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# Using social media data and machine learning to map recreational ecosystem services

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ABSTRACT

Crowdsourced geotagged social media data and machine learning approaches have emerged as promising tools for mapping ecosystem services, especially cultural ecosystem services that are difficult to assess. Here, we use recreation to show how social media data, machine learning, and spatial analysis techniques can improve our understanding of human-nature interactions and the mapping of recreational ecosystem services. We extracted 80,500 photographs taken in non-urban areas of the Tahoe Central Sierra Initiative project area in California between 2005 and 2019 that were posted to the photo sharing application Flickr and used these as a proxy for recreational visits to the area. Automated image content analysis was used to identify the objects and concepts in the photographs and uncover the types of nature experiences that are important to visitors. Additionally, variable importance, a Random Forest machine learning technique, was used to examine the environmental and landscape variables that drive recreation in the area and to create a classification model that predicts the recreation potential of the entire area based on important variables. The automated image content analysis identified 1,239 unique labels linked to recreation, with mountains, hills, and rocks being the most prominent features (22%). Our Random Forest model indicates that vegetation cover, land cover, elevation, smoke days, and landscape features are major drivers of recreation in the area and are of interest to visitors in the area. The model predicted that 25.9% of the area has the potential to support recreational visits. Most of these recreation potential areas are in protected areas (77.8%), predominantly in conifer forests (66%) and within national forest boundaries, especially the Tahoe National Forest area (37.6%). These results show that recreational ecosystem services vary across landscapes and illustrate the need for improved mapping approaches to determine the provision of ecosystem services in different places. The analysis provides novel insights into the various ways social media data and machine learning techniques can be powerful components of ecosystem service research and how they hold great potential for monitoring and informing management interventions on ecosystem service provision, especially in places with limited traditional onsite visitation data.

## 1. Introduction

Human well-being depends on natural capital for important services including fertile soil, fresh water, pollination, flood protection, and climate regulation (Maes et al., 2016; Remme et al., 2021; Daily, 2021; Bratman et al., 2019; Wolsko et al., 2019; Estoque et al., 2021). Mapping is essential to understanding how ecosystems contribute to human well-being and to support policies as well as adaptation strategies to pressures such as land use and climate change (Guo et al., 2023; Burkhard and Maes, 2017; Zhao et al., 2015; Daily and Ruckelshaus, 2022; Dasgupta, 2021). Although quantitative studies of ecosystem services have rapidly grown in recent years, cultural ecosystem services including, nature-based recreation, i.e., recreation that occurs in and depends on the natural environment, are underrepresented in the literature compared to provisioning and regulatory services. In addition to contributing to the well-being of residents and tourists alike, nature-based recreation plays a significant role in national, statewide, and surrounding local economies. However, recreation managers

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frequently lack basic information on the amount and extent of recreation use, especially at large spatial scales (McDaniel et al., 2021; Manley and Egoh, 2022; Karasov et al., 2020; Tew et al., 2019; Mayer and Woltering., 2018; Lee et al., 2019; Sinclair et al., 2018; Sinclair et al., 2020; Zhang et al., 2021; Hermes et al., 2018; Yoshimura and Hiura, 2017; Cheng et al 2019; Kosanic and Petzold, 2020; Morse et al., 2022). This is a key gap that can be filled in by studies that expand ecosystem service modeling capabilities to rapidly assess the inherent properties of landscapes, how people interact with their environment, and their preferred nature-based experiences (Rossi et al., 2020; Ghermandi et al., 2020).

Due to the subjectivity and intangibility of these cultural services, most studies rely on human interpretation and perception of ecosystems, societal context, individual values, and often the presence of beneficiaries in the physical environment (Guerrero et al., 2016; Tenerelli et al., 2016). As a result, visitation rates, prominent touristic sites, and other proxies are commonly regarded as comprehensive indicators of these cultural ecosystem services (Gosal et al., 2021; Nigussie et al., 2021; Havinga et al., 2020; Tiemann and Ring, 2022; Karasov et al., 2022; Hausmann et al., 2019). For nature-based recreation, most mapping and assessment tools rely on traditional administrative data and direct observations on the number and character of visitors, as well as the spatial and temporal extent of recreational activities (McDaniel et al., 2021; Wood et al., 2020; Oteros-Rozas et al., 2018; Hegetschweiler et al., 2022; Wilkins et al., 2021; Zhang et al., 2021; Wartmann et al., 2021; Wang et al., 2022; Llanos-Paez and Acuña, 2022). However, such conventional methods are limited in that they can be costly and have not always led to a deeper understanding of important cultural ecosystem services and the contribution of the natural environment to those services, as they are usually site specific, time consuming, and limited in both spatial coverage and content richness. Although a myriad of indicators can be used in research, depending on the objective of the study, most of these indicators do not necessarily capture both the biophysical and social aspects of the service (Manley and Egoh, 2022). This leads to greater uncertainty due to oversimplifications and generalizations of the nonlinear dynamics of ecosystem services. There is therefore an urgent need for studies that improve and spatially refine existing mapping approaches to fill in key data and methodological gaps associated with mapping socio-ecological systems, refine indicators for mapping ecosystem services, and improve our understanding, estimation, and reporting of model uncertainties.

Recently, technological advancements in social media, mobile networks, and smartphone technologies have created many streams of data and possibilities to address the data and research gaps in mapping cultural ecosystem services. Billions of posts, including text, videos, and geotagged photographs, with a wealth of spatial and temporal metadata of previously unavailable valuable beneficiary information on human-nature interactions, attitudes, and perceptions of nature based experiences from millions of users are uploaded to social media platforms such as Facebook, Twitter, and Instagram every year, revolutionizing ecosystem service research and ecological assessments (Toivonen et al., 2019; Cheng et al., 2019; Cardoso et al., 2021; Ruiz-Frau et al., 2020; Mouttaki et al., 2021; Manley and Egoh, 2022; Wilkins et al., 2021; Zhang et al., 2021; Havinga et al., 2020; Wood et al., 2020; McDaniel et al., 2021). Although data mining on social media platforms is a fast, large scale, and highly resource efficient source of data with the potential to inform estimates of visitation and improve our ability to assess rapid changes in ecosystems and their use at fine spatial and temporal resolutions compared to traditional monitoring systems, particularly in areas considered too costly or difficult for traditional monitoring, few studies have utilized this valuable resource. For example, several studies on recreation (Hamstead et al., 2018; Mouttaki et al., 2021; Manley and Egoh, 2022; Ciesielski and Stereńczak, 2021; Muñoz et al., 2020; Long et al., 2021; Karasov et al., 2022; Ghermandi, 2022; Richards and Lavorel, 2022) have used geotagged photographs from Flickr, a platform popular among nature photographers with over 90 million monthly active users (Ruiz-Frau et al., 2020) as a proxy for visitation. Some studies quantify the value of natural environments by predicting the spread of person-days of recreation measured from geotagged photographs posted to Flickr based on the locations of natural habitats and other features that factor into people's decisions about where to recreate (Sinclair et al., 2018; Lingua et al., 2022). For example, some indicators are focused on speculations that people love to go to mountains and water bodies such as lakes and rivers (and these have been used to map recreational services), but no evidence exists on which elements are most important for recreational activities. However, research in this area is still in its infancy, calling for more studies exploring the utility of big data and crowdsourced social media data for ecosystem service research.

While photo content analysis can be conducted manually, this is extremely time consuming (Cardoso et al., 2021; Cheng et al., 2019). New methodologies based on artificial intelligence and deep-learning approaches such as machine learning have emerged to potentially fill this gap, maximize the utility of crowdsourced data, and expand ecosystem service modeling capabilities. Machine learning, for example, reduces data processing time and allows for the rapid processing of data, and one of its key strengths is that it can support the analysis of larger datasets than many conventional methods (Reichstein et al., 2019; Scowen et al., 2021; Ochoa and Urbina-Cardona, 2017; Lautenbach et al., 2019; Scowen et al., 2021; Manley and Egoh, 2022). Such advancements allow us to rapidly assess the inherent properties of landscapes, how people interact with their environment, and their preferred nature-based experiences (Rossi et al., 2020; Ghermandi et al., 2020). For example, machine learning algorithms for image analysis such as Google Cloud Vision facilitate the automatic description and classification of photo content (Willcock, et al., 2018; Richards and Tunçer, 2018; Pal et al., 2020), but are rarely used in the ecosystem service literature. Additionally, algorithms such as Random Forest (a classification and regression tree) allow for the assessment of variable importance (i.e., predictive power) and the selection of relevant indicators for mapping ecosystem service provision (Scowen et al., 2021). Studies utilizing such information are still in their infancy, although they can help determine the factors that influence, for example, recreational visits, which is essential to understanding people's recreational values and crucial for planners and managers.

The main objective of this study is to use newly available techniques and data sources to improve ecosystem service modeling methods and reduce uncertainty in the mapping of cultural services. We specifically use recreational ecosystem services as an example to illustrate how crowdsourced social media data and machine learning can fill in key data and methodological gaps and help improve how we measure, map, and manage ecosystem services on public lands. Secondly, we aim to identify the key pointers and indicators influencing recreational activities that are useful for mapping the recreational potential of landscapes. Lastly, we seek to understand the extent to which California ecosystems, particularly protected areas, provide recreational services. We present a case study in California using visitation data from the photo sharing application Flickr, a Random Forest machine learning technique, automated image content analysis via Google Cloud Vision, environmental variables, and model-based analysis to assess the recreational ecosystem services in areas outside cities in the Tahoe Central Sierra Initiative (TCSI) project area. We use the locations of recreation users' social media posts to describe how their visits are distributed across the public lands in the TCSI and to evaluate nature-human interactions to uncover the types of nature experiences and unique qualities of landscapes that are important to recreational visitors. The novel approaches developed in this analysis will help land managers and decision makers answer critical questions related to factors influencing recreational visits, indicators for mapping the recreational potential of landscapes, and the impact of management and disturbance on nature-based recreation. Results of this study are crucial for informing the valuation of ecosystem services, improving mapping tools, and reducing uncertainty in the mapping of important areas for recreation. Although we focus on

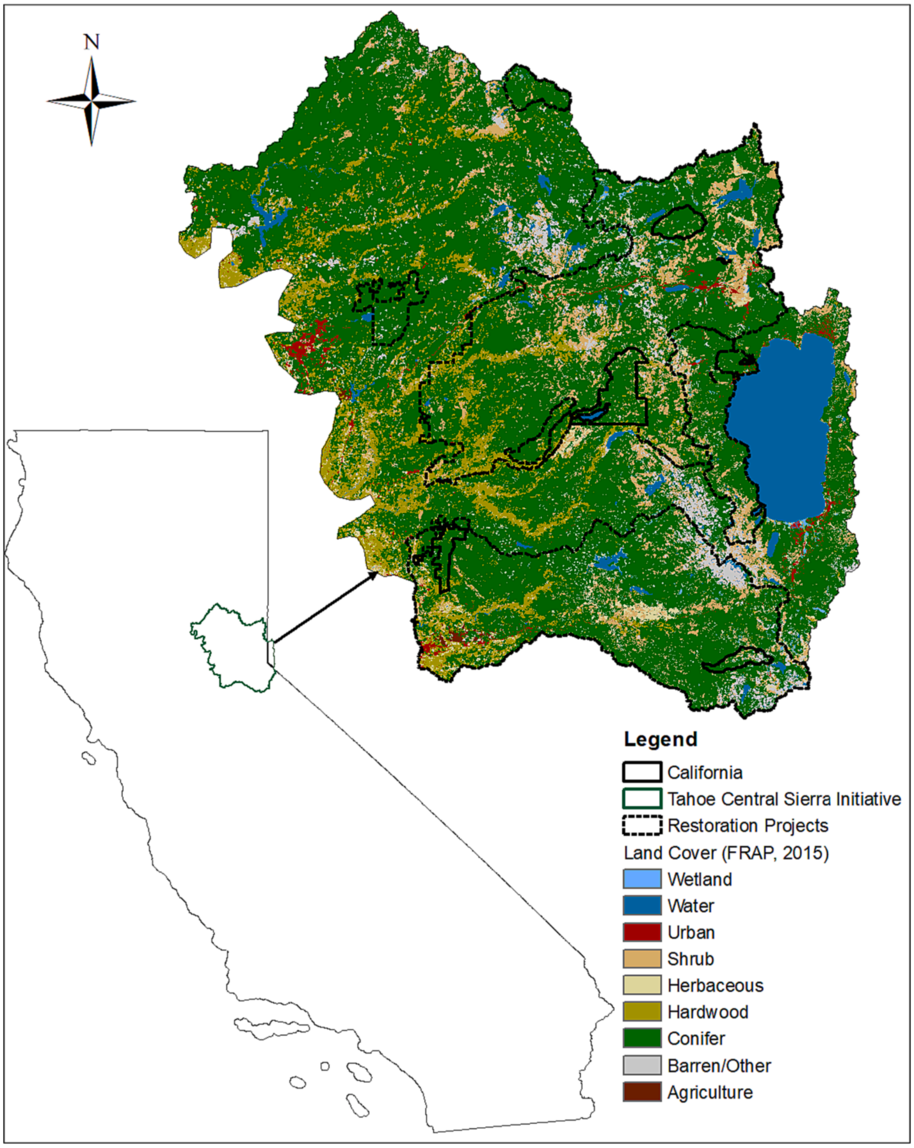


**Fig. 1.** Location as well as land cover characteristics of the Tahoe Central Sierra Initiative and forest restoration projects being undertaken in the state of California.

recreational ecosystem services, the methods developed in this study can also be used for identifying other ecosystem services, including provisioning and regulating services across various scales and management contexts.

## 2. Materials and methods

### 2.1. Study area

Within the Sierran Steppe-Mixed Forest-Coniferous Forest-Alp ecoregion of the Sierra Nevada lies the TCSI (Fig. 1), a pioneering 9,700 $km^2$ landscape-level forest restoration effort under the Sierra Nevada Watershed Improvement Program (California Tahoe Conservancy, 2019). The initiative 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). A healthy forest is expected to decrease the risk of severe, high-intensity wildfires, and lead to other desirable environmental outcomes, and improve, among other benefits, the recreational potential of the natural areas. Based on the California Department of Forestry and Fire Protection (CALFIRE) Fire and Resource Assessment Program (FRAP) (2015) land cover dataset (Fig. 1), the TCSI is predominantly conifer forest (68.2%). Hardwood forests, shrublands, and water make up 8.8%, 8.5%, and 6.6% of the area, respectively. A smaller proportion of the area is categorized as barren (4.1%), herbaceous (2.1%), urban (1.1%), wetland (0.4%), and agricultural land (0.2%). Six watersheds fall within the TCSI area, namely Yuba, Truckee, Lake Tahoe Basin, Upper Bear, North Fork American, and South Fork American. These forested watersheds contain large amounts of carbon, produce substantial amounts of wood products and clean energy, provide significant fish and wildlife habitat, and are a recreational playground for millions of visitors all year-round (Sierra Nevada Conservancy, 2021). For example, recreation is the foundation of Lake Tahoe Basin's $5 billion economy (Sierra Nevada Alliance, 2021). Lake Tahoe's crystal blue waters and snow-capped mountains draw an estimated 8 to 14 million annual visitors each year (Tahoe Regional Planning Agency, 2021; The Sierra Nevada Ally, 2021; California Tahoe Conservancy, 2021). The United States Department of Agriculture (USDA) Forest Service estimates that over 10.8 million people visit national forests located in the TCSI area (Tahoe National Forest, Eldorado National Forest, Plumas National Forest, and the Lake Tahoe Basin Management Unit) to recreate annually. These visitors

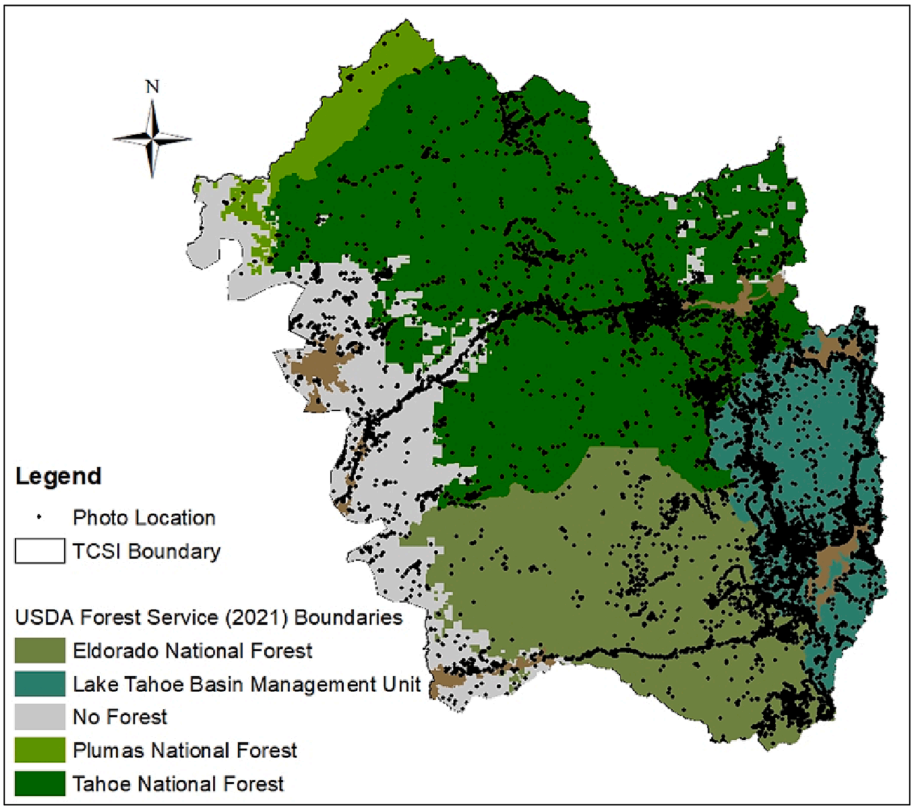


**Fig. 2.** Spatial distribution of Flickr photographs considered in the dataset for each USDA Forest Service national forest region within the TCSI (n = 80,500).

spend about $1.18 billion during their trips and contribute more than $828 million towards the wages and income of local businesses (USDA Forest Service, 2020a; USDA Forest Service, 2020b; USDA Forest Service, 2020c; USDA Forest Service, 2020d). Thus, our case study is a relevant baseline to characterize the current provision of ecosystem services such as nature-based recreation in the area that is home to approximately 200,000 people located in and around the ten cities within the TCSI boundary (Tahoe Truckee Community Foundation, 2020).

## 2.2. Data collection

### 2.2.1. Obtaining visitation data from Flickr

Flickr photographs taken between 1 January 2005 and 31 December 2019 in the TCSI were retrieved by querying the Flickr Application Programming Interface (API) using Python scripts. An API is an interface that developers can access to perform various tasks, which also enables different applications to communicate with each other (Robillard, 2009). 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 specifically used the dates the photographs were taken and a bounding box of coordinates defining the boundary of the TCSI to search for all geolocated posts (based on the latitude and longitude associated with each photograph). We chose Flickr because of easy access to public content through its API. Additionally, Wood et al. (2013) observed that the number of recreators 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. We excluded urban areas from the analysis to estimate recreational visits in natural landscapes outside cities. To do this, we filtered the resulting Flickr records using a United States Census Bureau (2021) urban area shapefile to discard any photographs taken within an urban area. This retained a unique dataset of photographs taken in the non-urban areas of the TCSI area, which were then downloaded along with their metadata. The data downloaded included the location, date, and time the photograph was taken, as well as the web address of the web page containing the photograph and details about the photographer, including their unique identifier and origin based on the location listed on their online profiles. Fig. 2 shows the spatial distribution of the photographs considered in the study and their locations across the USDA Forest Service national forest boundaries (USDA Forest Service, 2021) in the TCSI.

### 2.2.2. Selection of environmental variables

Understanding how different landscape features contribute to ecosystem service provision is essential for management and planning. It is assumed that the potential of a landscape to provide recreational opportunities is a function of its attractiveness to people (Schirpke et al., 2018; Mitchell et al., 2021). To understand the environmental features that might contribute to this aesthetic appeal and to assess the importance of different variables in influencing recreational activities in the TCSI focal area, potential explanatory variables considered to factor into people's decisions about where to recreate were identified from the literature. This includes studies by Scholte et al. (2018), Oteros-Rozas et al. (2018), Paracchini et al. (2014), Grêt-Regamey et al. (2015), Egoh et al. (2012), Casado-Arzuaga et al. (2014), and Zulian et al. (2013). These variables include characteristics of both the biophysical environment, such as vegetation cover, and infrastructure, such as roads, that promote the recreational opportunity of landscapes, as well as a series of site and context-specific variables. Our variables of interest included: land cover types; habitat diversity; vegetation and forest cover; number of smoke days; elevation; presence and distance to access routes (roads, rail, and trails); presence of flowers, recreational sites, protected areas, and parks; population density; and presence and proportion of water (lakes and other water bodies). Appendix Table 1 lists all datasets used in the analysis along with their sources. After downloading the necessary datasets for the study area, spatial analysis techniques, including the zonal tool in Geographic Information System

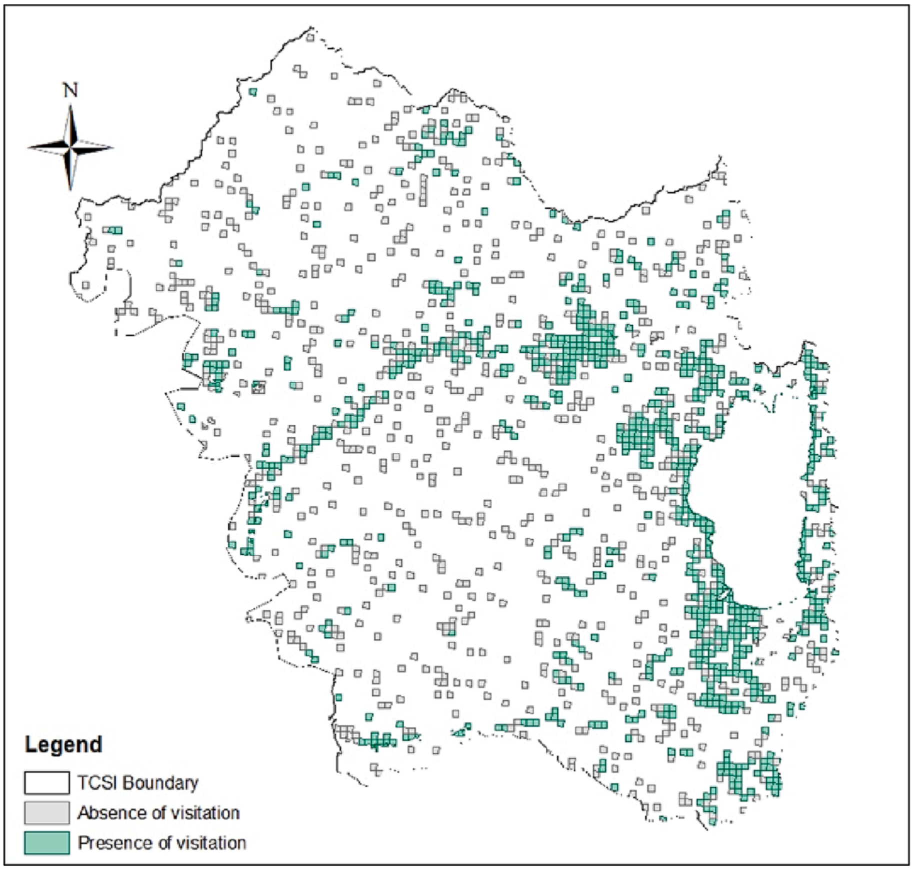


**Fig. 3.** Presence and absence of visitation in the TCSI in 2012.

software ArcMap® (version 10.3), were used to summarize the data layers and the Flickr visitation data across one-kilometer grids of the study area created using the ArcGIS geoprocessing tool (https://pro.arcgis.com/).

### 2.3. Data analysis

#### 2.3.1. Automated image content analysis using Google Cloud Vision API

To uncover the types of nature experiences and unique ecosystems, wildlife, and scenic qualities of landscapes that are important to recreational visitors in the TCSI, we used the automated content analysis tool, Google Cloud Vision (https://cloud.google.com/vision). Google Cloud Vision is a machine learning algorithm with the ability to detect broad sets of categories within an image, including labels, text, faces, landmarks, logos, and image properties, but it is rarely used in ecosystem service research. In our analysis, this was useful for identifying the types of nature most photographed by visitors to the TCSI and useful for mapping hotspots of different categories of human-nature interactions across different landscapes. For each Flickr photograph downloaded for the TCSI, we extracted the web address of the photograph from the metadata and then passed this web address to the Google Cloud Vision API label detection function using the R package 'googleCloudVisionR' (Pal et al., 2020). The API returned a list of labels for each photograph and a confidence score, which ranges from 0 (no confidence) to 1 (very high confidence) associated with each label. Following Runge et al. (2020), we limited our analysis to any labels with a score of 0.6 or higher up to a maximum of 20 labels for each photograph (the median number of labels per photograph in our dataset is 20). Our analysis focuses on nature-based recreation, i.e., recreational activities involving physical and experiential interactions with the natural environment (Cortinovis et al., 2018). As such, we excluded labels associated with the built environment or agricultural activities, including those depicting agricultural crops, food, plantations, and livestock. We manually categorized all labels and classified them into ten categories that depict: 1) trees; 2) other vegetation types; 3) accessibility; 4) wildlife; 5) rocks, hills, and mountains; 6) water; 7) recreational activities; 8) accommodation; 9) general landscape features; and 10) attractions (Appendix Table 2). To assess the performance and consistency of the classification criteria of Google Cloud Vision as well as to reduce the subjectivity associated with content analysis, we performed manual content analysis on a random sample of 385 photographs determined using the Cochran formula (Cochran, 1963; Israel, 1992) to evaluate Google Cloud Vision's performance in identifying labels from photographs. Cohen's Kappa coefficient (Cohen, 1960) via the R package 'irr' (Gamer et al., 2012) was used to assess the level of agreement between the manual coding and Google Cloud Vision derived labels.

#### 2.3.2. Environmental variable analysis using machine learning

The resolution of the geotagged photographs can be leveraged to assess the importance of different variables in influencing recreational activities in the area. Here, we used the non-urban Flickr records for 2012, one of the years with the highest visitation (n = 8,350), in combination with the potential explanatory environmental and landscape variables considered to factor into people's decisions about where to recreate and those that might contribute to the potential of a landscape to provide opportunities for recreation identified from the literature (see list in Appendix Table 1). First, we examined these candidate variables for correlation and ran collinearity diagnostics to detect and filter highly correlated variables. Collinearity, a situation where two variables have near perfect linear combinations of one another, and multicollinearity, which involves more than two variables, make it difficult to come up with reliable estimates of the individual coefficients and potentially

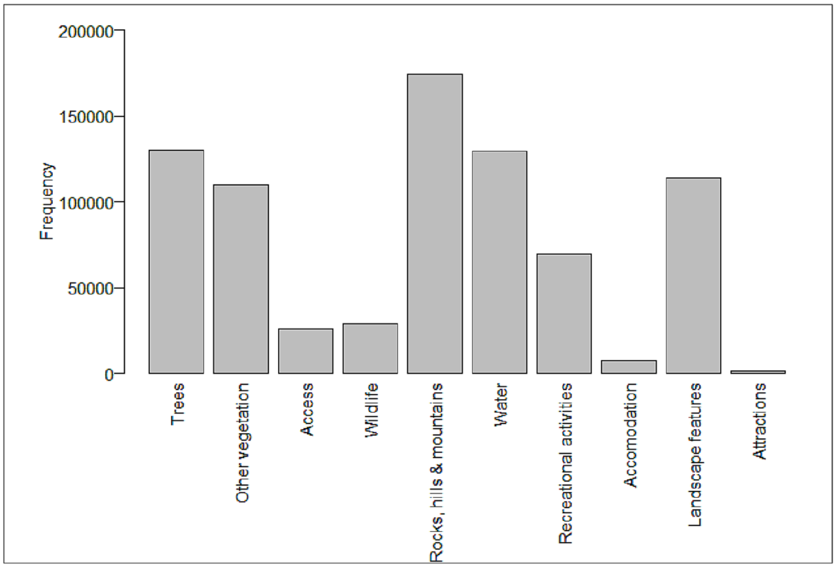


**Fig. 4.** Classification of important objects and landscape features associated with recreation in the TCSI.

result in incorrect conclusions about the relationship between outcome and predictor variables (Hebbali, 2020). We used the 'olsrr' package in R (Hebbali, 2020) to measure the presence of collinearity and multicollinearity. We specifically examined the correlation matrix for predictor variables that correlate highly and computed the Variance Inflation Factor (VIF), a measure of how much the variance of the estimated regression coefficient is inflated by the existence of correlation among the predictor variables in the model. We also estimated the tolerance statistic, which quantifies the percentage of variance in the predictor that cannot be accounted for by other predictors, and computed Eigenvalues, which show the variance of each linear combination. Variables that were found to be highly correlated were removed from the analysis.

Based on the 2012 presence and absence of visitation data from Flickr for each 1 km grid (Fig. 3) and the spatial layers of the explanatory variables, the Forest-based Classification and Regression toolset in ArcGIS Pro was used to train and construct a classification model for predicting the presence or absence of recreational visits in different areas based on the associated explanatory variables. We specifically left out the area covered by Lake Tahoe and focused on 875 grids that had visitation and an equal number of randomly selected grids that had no visitation. The Forest-based Classification and Regression tool utilizes Random Forest, a supervised machine learning method that uses predefined input-output pairs to train a model and derive outputs based on the known values provided as part of a training dataset (ESRI, 2021). Unlike in unsupervised learning processes where there is no specific feedback supplied for input data and the machine learning algorithm detects patterns, in supervised learning, the user specifies which variables (i.e., outputs) are considered dependent on others (i.e., inputs) (Hastie et al., 2009; Mjolsness and DeCoste, 2001). Random Forest has been shown to perform comparatively as well as traditional spatial methods and is effective at solving spatial problems (Breiman, 2001; Fox et al., 2020; Manley and Egoh, 2022). For example, Manley and Egoh (2022) used social media data from Flickr along with social and biophysical data to create a Random Forest regression model that connects the summer demand for recreational ecosystem services to social, environmental, and climate variables in California. Random Forest can also handle many predictors, is robust to correlated explanatory variables, and allows for varying functional relationships between the predictor and response variables (Larson et al., 2018). In addition to being a data driven model that can model without making a priori assumptions about the input data, the Random Forest algorithm adds a large amount of randomness into the regression analysis and effectively avoids model overfitting (Manley and Egoh, 2022; Willcock et al., 2018; Rammer and Seidl, 2019; Scowen et al., 2021). This is a key advantage of the algorithm for our analysis, considering that recreation is based upon a large set of complexly interacting variables, which makes it vulnerable to overfitting.

#### 2.3.3. *Making predictions about visitation in the TCSI*

After training a Random Forest model and assessing its accuracy, it can then be used to generate predictions of unknown values in a dataset that has the same associated explanatory variables (ESRI, 2021). In the Forest-based Classification and Regression toolset, predictions can be performed for both categorical variables (classification) and continuous variables (regression). In addition, the toolset also calculates the importance of each explanatory variable to the model and reports variables with the top twenty importance scores, helping us better understand which variables drive the results of the model. We trained and assessed various classification models based on the presence and absence of visitation data (Fig. 3), as well as the potential explanatory variables of visitation (Appendix Table 1), in the Forest-based Classification and Regression toolset before selecting the best classification model. The best model was then used in predict mode to map the recreational potential of different areas in the TCSI for recreational visits (i.e., the presence or absence of recreational visits). This was achieved by assigning the same explanatory variables used to train the model to all grid locations in the TCSI.

## 3. Results

The analysis was able to illustrate how crowdsourced geotagged data from Flickr and machine learning techniques, together with environmental variables and model-based analysis, can be used to support assessments looking at cultural ecosystem services such as recreation in natural lands. The following sections present results for the various analyses undertaken to illustrate how these approaches can be leveraged to identify the types of nature experiences and unique qualities of landscapes that are important to recreational visitors, identify key variables influencing recreational activities in the TCSI that are useful for mapping the recreational potential of natural lands, and illustrate the recreation potential of natural lands in the TCSI.

**Table 1**
Variable Importance table of key indicators of recreation in the TCSI.

| Variable | Importance | Percentage (%) |
|---|---|---|
| Variety of Existing Vegetation Cover | 7.22 | 11 |
| Variety of Land Cover | 7.18 | 11 |
| Majority Existing Vegetation Cover | 5.50 | 9 |
| Elevation | 4.79 | 7 |
| Distance to Rail | 4.76 | 7 |
| Number of Smoke Days | 4.73 | 7 |
| Percentage of Forest | 4.10 | 6 |
| Main Land Cover | 4.10 | 6 |
| Population Density | 4.08 | 6 |
| Distance to Trails | 3.91 | 6 |
| Distance to Roads | 3.33 | 5 |
| Percentage of Water | 1.92 | 3 |
| Presence of Protected Areas | 1.64 | 3 |
| Presence of Water | 1.61 | 3 |
| Presence of Access Routes | 1.54 | 2 |
| Number of Recreational Opportunities | 1.49 | 2 |
| Presence of Parks | 1.14 | 2 |
| Presence of Recreational Opportunities | 0.82 | 1 |
| Presence of Forests | 0.17 | 0 |

### *3.1. Distribution of Flickr photographs taken in the TCSI*

Our analysis retained a unique dataset of 80,500 photographs taken in non-urban areas of the TCSI area uploaded by approximately 5,000 users. The median number of photographs taken by each photographer was 3, and 86% of photographers uploaded fewer than 20 photographs. The maximum number of photographs uploaded by a single photographer was 8,244 (only 4 photographers uploaded more than 1,000 photographs). From the spatial distribution of the photographs (Fig. 2), it can be observed that there is some clustering of the photographs, for example, at focal points and along linear features such as access routes.

### *3.2. Nature experiences and unique qualities of landscapes that are important to visitors from image content analysis*

The Google Cloud Vision algorithm was able to access 80,050 photographs and assign 4,561 unique labels to them. These labels included descriptors of physical objects (e.g., 'tree', 'woody plant', and 'water'), activities (e.g., 'skiing', 'hiking', and 'backpacking'), and concepts such as 'leisure' and 'fun'. Of all labels, only 1,239 were linked to recreation. Fig. 4 shows the 1,239 labels summarized across the ten categories described in Appendix Table 2 for all photographs (up to a maximum of 20 labels each). For each category, the top five labels obtained from the analysis are illustrated in the table. Overall, photographs depicting mountains, hills, and rocks had the greatest percentage contribution to labels retrieved (22%), followed by those focusing on trees (16%), water (16%), general landscape views (14%), and other vegetation (14%).

Cohen's Kappa resulted in a good agreement (93%) between the manual coding and Google Cloud Vision derived labels (Kappa statistic = 0.918), indicating that Google Cloud Vision automatically describes and classifies photo content with a high level of accuracy.

### *3.3. Key environmental variables for mapping the recreational potential of natural lands*

Our multicollinearity tests yielded VIF values within tolerance (VIF less than 10 with a tolerance statistic not less than zero), and no presence of small eigenvalues (close to zero) which would have indicated

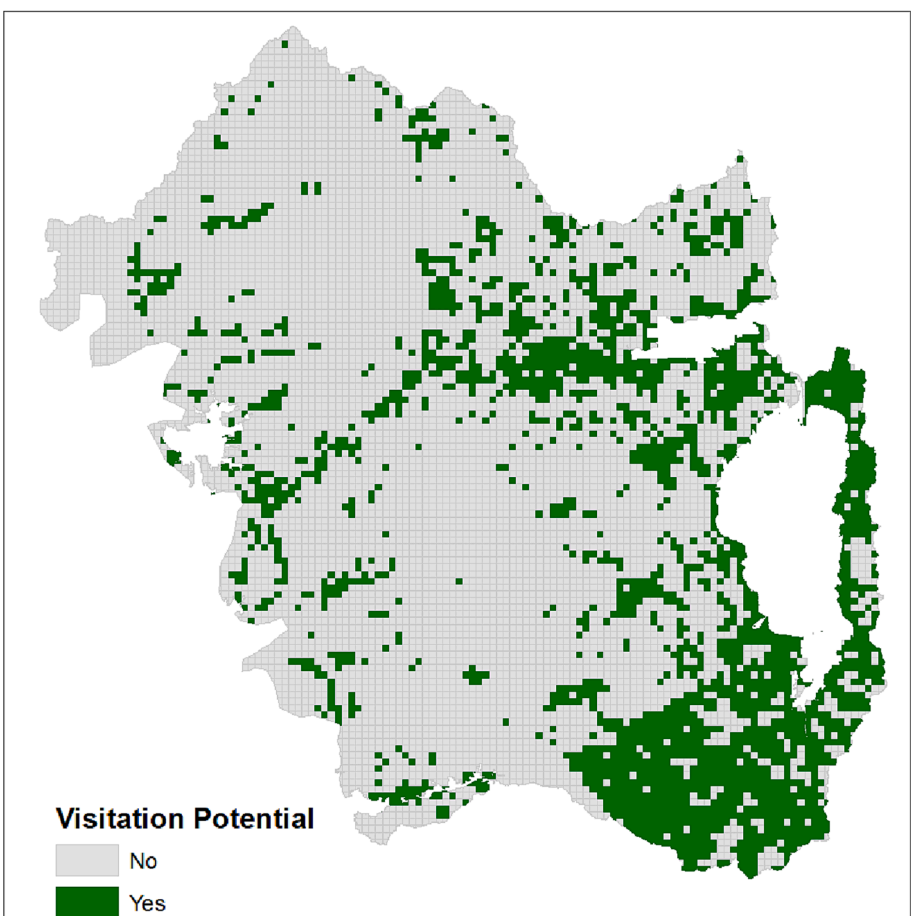


**Fig. 5.** Predicted recreational potential map for the TCSI from the Random Forest model.

multicollinearity. However, the pairwise correlations between the number of parks and presence of parks, majority existing vegetation cover and majority vegetation type, variety of existing vegetation type and variety of existing vegetation cover, change in smoke days, and number of smoke days were greater than 0.75, implying some degree of correlation. Our final classification model yielded an accuracy of 0.99 after filtering and was able to predict the presence and absence of recreational visits based on the given training dataset. After training the Random Forest model, results show that vegetation cover (both majority and variety) and variety of land cover types have the most predictive power. The number of smoke days, elevation, and distance to rail have also proven to be important factors in determining recreational visits in the TCSI. The top variables found to significantly affect the presence or absence of recreational visits to the TCSI are shown in Table 1. Variables with high "importance" are drivers of the outcome in the model, and their values have a significant impact on predicting the presence or absence of visitation in the TCSI. According to ESRI (2021), importance is calculated using Gini coefficients and can be thought of as the number of times a variable is responsible for a split in the decision tree and the impact of that split divided by the number of trees. The percentage (%) column highlights the percentage of the total sum of Gini coefficients for each variable.

### *3.4. Recreational potential of the TCSI's natural lands*

Our Random Forest classification model was able to predict the presence and absence of visitation in different areas across the TCSI (Fig. 5). Of the 9,531 1-km grids used in the analysis, 2,471 (25.9%) were predicted to have the potential to support recreational visits in the TCSI.

Most of the grids with high recreation potential are predominantly in protected areas (77.8%) listed in the California Protected Areas Database (GreenInfo Network, 2021). These high recreation potential areas are mainly located in conifer forests (66%), shrublands (13%), and barren lands (7%). A smaller proportion of the high recreation potential grids occur over hardwood forest (5%), water (5%), herbaceous cover (3%), and wetland (1%) land cover categories. Most of the grids predicted for recreational visits fall within the Tahoe National Forest (37.6%), Eldorado National Forest (33.4%), and Lake Tahoe Basin Management Unit (24.8%). Few grids are predicted for recreation in areas outside of USDA Forest Service national forest boundaries (11.4%) and Plumas National Forest (1.3%).

## 4. Discussion

We set out to explore the utility of crowdsourced social media data and machine learning techniques to improve our understanding and mapping of ecosystem services, particularly recreational ecosystem services in natural lands. Recently, there have been concerted efforts to utilize social media data and emerging artificial intelligence in assessing cultural ecosystem services such as recreation. Availability and access to crowdsourced data provide an opportunity to connect the biophysical and social aspects of ecosystem services, a key gap that has previously resulted in an incomplete understanding of the impacts of ecosystems and the ecosystem services they provide to human well-being (Manley and Egoh, 2022). Several studies, including Sonter et al. (2016), Arslan and Örücü (2021), Mancini et al. (2018), Richards and Tunçer (2018), Cheng et al. (2019), Cardoso et al. (2021), and Zhang et al. (2021), have used geo-tagged photographs from social media to understand the spatial patterns of nature-based recreational visits. However, as our analysis illustrates, there are other important possibilities besides mapping visitation that social media data offers to ecosystem service research that are yet to be tapped upon. For example, our study adds to the few studies that have included image content analysis to understand the unique qualities of the environment that are of most interest to people or sought to refine the indicators used for mapping the recreational potential of landscapes (Richards and Tunçer, 2018; Figueroa-Alfaro and Tang, 2017). This is particularly important for improving methods that reduce uncertainty in the mapping of ecosystem services. Non-market valuation approaches such as the travel cost method, for example, typically rely on limited administrative data and surveys to get visitation data (Nyelele et al., 2023; Bowker et al., 2009). As such, approaches such as ours that take advantage of emerging data sources and methodologies are critical in filling important gaps and expanding ecosystem service modeling capabilities to rapidly assess the inherent properties of landscapes, how people interact with their environment, and their preferred nature-based experiences (Rossi et al., 2020; Ghermandi et al., 2020). Additionally, algorithms such as Random Forest allow for the assessment and selection of relevant indicators for mapping ecosystem service provision (Scowen et al., 2021). Such information can help determine the factors that influence, for example, recreational visits, which is essential to understanding people's recreational values and crucial for planners and managers.

With growing demand for outdoor recreation and increasing pressure on parks and protected areas, such an analysis can be used to influence decision making around the management of natural areas for ecosystem service provision. Content analysis provides us an opportunity to look beyond photograph density in assessing the recreational potential of sites and instead explore people's preferences and features of the environment that attract their attention when they recreate. Our image content analysis shows that mountains, hills, and rocks were either more common, more noticeable, or of greater interest to the visitor community, followed by trees, water, and general landscape views of the area. This result is also mirrored in the results of the variable importance analysis, which identified vegetation cover, land cover, and elevation as some of the most important variables for predicting recreational visits. This is not surprising considering that the Sierra Nevada contains the headwaters of 24 major river basins, has higher elevations, and has a unique character of forests defined by tall trees, a relatively mild climate, and low forest density (Bales et al., 2011). Lake Tahoe, a year-round outdoor paradise, is not only one of the largest alpine lakes anywhere but is also one of the highest lakes, attracting hikers to its tall peaks (Freel Peak, Monument Peak, Pyramid Peak, and Mount Tallac) that offer a picturesque view of the lake below. Although these findings are in line with observations by van Zanten (2016) and Oteros-Rozas et al. (2018) that some of the best predictors of recreational value are geomorphological features such as hills and mountains, interestingly, few studies (Peña et al., 2015; Paracchini et al., 2014; Tenerelli et al., 2016; Weyland and Laterra, 2014) have included them as important determinants of recreational activity.

The variable importance analysis sought to identify key pointers and indicators influencing recreational activities that are useful for mapping the recreational potential of landscapes. Previous studies have used several indicators such as accessibility (e.g., proximity to roads), presence of recreational outdoor opportunities, scenic beauty, and visitor numbers to map recreational services (Schägner et al., 2016; Egoh et al., 2012; Byczek et al., 2018; Paracchini et al., 2014). Our variable importance results show that although these factors are important, heterogeneity may play a bigger role in choosing where to recreate. We found two factors associated with heterogeneity (variety of vegetation cover and variety of land cover types) to be the most important factors. Interestingly, Harrison et al. (2014) found a very strong relationship between recreational services and biodiversity, in particular species richness and abundance. However, very few studies have used species richness or vegetation richness as a proxy for mapping recreational services except in cases such as hunting and angling (Egoh et al., 2012; Villamagna et al., 2014; Grima et al., 2019). Although our image content analysis did not show accessibility as an important driver of recreation, similar to Paracchini et al. (2014) and mostly listed in Egoh et al. (2012), accessibility, specifically distance to rail, came up as an important variable in the variable importance analysis. Additionally, the spatial distribution of the photographs (Fig. 2) highlights that photograph locations follow a linear pattern, implying that areas along access routes, for example, roads, trails, and other paths, that are easily accessible are also easier to photograph. This is not surprising, as distance from roads and viewsheds has been used to map recreational services (Reyers et al., 2009; Karasov et al., 2020; Ihtimanski et al., 2020), implying that even though people prefer undisturbed and pristine areas, they cannot reach those areas without access routes. One of the most interesting results from the variable importance analysis is the importance of smoke days in predicting visitation. Climatic variables such as temperature, precipitation, and humidity, as well as air quality, are hardly included in mapping recreational services but are some of the most important aspects that people consider when going out. California is marred with frequent wildfires (Seipp et al., 2023), and smoke has increasingly become a fixture on the Western landscape, making recreational activities unattractive on certain days due to bad air quality linked to severe human health impacts and often resulting in forest and park closures. For example, Gellman et al. (2022) found that campers on public lands experience at least 400,000 days of wildfire smoke each year on public lands in the western USA. Such an analysis is helpful in identifying and refining important indicators for mapping certain services and reducing the uncertainty in our mapping approaches.

Random Forest allowed us to test and then use important explanatory variables shown to be influential in determining recreational activities in the TCSI to predict the presence or absence of recreational visitation in the area. Merrill et al. (2020) were also able to develop a Random Forest-based model to predict visitation to a range of water recreation areas using cellphone data and other explanatory variables in New England, USA. Manley and Egoh (2022) also demonstrate the effectiveness of Random Forest in predicting the impact of different environmental and climatic factors on recreational ecosystem services in California. Our focus was not on estimating absolute visitation numbers since our Flickr dataset does not capture all the recreational visits to the area. Instead, we focused on using social media-based visitation data and machine learning to determine whether an area within the TCSI has the potential to "host" recreational visits, given the unique characteristics of the landscape. It is interesting to note that while our classification and prediction model were based on 2012 Flickr visitation data, our predicted presence and absence of visitation map (Fig. 5) mimics the observed overall visitation patterns for 2005-2019 depicted on Fig. 2. This adds confidence to the accuracy of our model to predict areas that can support recreation based on the explanatory variables we used. Interestingly, most of the areas predicted to host recreational visits fall mainly within national forest boundaries and in protected areas. Such findings support calls for the conservation and protection of outstanding ecosystems to retain important functions for conserving valued species, habitats, and landscapes in their natural or semi-natural state. Our methodology and results can be used to highlight key areas that should be preserved for an array of conservation and cultural ecosystem services and benefits, including those related to recreation.

While the approach used in the analysis improves our understanding of recreational ecosystem services and demonstrates the utility of publicly available datasets and machine learning techniques in mapping cultural ecosystem services such as recreation, it is not without limitations. 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. To overcome this, we filtered photographs to focus on those taken in natural lands and looked at the image content to obtain labels related to nature-based recreation. Other studies (e.g., Schirpke et al., 2021; Hirahara, 2021) have overcome this limitation through text analysis of user generated tags from the photograph metadata or essays written by forest recreation participants to obtain deeper insights into people's experiences, preferences, or emotions related to cultural ecosystem services such as recreation. A further potential limitation of relying on social media data for proxy counts of visitation, more specifically a single photograph platform (Flickr), is 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 (Nyelele et al., 2023; Hausmann et al., 2019; Wood et al., 2013; Toivonen et al., 2019). Although Flickr is the most popular source of geotagged photographs for cultural ecosystem service research due to its global popularity and open API (Ruiz-Frau et al., 2020), 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 have restricted access through their APIs.

Additionally, Flickr has previously been validated as an effective proxy of visitation (Wood et al., 2013; Wood et al., 2020; Manley and Egoh, 2022), and thus we can deduce trends in the use and demand of ecosystem services based on the data. While we cannot completely rule out errors in the datasets and techniques used in our analysis, our accuracy assessment, specifically the weighted Cohen's Kappa agreement index between the manual and automated classification (93%), indicates a good result of the automated content analysis. It must be stressed that the particular focus of this study was to show a methodology that could be used in different areas where crowdsourced data, environmental data, and landscape data can be obtained and that may be applicable to other ecosystem services. Although our analysis and findings may be site specific, they can be extended to other areas and scales. This will help improve forest and land use management and decision making including the identification of focal areas for prioritizing management actions that improve ecosystem service provision. Our study has illustrated how the concurrent use of crowdsourced social media data and machine learning has great potential to close key data and methodological gaps in ecosystem service research by improving estimates of visitation and the ability to assess changes in recreation use.

Future work can build on this work and harness geotagged social media data from a variety of platforms and machine learning resources to improve estimates of visitation trends across space and time that can be used to inform assessments and management actions related to ecosystem service provision. There is also the potential to incorporate big data and social media data to study and improve the valuation of recreational ecosystem services, and other cultural ecosystem services as well as provisioning and regulating services across various scales and management contexts. This will be important in facilitating sustainable land use management and informing policy and decision making.

## 5. Conclusions

Using recreation as an example, this study provides novel insights into the variety of ways social media and machine learning can be used to improve the mapping of cultural ecosystem services that rely on visitation estimates, especially in places with limited traditional onsite visitation data. Results from the study reveal that recreational visits are related to a variety of environmental and landscape characteristics of the area, including vegetation cover, elevation, landforms, and smoke days. This supports the conclusion that recreational ecosystem services from natural lands are not the same across landscapes, and improved mapping approaches are needed to determine the provision of ecosystem services across landscapes. Additionally, the study has demonstrated how environmental and landscape variables deemed as important possible drivers of recreational visits can be used to map recreational potential in the absence of visitation data, filling in key data availability gaps in ecosystem service research. Furthermore, results from the image content analysis have helped us evaluate nature-human interactions to uncover the types of nature experiences and unique qualities of landscapes that are important to recreational visitors, providing us with an additional layer of information that has the potential to guide more decision-

**Table A1**
Description of environmental variables used in the analysis and their sources.

| Data | Description | Source |
|---|---|---|
| Existing Vegetation Types | Current distribution of the terrestrial ecological systems. | LANDFIRE, Earth Resources Observation and Science Center (EROS), U.S. Geological Survey (https://www.landfire.gov). |
| Land Cover Types | Land cover data depicting the spatial distribution of habitat types within California. | California Department of Forestry and Fire Protections CALFIRE Fire and Resource Assessment Program (CALFIRE-FRAP) (https://wildlife.ca.gov/Data/VegCAMP). |
| Existing Vegetation Cover | Vertically projected percent cover of the live canopy layer for a 30-m cell. | LANDFIRE, Earth Resources Observation and Science Center (EROS), U.S. Geological Survey (https://www.landfire.gov). |
| Change in Smoke Days | Change in the number of smoke days between two consecutive years as detected from satellite observations. | NOAA/NESDIS Satellite Analysis Branch's Hazard Mapping System (https://www.ospo.noaa.gov). |
| Distance to Rail | Distance to railroad features. | U.S. Geological Survey, National Geospatial Technical Operations Center USGS National Transportation Dataset (NTD) (https://www.usgs.gov/core-science-systems/national-geospatial-program/national-map). |
| Smoke Days | Presence and absence of smoke as well as number of smoke days detected from satellite observation. | NOAA/NESDIS Satellite Analysis Branch's Hazard Mapping System (https://www.ospo.noaa.gov). |
| Presence and number of access routes | Presence and absence of access features (roads, rail, trail etc.). | U.S. Geological Survey, National Geospatial Technical Operations Center USGS National Transportation Dataset (NTD) (https://www.usgs.gov/core-science-systems/national-geospatial-program/national-map) and U.S. Forest Service (https://data.fs.usda.gov/geodata/edw/datasets.php). |
| Elevation | Digital Elevation Model (DEM) representation of the bare ground (bare earth) topographic surface of the Earth. | United States Geological Survey (USGS) (https://www.usgs.gov/). |
| Proportion of Forest (%) | Proportion of area covered by forest. | California Department of Forestry and Fire Protections CALFIRE Fire and Resource Assessment Program (CALFIRE-FRAP) (https://wildlife.ca.gov/Data/VegCAMP). |
| Population Density | Number of people per unit of area (obtained at the census block group level). | U.S. Census Bureau (https://data.census.gov/cedsci/). |
| Distance to Trails | Distance to the National Forest System trail locations | U.S. Forest Service (https://data.fs.usda.gov/geodata/edw/datasets.php). |
| Presence of Flowers | Presence and absence of flowers in the area. | Consortium of California Herbaria Portal 2 (CCH2) (https://ucjeps.berkeley.edu/consortium). |
| Distance to Roads | Distance to road features. | U.S. Geological Survey, National Geospatial Technical Operations Center USGS National Transportation Dataset (NTD). (https://www.usgs.gov/core-science-systems/national-geospatial-program/national-map). |
| Recreational Opportunities | Recreational sites, areas, activities, and facilities available to visitors that the Forest Service collects through the Recreation Portal. | U.S. Forest Service (https://data.fs.usda.gov/geodata/edw/datasets.php). |
| Presence of Protected Areas | Presence and absence of lands that are owned in fee and protected for open space purposes by over 1,000 public agencies or non-profit organizations. | California Natural Resources Agency California Protected Areas Database (CPAD). (https://gis.cnra.ca.gov). |
| Proportion of Water (%) | Proportion of the area covered by water. | California Department of Forestry and Fire Protections CALFIRE Fire and Resource Assessment Program (CALFIRE-FRAP) (https://wildlife.ca.gov/Data/VegCAMP). |
| Presence or absence of Water | Presence and absence of water bodies such as rivers and lakes in area. | California Department of Forestry and Fire Protections CALFIRE Fire and Resource Assessment Program (CALFIRE-FRAP) (https://wildlife.ca.gov/Data/VegCAMP). |
| State parks | Presence and absence as well as number of parks in an area based on state park boundaries. | California State Parks Park Boundaries. (https://www.parks.ca.gov). |
| Habitat Types | Major habitat type and variety of types in the area | California Department of Forestry and Fire Protections CALFIRE Fire and Resource Assessment Program (CALFIRE-FRAP) (https://wildlife.ca.gov/Data/VegCAMP). |
| Presence of forests | Presence and absence of forests in the area | California Department of Forestry and Fire Protections CALFIRE Fire and Resource Assessment Program (CALFIRE-FRAP) (https://wildlife.ca.gov/Data/VegCAMP). |
| Fire | Active fires detected in an area each day | NOAA/NESDIS Satellite Analysis Branch's Hazard Mapping System (https://www.ospo.noaa.gov/) Monitoring Trends in Burn Severity (MTBS) (https://www.mtbs.gov). |
| Rare vegetation types | Vegetation types mapped and ranked as rare. | California Department of Fish and Wildlife (CDFW) https://wildlife.ca.gov/). |

making regarding areas to focus on for management action and forest restoration activities that enhance and protect the recreational opportunities that are important to visitors. Although the study is based on a prototype area, the TCSI, with a particular focus on non-urban areas, the methodological and conceptual approaches of this analysis can be used to advance the mapping of recreational ecosystem services as well as other ecosystem services and the planning and evaluation of priority action by leveraging on social media and machine learning approaches to improve ecosystem service provision, assessment, and mapping of ecosystem services in different landscapes.

## Declaration of Competing Interest

The authors declare that they have no known competing financial

**Table A2**
Prominent labels in each category.

| Category | Description | Top five labels |
|---|---|---|
| 1. Trees | Photographs focusing on trees | Tree, forest, larch, evergreen, woody plant |
| 2. Other vegetation | Photographs depicting vegetation other that trees | Plant, grass, plant community, grasslands, shrub |
| 3. Accessibility | Photographs of roads, rail, vegetated trails, and other features that facilitate access to places | Road, road surface, trail, thoroughfare, bridge |
| 4. Wildlife | Photographs highlighting the experiential use and enjoyment of wildlife | Wildlife, terrestrial animal, carnivore, vertebrate, fawn |
| 5. Rocks, hills, and mountains | Photographs of mountains, hills, and other rock features | Mountain, mountain range, hill, rock, slope |
| 6. Water | Photographs showing views of water bodies including lakes, rivers, and other hydrologic features | Water, lake, watercourse, water resources, coastal and oceanic landforms |
| 7. Recreational activities | Physical use of landscapes – photographs of sport and recreational activities, such as skiing, climbing, hiking, camping, and others | Winter sport, ski, backpacking, hiking, cross country skiing |
| 8. Accommodation | Photographs showing accommodation linked to recreation e.g., cabins, campgrounds, and cottages | Cottage, tent, hut, log cabin, tarpaulin |
| 9. Landscapes | Photographs for which the focus is a wide and large-scale view of the landscape | Landscape, natural environment, glacial landform, plain, natural environment |
| 10. Attractions | Photographs depicting attractions such as (e.g., historical buildings, ruins) | Landmark, temple, monument, historic sight, statue |

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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## Appendix A

Tables A1 and A2.

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