subject to market decisions and corporate strategies. For example, our period of increased visitation in 2012 and 2013 might be due to major improvements that popularized Flickr in late 2012. Yahoo! launched Flickr 2.0, the iPhone application that Flickr users had wanted for years with improved features, as well as an Android version of the application with more storage in 2013 (Shoam, 2021).

Findings from this analysis have shown that, despite limitations, social media data can be a rapid and readily accessible source of data for ecosystem service research. To improve valuation approaches that rely on visitation, future studies can build on this work and use such data to improve estimates of visitation trends across space and time. For example, studies can explore how to include data from multiple social media data streams, especially popular streams such as Facebook, Instagram, and Twitter that have better data but restricted access through their APIs. Also, studies can expand the work further to estimate the demand curve and consumer surplus (Parsons, 2003). Additionally, studies can utilize new methodologies based on artificial intelligence and deep-learning approaches such as machine learning that have emerged to maximize the utility of crowdsourced data and expand ecosystem service modeling capabilities. There is also the potential to incorporate big data and social media data to study and improve the valuation of many other cultural services as well as other ecosystem services, including provisioning and regulating services across various

scales and management contexts. Such studies are timely, and improved approaches will be useful for informing ongoing efforts to leverage increased funding for forest restoration and to support goals that seek to strengthen America's forests, boost wildfire resilience, combat global deforestation, and retain forest ecosystems as well as sustainable supplies of forest ecosystem services and benefits for years to come (The White House, 2022).

CRediT authorship contribution statement

Charity Nyelele: Conceptualization, Data curation, Formal analysis, Methodology, Validation, Visualization, Writing – original draft. **Catherine Keske:** Conceptualization, Data curation, Formal analysis, Methodology, Validation, Visualization, Writing – original draft. **Min Gon Chung:** Conceptualization, Data curation, Formal analysis, Methodology, Validation, Visualization, Writing – original draft. **Han Guo:** Conceptualization, Data curation, Formal analysis, Methodology, Validation, Visualization, Writing – original draft. **Benis N. Ego:** Conceptualization, Data curation, Formal analysis, Methodology, Validation, Visualization, Writing – original draft.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

We used publicly available data.

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Appendices

Appendix 1

Annual average Consumer Price Index Research Series (CPI-U-RS) for 2005–2019.

Year	CPI-U-RS	2019 adjustment factor
2005	286.9	1.31
2006	296.2	1.27
2007	304.6	1.24
2008	316.3	1.19
2009	315.2	1.19
2010	320.4	1.18
2011	330.5	1.14
2012	337.5	1.12
2013	342.5	1.1
2014	348.3	1.08
2015	348.9	1.08
2016	353.4	1.07
2017	361	1.04
2018	369.8	1.02
2019	376.5	1

References

- Tahoe Regional Planning Agency, 2021. Sustainable recreation and transportation. Retrieved November 4, 2021, from <https://eip.laketahoeinfo.org/EIPFocusArea/Detail/3>.
- Sierra Nevada Alliance, 2021. Highlights: Officials promise to protect Lake Tahoe with \$415 million. Retrieved November 5, 2021, from <https://sierranevadaalliance.org/wp-content/uploads/Sierra-Resource-CO-8.23.2017.html>.
- The Sierra Nevada Ally, 2021. Overtourism takes a toll on Lake Tahoe's recreational resources. Retrieved November 4, 2021, from <https://www.sierranevadaally.org/2021/04/29/overtourism-takes-a-toll-on-lake-tahoes-recreational-resources/>.
- Amoako-Tuffour, J., Martínez-Espinoira, R., 2012. Leisure and the net opportunity cost of travel time in recreation demand analysis: an application to Gros Morne National Park. *J. Appl. Econ.* 15 (1), 25–49.
- Baerenklau, K.A., 2010. A latent class approach to modeling endogenous spatial sorting in zonal recreation demand models. *Land Econ.* 86 (4), 800–816.
- Balmford, A., Green, J.M., Anderson, M., Beresford, J., Huang, C., Naidoo, R., Walpole, M., Manica, A., 2015. Walk on the wild side: estimating the global magnitude of visits to protected areas. *PLoS Biol.* 13 (2), e1002074.
- Bartczak, A., Lindhjem, H., Navrud, S., Zandersen, M., Zylicz, T., 2008. Valuing forest recreation on the national level in a transition economy: the case of Poland. *Forest Policy Econ.* 10 (7–8), 467–472.
- Bawa, R.S., 2017. Effects of wildfire on the value of recreation in western North America. *J. Sustain. For.* 36 (1), 1–17.
- Bigirwa, D., Msese, L.R., Rwakalaza, R., Bilame, O., 2021. Measuring the economic use values of recreation resources in protected areas, evidence from Nyerere national park in Tanzania. *Am. J. Environ. Resour. Econ.* 6 (2), 54–65.
- Bilmes, L.J., Loomis, J.B., 2019. Valuing US National Parks and Programs: America's Best Investment. Routledge.
- Bowker, J.M., Starbuck, C.M., English, D.B., Bergstrom, J.C., Rosenberger, R.S., McCollum, D.W., 2009. Estimating the net economic value of national forest recreation: an application of the national visitor use monitoring. Database No.
- Bratman, G.N., Anderson, C.B., Berman, M.G., Cochran, B., de Vries, S., Flanders, J., Folke, C., Frumkin, H., Gross, J.J., Hartig, T., Kahn, P.H., Kuo, M., Lawler, J.J., Levin, P.S., Lindahl, T., Meyer-Lindenberg, A., Mitchell, R., Ouyang, Z., Roe, J., Scarlett, L., Smith, J.R., van den Bosch, M., Wheeler, B.W., White, M.P., Zheng, H., Daily, G.C., 2019. Nature and mental health: An ecosystem service perspective. *Sci. Adv.* 5 (7).
- California Department of Forestry and Fire Protections (CALFIRE) Fire and Resource Assessment Program (FRAP), 2015. Vegetation (fveg)—CALFIRE FRAP [ds1327]. Retrieved October 21, 2021, from <https://map.dfg.ca.gov/metadata/ds1327.html>.
- California Tahoe Conservancy, 2019. Tahoe Conservancy accepts \$1.95 million grant to co-manage 2.4 million-acre Tahoe-Central Sierra Initiative. Retrieved November 9, 2021, from <https://tahoe.ca.gov/tahoe-conservancy-accepts-1-95-million-grant-to-co-manage-tahoe-central-sierra-initiative/>.
- California Tahoe Conservancy, 2021. Recreation & Public Access. Retrieved November 9, 2021, from <https://tahoe.ca.gov/recreation-public-access/>.
- Ciesielski, M., Stereńczak, K., 2021. Using Flickr data and selected environmental characteristics to analyse the temporal and spatial distribution of activities in forest areas. *Forest Policy Econ.* 129, 102509.
- Clemente, P., Calvache, M., Antunes, P., Santos, R., Cerdeira, J.O., Martins, M.J., 2019. Combining social media photographs and species distribution models to map cultural ecosystem services: The case of a Natural Park in Portugal. *Ecol. Ind.* 96, 59–68.
- Czajkowski, M., Giergiczyński, M., Kronenberg, J., Englin, J., 2019. The individual travel cost method with consumer-specific values of travel time Savings. *Environ. Resour. Econ.* 74 (3), 961–984.
- Daily, G.C., 2021. The next steps for valuing nature in decision making. *Environ. Sci. Policy Sustain. Dev.* 63 (6), 17–20.
- Daily, G.C., Ruckelshaus, M., 2022. 25 years of valuing ecosystems in decision-making. *Nature* 606 (7914), 465–466.
- Dorwart, C.E., Moore, R.L., Leung, Y.F., 2009. Visitors' perceptions of a trail environment and effects on experiences: a model for nature-based recreation experiences. *Leis. Sci.* 32 (1), 33–54.
- Duane, T.P., 1996. Recreation in the Sierra. In *Sierra Nevada ecosystem project, final report to Congress* Vol. 2, 557–610.
- Duffield, J.W., Neher, C.J., Patterson, D.A., Deskins, A.M., 2013. Effects of wildfire on national park visitation and the regional economy: A natural experiment in the Northern Rockies. *Int. J. Wildland Fire* 22 (8), 1155–1166.
- English, E., von Haefen, R.H., Herriges, J., Leggett, C., Lupi, F., McConnell, K., Welsh, M., Domanski, A., Meade, N., 2018. Estimating the value of lost recreation days from the Deepwater Horizon oil spill. *J. Environ. Econ. Manag.* 91, 26–45.
- English, D.B., White, E.M., Bowker, J.M., Winter, S.A., 2020. A Review of the Forest Service's National Visitor Use Monitoring (NVUM) Program. *Agric. Resour. Econ. Rev.* 49 (1), 64–90.
- Ezebil, E.E., 2016. Economic value of a non-market ecosystem service: an application of the travel cost method to nature recreation in Sweden. *Int. J. Biodivers. Sci. Ecosyst. Serv. Manag.* 12 (4), 314–327.
- Fagerholm, N., Eilola, S., Arki, V., 2021. Outdoor recreation and nature's contribution to well-being in a pandemic situation-Case Turku, Finland. *Urban Forest. Urban Green.* 64, 127257.
- Gellman, J., Walls, M., Wibbenmeyer, M., 2022. Wildfire, smoke, and outdoor recreation in the western United States. *Forest Policy Econ.* 134, 102619.
- Ghermandi, A., 2018. Integrating social media analysis and revealed preference methods to value the recreation services of ecologically engineered wetlands. *Ecosyst. Serv.* 31, 351–357.
- Ghermandi, A., Sinclair, M., 2019. Passive crowdsourcing of social media in environmental research: A systematic map. *Glob. Environ. Chang.* 55, 36–47.
- Gnedenko, E., 2021. Forests and Land Management. In *Environmental and Natural Resource Economics*. Routledge, pp. 545–574.
- Hale, R.L., Cook, E.M., Beltrán, B.J., 2019. Cultural ecosystem services provided by rivers across diverse social-ecological landscapes: A social media analysis. *Ecol. Ind.* 107, 105580.
- Hausmann, A., Toivonen, T., Slotow, R., Tenkanen, H., Moilanen, A., Heikinheimo, V., Di Minin, E., 2018. Social media data can be used to understand tourists' preferences for nature-based experiences in protected areas. *Conserv. Lett.* 11 (1), e12343.
- Hermes, J., Van Berkel, D., Burkhard, B., Plieninger, T., Fagerholm, N., von Haaren, C., Albert, C., 2018. Assessment and valuation of recreational ecosystem services of landscapes. *Ecosyst. Serv.* 31, 289–295.
- The White House, 2022. FACT SHEET: President Biden Signs Executive Order to Strengthen America's Forests, Boost Wildfire Resilience, and Combat Global Deforestation. Retrieved May 1, 2022, from <https://www.whitehouse.gov/briefing-room/statements-releases/2022/04/22/fact-sheet-president-biden-signs-executive-order-to-strengthen-americas-forests-boost-wildfire-resilience-and-combat-global-deforestation/>.
- Keeler, B.L., Wood, S.A., Polasky, S., Kling, C., Filstrup, C.T., Downing, J.A., 2015. Recreational demand for clean water: evidence from geotagged photographs by visitors to lakes. *Front. Ecol. Environ.* 13 (2), 76–81.
- Kim, M.K., Jakus, P.M., 2019. Wildfire, national park visitation, and changes in regional economic activity. *J. Outdoor Recreat. Tour.* 26, 34–42.
- Kubo, T., Uryu, S., Yamano, H., Tsuge, T., Yamakita, T., Shirayama, Y., 2020. Mobile phone network data reveal nationwide economic value of coastal tourism under climate change. *Tour. Manag.* 77, 104010.
- Lankia, T., Kopperoinen, L., Pouta, E., Neuvonen, M., 2015. Valuing recreational ecosystem service flow in Finland. *J. Outdoor Recreat. Tour.* 10, 14–28.
- Lee, H., Seo, B., Koellner, T., Lautenbach, S., 2019. Mapping cultural ecosystem services 2.0-Potential and shortcomings from unlabeled crowd sourced images. *Ecol. Ind.* 96, 505–515.
- Leh, F.C., Mokhtar, F.Z., Rameli, N., Ismail, K., 2018. Measuring recreational value using travel cost method (TCM): a number of issues and limitations. *Int. J. Acad. Res. Business Social Sci.* 8 (10), 1381–1396.
- Loomis, J., 2006. A comparison of the effect of multiple destination trips on recreation benefits as estimated by travel cost and contingent valuation methods. *J. Leis. Res.* 38 (1), 46–60.
- Loomis, J., Keske, C., 2012. Did the great recession reduce visitor spending and willingness to pay for nature-based recreation? Evidence from 2006 and 2009. *Contemp. Econ. Policy.* 30 (2), 238–246.
- Mancini, F., Coghill, G.M., Lusseau, D., Preis, T., 2018. Using social media to quantify spatial and temporal dynamics of nature-based recreational activities. *PLoS One* 13 (7), e0200565.
- Manley, K., Ego, B.N., 2022. Mapping and modeling the impact of climate change on recreational ecosystem services using machine learning and big data. *Environ. Res. Lett.* 17 (5), 054025.
- Manley, K., Nyelele, C., Ego, B.N., 2022. A review of machine learning and big data applications in addressing ecosystem service research gaps. *Ecosyst. Serv.* 57, 101478.
- Mäntymaa, E., Jokinen, M., Juutinen, A., Lankia, T., Louhi, P., 2021. Providing ecological, cultural, and commercial services in an urban park: a travel cost-contingent behavior application in Finland. *Landsc. Urban Plan.* 209, 104042.
- Mayer, M., Wolter, M., 2018. Assessing and valuing the recreational ecosystem services of Germany's national parks using travel cost models. *Ecosyst. Serv.* 31, 371–386.
- Montagnini, F., Levin, B., Berg, K.E., 2022. Introduction. Biodiversity Islands: strategies for conservation in human-dominated environments. In: *Biodiversity Islands: Strategies for Conservation in Human-Dominated Environments*. Springer, Cham, pp. 3–37.
- Muñoz, L., Hausner, V.H., Runge, C., Brown, G., Daigle, R., Graham, L., 2020. Using crowdsourced spatial data from Flickr vs. PPGIS for understanding nature's contribution to people in Southern Norway. *People Nat.* 2 (2), 437–449.
- Oteros-Rozas, E., Martín-López, B., Fagerholm, N., Bieling, C., Plieninger, T., 2018. Using social media photos to explore the relation between cultural ecosystem services and landscape features across five European sites. *Ecol. Ind.* 94, 74–86.
- Paracchini, M.L., Zulian, G., Kopperoinen, L., Maes, J., Schägner, J.P., Termansen, M., Zandersen, M., Perez-Soba, M., Scholefield, P.A., Bidoglio, G., 2014. Mapping cultural ecosystem services: a framework to assess the potential for outdoor recreation across the EU. *Ecol. Ind.* 45, 371–385.
- Parsons, G.R., 2003. The travel cost model. In: *A Primer on NonMarket Valuation*. Springer, Dordrecht, pp. 269–329.
- Parsons, G., Leggett, C.G., Herriges, J., Boyle, K., Bockstael, N., Chen, Z., 2021. A site-portfolio model for multiple-destination recreation trips: valuing trips to national parks in the Southwestern United States. *J. Assoc. Environ. Resour. Econ.* 8 (1), 1–25.
- Quesnel Seipp, K., Maurer, T., Elias, M., Saksa, P., Keske, C., Oleson, K., Ego, B., Cleveland, R., Nyelele, C., Goncalves, N., Hemes, K., Wyrsc, P., Lewis, D., Chung, M.G., Guo, H., Conklin, M., Bales, R., 2023. A multi-benefit framework for funding forest management in fire-driven ecosystems across the Western US. *J. Environ. Manage.* 344, 118270.
- R Core Team, 2022. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria <http://www.R-project.org/>.
- Rashidi, T.H., Abbasi, A., Maghrebi, M., Hasan, S., Waller, T.S., 2017. Exploring the capacity of social media data for modelling travel behaviour: Opportunities and challenges. *Transp. Res. Part C: Emerg. Technol.* 75, 197–211.

- Remme, R.P., Frumkin, H., Guerry, A.D., King, A.C., Mandl, L., Sarabu, C., Bratman, G. N., Giles-Corti, B., Hamel, P., Han, B., Hicks, J.L., James, P., Lawler, J.J., Lindahl, T., Liu, H., Lu, Y.i., Oosterbroek, B., Paudel, B., Sallis, J.F., Schipperijn, J., Sosic, R., de Vries, S., Wheeler, B.W., Wood, S.A., Wu, T., Daily, G.C., 2021. An ecosystem service perspective on urban nature, physical activity, and health. *Proc. Natl. Acad. Sci.* 118 (22).
- Richards, D.R., Friess, D.A., 2015. A rapid indicator of cultural ecosystem service usage at a fine spatial scale: content analysis of social media photographs. *Ecol. Ind.* 53, 187–195.
- Richards, D.R., Tunçer, B., 2018. Using image recognition to automate assessment of cultural ecosystem services from social media photographs. *Ecosyst. Serv.* 31, 318–325.
- Rogers, A.A., Dempster, F.L., Hawkins, J.I., Johnston, R.J., Boxall, P.C., Rolfe, J., Kragt, M.E., Burton, M.P., Pannell, D.J., 2019. Valuing non-market economic impacts from natural hazards. *Nat. Hazards* 99 (2), 1131–1161.
- Rosenberger, R.S., 2018. Oregon Outdoor Recreation Metrics: Health, Physical Activity, and Value. Total Net Economic Value from Residents' Outdoor Recreation Participation in Oregon. Oregon State University, College of Forestry.
- Rosenberger, R.S., Loomis, J.B., 1999. The value of ranch open space to tourists: combining observed and contingent behavior data. *Growth Chang.* 30 (3), 366–383.
- Ruiz-Frau, A., Ospina-Alvarez, A., Villasante, S., Pita, P., Maya-Jariego, I., de Juan, S., 2020. Using graph theory and social media data to assess cultural ecosystem services in coastal areas: method development and application. *Ecosyst. Serv.* 45, 101176.
- Russell, R., Guerry, A.D., Balvanera, P., Gould, R.K., Basurto, X., Chan, K.M.A., Klain, S., Levine, J., Tam, J., 2013. Humans and nature: how knowing and experiencing nature affect well-being. *Annu. Rev. Env. Resour.* 38 (1), 473–502.
- Sánchez, J.J., Marcos-Martinez, R., Srivastava, L., Soonsawad, N., 2021. Valuing the impacts of forest disturbances on ecosystem services: An examination of recreation and climate regulation services in US national forests. *Trees Forests People* 5, 100123.
- Sandifer, P.A., Sutton-Grier, A.E., Ward, B.P., 2015. Exploring connections among nature, biodiversity, ecosystem services, and human health and well-being: Opportunities to enhance health and biodiversity conservation. *Ecosyst. Serv.* 12, 1–15.
- Sardana, K., Bergstrom, J.C., Bowker, J.M., 2016. Valuing setting-based recreation for selected visitors to national forests in the southern United States. *J. Environ. Manage.* 183, 972–979.
- Shoam, A., 2021. What Ever Happened to Flickr? Retrieved March 2, 2022, from <https://www.techspot.com/article/2384-flickr/>.
- Shrestha, R.K., Stein, T.V., Clark, J., 2007. Valuing nature-based recreation in public natural areas of the Apalachicola River region, Florida. *J. Environ. Manag.* 85 (4), 977–985.
- Sierra Nevada Conservancy, 2021. Tahoe-Central Sierra Initiative. Retrieved November 5, 2021, from <https://sierranevada.ca.gov/what-we-do/tcsi/>.
- Sinclair, M., Ghermandi, A., Sheela, A.M., 2018. A crowdsourced valuation of recreational ecosystem services using social media data: An application to a tropical wetland in India. *Sci. Total Environ.* 642, 356–365.
- Sinclair, M., Mayer, M., Woltering, M., Ghermandi, A., 2020. Valuing nature-based recreation using a crowdsourced travel cost method: A comparison to onsite survey data and value transfer. *Ecosyst. Serv.* 45, 101165.
- Smith, A., Anderson, M., 2018. Social media use in 2018. Pew Research Center. Retrieved March 5, 2022, from www.pewinternet.org/2018/03/01/social-media-use-in-2018/.
- Smith, V.K., Desvousges, W.H., McGivney, M.P., 1983. The opportunity cost of travel time in recreation demand models. *Land Econ.* 59 (3), 259–278.
- Sonter, L.J., Watson, K.B., Wood, S.A., Ricketts, T.H., Yang, J., 2016. Spatial and temporal dynamics and value of nature-based recreation, estimated via social media. *PLoS One* 11 (9), e0162372.
- Teles da Mota, V., Pickering, C., 2020. Using social media to assess nature-based tourism: Current research and future trends. *J. Outdoor Recreat. Tour.* 30, 100295.
- Toivonen, T., Heikinheimo, V., Fink, C., Hausmann, A., Hiiippala, T., Järvi, O., Tenkanen, H., Di Minin, E., 2019. Social media data for conservation science: A methodological overview. *Biol. Conserv.* 233, 298–315.
- US Census Bureau, 2020. Cartographic Boundary Files – Shapefile. Retrieved March 3, 2022, from <https://www.census.gov/geographies/mapping-files/time-series/geo/cartographic-boundary.2020.html>.
- US Census Bureau, 2021. Current versus Constant (or Real) Dollars. Retrieved January 21st, 2021, from <https://www.census.gov/topics/income-poverty/income/guidance/current-vs-constant-dollars.html>.
- Ward, F.A., Loomis, J.B., 1986. The travel cost demand model as an environmental policy assessment tool: a review of literature. *West. J. Agric. Econ.* 164–178.
- White, E.M., Bergerson, T.R., Hinman, E.T., 2020. Research note: Quick assessment of recreation use and experience in the immediate aftermath of wildfire in a desert river canyon. *J. Outdoor Recreat. Tour.* 29, 100251.
- Wolsko, C., Lindberg, K., Reese, R., 2019. Nature-based physical recreation leads to psychological well-being: Evidence from five studies. *Ecopsychology* 11 (4), 222–235.
- Wood, S.A., Guerry, A.D., Silver, J.M., Lacayo, M., 2013. Using social media to quantify nature-based tourism and recreation. *Sci. Rep.* 3 (1), 1–7.
- Wood, S.A., Winder, S.G., Lia, E.H., White, E.M., Crowley, C.S., Milnor, A.A., 2020. Next-generation visitation models using social media to estimate recreation on public lands. *Sci. Rep.* 10 (1), 1–12.
- Zhang, H., van Berkel, D., Howe, P.D., Miller, Z.D., Smith, J.W., 2021. Using social media to measure and map visitation to public lands in Utah. *Appl. Geogr.* 128, 102389.