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Review Paper

Digital windows into nature's values: A critical review of cultural ecosystem services research with social media data

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ABSTRACT

Understanding how people relate to nature is essential for addressing today's complex social-ecological challenges. Cultural ecosystem services offer a valuable lens for exploring the non-material dimensions of human–nature relations. In recent years, social media data have reshaped this research field, enabling novel insights but also introducing important challenges. This study systematically reviews and critically analyzes 218 peer-reviewed articles on cultural ecosystem service assessments that use social media data. We examine geographic and biome-specific coverage, platforms and media formats employed, and key methodological developments, including the increasing role of artificial intelligence for automated content analysis. We further investigate how cultural ecosystem services are conceptualized and classified, organizing thematically similar categories from the literature into semantically coherent clusters, thereby highlighting tensions between universal frameworks and context-specific approaches. Despite growing interest and rapid methodological innovation, the field continues to grapple with platform-specific biases, data accessibility limitations, and a lack of coherence in cultural ecosystem services definitions and identification criteria. The continued reliance on a few dominant sources, particularly Flickr, and the prevalence of studies that draw data from only one platform raise concern about representativeness and long-term sustainability. To support future research, we propose a set of considerations aimed at strengthening analytical rigor and cross-study comparability. These include distinguishing between user-expressed and researcher-inferred experiences, differentiating ecosystem services from the benefits the generate, and explicitly addressing the "ecological" and "use" clauses of ecosystem services frameworks. While challenges remain, research in this area holds substantial promise for enabling scalable, near real-time, and nuanced assessments of cultural human–nature relationships.

1. Introduction

Understanding how people relate to nature is essential for addressing today's intertwined social-ecological challenges. The cultural ecosystem services (CES) approach has been foundational in the exploration of the nonmaterial dimension of human–nature relations, which underpins not only individual wellbeing and cultural identity but also collective environmental stewardship (Andersson et al., 2015). Due to the central and pervasive role of culture in shaping human interactions with nature (Díaz et al., 2018), an adequate understanding and characterization of CES and their impacts on human wellbeing plays a critical role in informing effective conservation and sustainable environmental management strategies (Kosanic and Petzold, 2020; Nowak-Olejnik et al., 2022). Compared to regulating and provisioning ecosystem services, CES such as landscape aesthetics, cultural heritage, outdoor recreation or social interactions, are generally considered to be more rooted in place, culture, and context. As a consequence, they are often regarded as more subjective and intangible, making them less likely to be included in large-scale assessments (Chan et al., 2016; Fish et al., 2016). As a result, CES assessments have been less frequent, less systematic, and narrower in scope, at least in part due to their reliance on resource-intensive, qualitative, and participatory methods (Cheng et al., 2019).

In recent years, however, new forms of digital data and computational methods have begun to reshape how cultural human-nature

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relations are studied (Schirpke et al., 2023). In particular, studies based on social media (SM) data have opened new opportunities for quantitative and spatial assessments of CES, including across large geographical scales (Van Zanten et al., 2016). These novel approaches enable, for instance, broader comparisons across regions, insights into spatial and temporal patterns of nature appreciation, real-time monitoring of CES, and the identification of emerging trends in human–nature interactions (Ghermandi et al., 2023). Previous studies have suggested that SM data can help address several shortcomings of traditional CES assessment methods (e.g., surveys), as they are less resource-intensive to collect, easier to update, less susceptible to interviewer and response biases, and capable of capturing information from large population samples (Ghermandi et al., 2020a; Langemeyer et al., 2023; Tenerelli et al., 2016). The insights derived from SM data are thus often regarded as valuable complements to, and enrichment of, those obtained through more conventional techniques (Depietri et al., 2021; Heikinheimo et al., 2017).

CES assessments based on SM data, however, also present unique challenges. SM data are inherently biased, reflecting uneven access to technology and platform use across demographic and geographic groups (Arts et al., 2015). Moreover, SM data are opportunistic, generated for purposes other than scientific research (Ghermandi and Sinclair, 2019), and are affected by platform affordances, i.e., the actions and interactions that each platform enables for its users (Van Raemdonck et al., 2025) and the type of media used (e.g., text, photo, video) (Calcagni et al., 2022). Given that different platforms attract different types of users and serve different purposes, concerns arise about the representativeness and inclusivity of the resulting findings, particularly for marginalized communities or regions with limited digital engagement and when data from a single platform or media type are sampled (Ghermandi et al., 2023). Additionally, the methodologies employed in SM data analysis (e.g., for manual or automated content analysis) may give rise to further challenges and limitations. For instance, the use of AI and machine learning techniques for tasks like image recognition or text classification can result in limitations concerning algorithmic transparency, interpretability, and sensitivity to cultural nuance (Scowen et al., 2021).

Beyond technical limitations, the growing use of digital data and computational methods in CES research brings to the fore a deeper epistemological tension. CES are fundamentally shaped by cultural context and grounded in specific places (Bieling et al., 2014; Chan et al., 2012), yet CES assessments—particularly those conducted at large scales—often rely on standardized categories designed for consistency rather than contextual nuance (Haines-Young, 2023). This generalization risks losing the diversity of meanings, values, and emotional attachments people associate with the natural environment (Nowak-Olejnik et al., 2022), which might obscure the characteristics that make CES distinctive. Moreover, the classification of CES in leading international frameworks—such as the Millennium Ecosystem Assessment (MEA, MEA, 2005), The Economics of Ecosystems and Biodiversity (TEEB, TEEB, 2010), and the Common International Classification of Ecosystem Services (CICES, Haines-Young, 2023)—is characterized by conceptual ambiguity. These frameworks not only employ different sets of categories, but their definitions of specific CES may lack specificity or be perceived as overlapping. As a result, researchers may adopt varying approaches to operationalizing identification of cultural services in SM content, raising concerns about the consistency and comparability of findings across studies. This calls for more reflexive classification approaches that ask not only how CES are ontologically framed and how categories are defined, but also which epistemological criteria are used to identify them in SM content (Fish et al., 2016; Hoelting et al., 2024a; Langemeyer and Connolly, 2020). The growth in the number of CES assessments relying on SM data, combined with the rapid evolution of data sources and analytical tools, points to an urgent need for critical stock-taking of current practices, and for strategic guidance of future developments, in order to ensure methodological rigor, inclusivity, and comparability across future studies. Previous reviews, however, either lacked a specific focus on CES assessments (Ghermandi et al., 2023; Ghermandi and Sinclair, 2019; Schirpke et al., 2023) or do not reflect the field's rapid growth and methodological developments that have occurred in recent years (Zhang et al., 2020).

This paper systematically reviews and critically analyzes the scientific literature on the use of SM data in CES assessments. The objectives are:

1) To examine the current landscape and emerging trends, with particular attention to the geographic and biome-specific distribution of studies, the types of SM platforms and data sources used, and the media formats (e.g., text, photos) analyzed.
2) To investigate methodological dimensions, focusing on the tools and techniques employed for automated content analysis and epistemological assumptions, especially in light of the increasing integration of artificial intelligence (AI) and machine learning in this field.
3) To examine how CES are conceptualized and implemented across the reviewed studies, focusing on the categories and classification systems applied, as well as the definitions, operational approaches, and criteria used for identification.

We conclude by identifying persistent tensions and gaps in the literature and propose a set of cross-platform and cross-media considerations to inform and guide future research efforts.

2. Materials and methods

2.1. Literature search and selection

We conducted a systematic review in accordance with the PRISMA guidelines (Page et al., 2021). Studies for the review were identified and retrieved using the Scopus database (McDonough et al., 2017) through a search conducted on 23 November 2024. Scopus is widely recognized for systematic reviews because of its extensive coverage across academic disciplines (Baas et al., 2020). An initial comparison of databases confirmed Scopus as the most comprehensive source. The search string was designed to identify peer-reviewed research articles published between 2012 and 2024. It targeted research articles that included terms related to SM data in the title, abstract, or keywords. SM-related search terms fell into two categories. The first included generic descriptors such as "social media" and related terms that overlap with SM research (i.e., "user-generated content", "digital footprint", and "digital trace"). The second comprised terms referring explicitly to 15 specific SM platforms that were identified in prior reviews (Ghermandi et al., 2023; Ghermandi and Sinclair, 2019; Zhang et al., 2020). In line with Meikle's (2024) definition of social media as "networked data platforms that combine public with personal communication," we excluded platforms such as iNaturalist and Wikipedia, which do not fulfill what Meikle identifies as a central use of social media—namely, enabling networked individuals to "make and circulate their own meanings"—but instead focus primarily on the production and organization of objective knowledge. To ensure relevance for the ecosystem services field of research, the search was restricted to studies that explicitly referenced "ecosystem service" or "nature's contributions to people" in their title, abstract or keywords. Moreover, we focused on publications in English due to language limitations and to avoid misinterpretation. To contextualize the studies using SM data within the broader field of CES research, we conducted a second search using the same search string but excluding all SM-related keywords and replacing "ecosystem services" with "cultural ecosystem services". The full search strings are provided in Appendix A.

A total of 285 articles were initially identified, of which 67 were removed upon inspection as they did not involve actual analysis of SM data, their analysis did not focus on ecosystem services, or they were review papers (see PRISMA flow diagram in Appendix B). References to the remaining 218 articles are listed in Appendix C.

2.2. Classification and analysis of the literature

2.2.1. Descriptive analysis

From the 218 articles, we first extracted bibliographic data such as the year of publication and the journal in which each article was published. We further classified ecosystem types based on the Ecosystem Services Valuation Database (ESVD) 2.0 biome classification (https://www.esvd.info/classifications; accessed 2 December 2024). To accommodate studies spanning multiple ecosystems across different biomes (e.g., studies focused on administrative regions or river basins) or lacking a clear geographical scope (e.g., keyword-based studies without spatial boundaries), we added a new class, "Other", to the classification. Additionally, due to the lack of a clear distinction between marine and coastal biomes in the reviewed articles, we merged them into a single category.

We further categorized the studies based on whether they exclusively focused on protected areas, including in this category also designations such as UNESCO World Heritage Site, Ramsar wetlands, and biosphere reserves. The countries in which the studied ecosystems were located were also noted. Studies spanning case-study sites across multiple countries and global analyses were grouped under the class "Supranational/global".

To characterize the SM data analysis in each of the study, we manually reviewed each article to identify: (1) the specific SM platform(s) used as data source(s); (2) the size of the data sample analyzed (i.e., usable sample size, after pre-processing and data cleaning); and (3) whether the study analyzed only the metadata (e.g., timestamps, geolocations) or explored also the actual textual and/or visual content of posts. The former included also studies that only used keyword filtering at the data collection stage but not in the analysis. For studies involving content analysis we distinguished between manual and automated approaches, documenting for the latter the specific techniques employed to extract information. We estimated the statistical significance of the observed differences between usable sample sizes across studies based on the type of analysis performed (i.e., metadata only, manual content analysis, automated content analysis) or the type of analyzed media (i.e., photos, texts, texts and photos) using the Kruskal-Wallis test and Dunn's post hoc test with Bonferroni adjustment for multiple comparisons. Effect sizes for the Kruskal-Wallis tests were calculated with the eta-squared (η^2) method and interpreted based on the conventional benchmarks in Cohen (2013). These statistical analyses were performed in R with the "rstatix" package (Kassambara, 2019).

2.2.2. Content analysis

From the studies that conducted manual or automated content analysis, we selected those that categorized texts and/or images into distinct categories based on criteria such as the type(s) of CES represented or the presence of specific natural or built environment elements. For each study, we recorded the category names, resulting in 476 unique categories from 117 studies (e.g., "Recreational activities," "Fauna and flora," "Facilities and infrastructure"). As a starting point for structuring the discussion of the studies' scope of analysis and classification criteria they applied, we used Claude 3.7 Sonnet (https://claude.ai/) to group these categories based on semantic similarities in their names. The prompt was iteratively tested and refined until the output was deemed satisfactory by the authors. The final version of the prompt is provided in Appendix D. This process yielded 16 distinct groups, nine of which were associated with CES: Aesthetic and sensory experience, Cultural heritage, Educational and scientific, Existence and bequest values, Health and wellbeing, Observational recreation, Physical recreation, Social interaction, and Spiritual and religious. The remaining groups were related to elements of the natural or built environment (Agricultural and rural, Built environment, Infrastructure and facilities, Natural elements, Transportation, and Wildlife and biodiversity), with an additional "Miscellaneous" group for categories that did not fit elsewhere. A detailed breakdown of category assignments is provided in Appendix E.

For each of the CES-related groups, we manually reviewed category descriptions and examples from the original studies to critically assess consistency—or inconsistency—in definitions and approaches across studies. Where definitions or examples of the criteria used for the identification of CES in texts and/or photos were explicitly given, we classified studies based on their focus on (i) activities or actions (e.g., hiking, birdwatching), (ii) physical elements of the natural or built environment (e.g., educational information boards, landmarks), (iii) abstract concepts including affective states (e.g., scenery, tranquility), or (iv) a combination thereof. Finally, for all studies that differentiated multiple CES types based on visual and/or textual SM content, we recorded whether they adhered to an internationally recognized classification—such as the MEA, TEEB, and CICES v5.2 classifications—or instead developed an *ad hoc* classification, either top-down (i.e., using predefined CES types) or bottom-up (e.g., through cluster analysis of content).

3. Results

3.1. Status and trends

Among the studies reviewed, there is a clear and steady upward trend in the number of publications over time, from a single study in 2013 (Casalegno et al., 2013) to 40 studies in 2023 (Fig. 1 and Fig. 2). Half of the studies in the dataset were published between 2022 and November 2024. In particular, there has been a rapid uptake of studies in recent years in Europe and in Asia, while especially Africa and Oceania remain largely underrepresented. The study sites are spread across 42 countries, notably China (43 studies) and the USA (20 studies), and including 29 studies that have either a transnational (e.g., case studies in multiple countries, transboundary ecosystems) or a global scope. Overall, the 218 analyzed studies were published across 81 different journals, with slightly less than one-third appearing in three journals: Ecosystem Services (N = 33), Ecological Indicators (N = 16), and Landscape and Urban Planning (N = 15). They represent 11% of all CES studies published over the same period and available in Scopus, a fraction that has been growing over time (Fig. A1 in Appendix A).

Ten different biomes are represented in the dataset. The largest fraction of studies pertains to urban green and blue infrastructure (53 studies), with a rapid growth especially since 2021 when most of them (N = 36) were published. Coastal and marine ecosystems are investigated in 29 studies, followed by forests, both temperate (N = 14) and tropical (N = 6), and water ecosystems, both rivers and lakes (N = 15) and inland wetlands (N = 5). About a third of the study sites cannot be assigned to a specific biome. This may be because the analysis is performed at the level of an administrative subdivision (N = 34) or of the river basin (N = 4), data pertain to a mixed ecosystem or multiple ecosystems with different characteristics (N = 30), or data collection and analysis are not spatially bounded (N = 6). About a fourth of the studies (N = 50) focus exclusively on protected areas, while the rest examine ecosystems that are at least partially outside formally protected areas.

Overall, the analyzed studies used data from 28 different SM platforms. Over time, Flickr consistently remains by far the preferred SM platform for ecosystem services research, with more than half of the studies using data from it either alone (N = 96) or in combination with data from other platforms (N = 26). After Flickr, the platforms that are most frequently investigated (alone or in combination with others) are Twitter (now X) and Instagram (N = 19 for both), followed by Dianping and Weibo (N = 15 each), two SM platforms that are widely used in China. For comparison, data from YouTube, one of the SM platforms with the largest number of users worldwide, have been analyzed in only one study in the dataset.

Some trends over time can be clearly discerned. The vast majority of

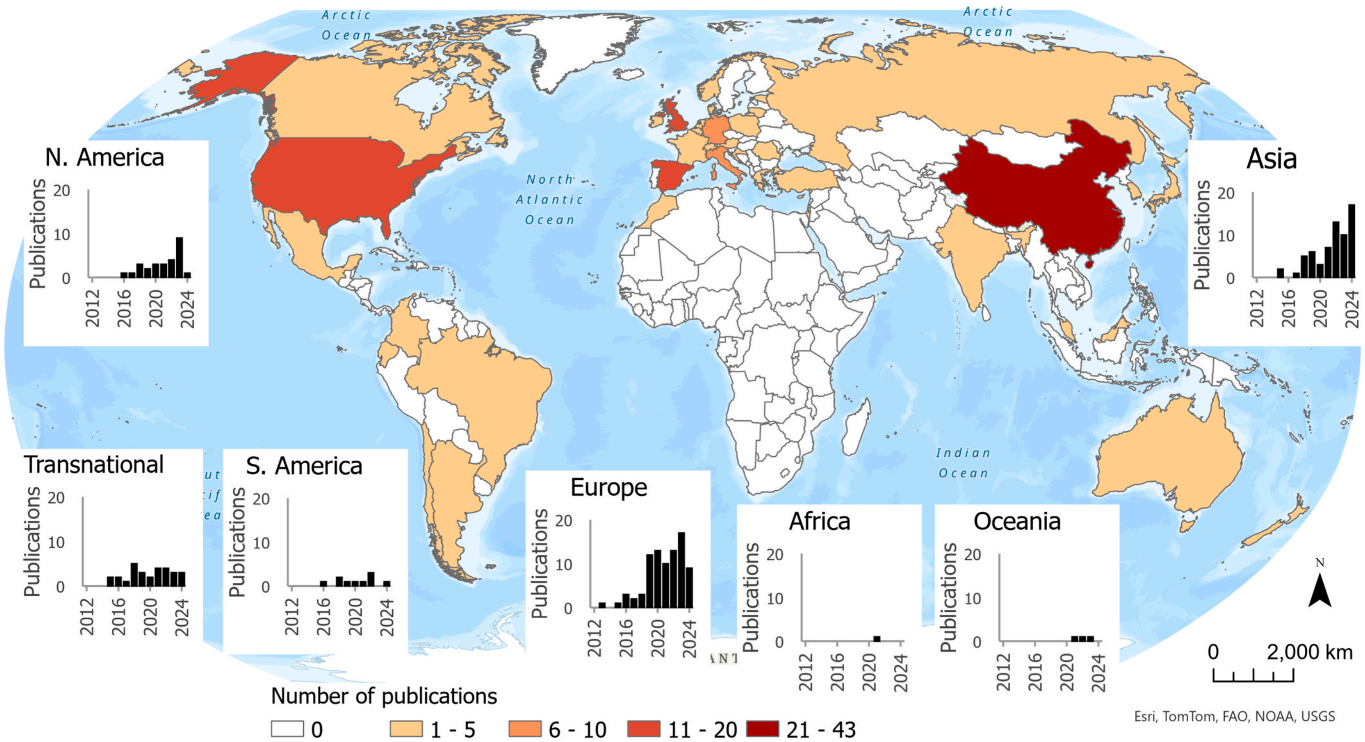

Fig. 1. Distribution of analyzed studies (N = 218) by country and over time by continent.

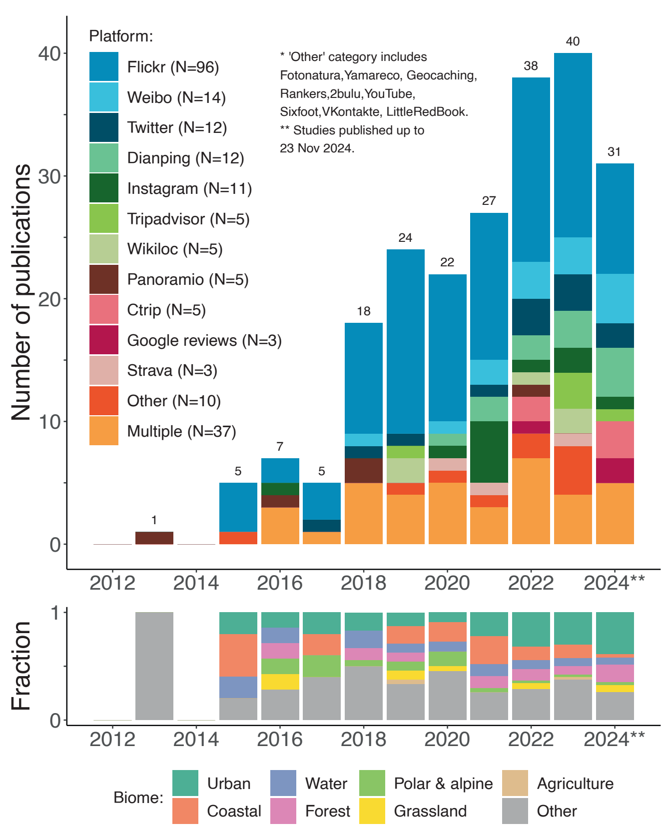

Fig. 2. Number of publications over time by investigated social media platform (s) and fraction of publications by biome.

studies (83%) still relies on data from one single platform, with the fraction of multi-platform studies actually showing a decline over time (Fig. 3A). This is despite multiple studies showing the potential of multi-platform data to provide better empirical results (Ghermandi, 2022) and attenuate some of the biases inherent in SM data (Gugulica and Burghardt, 2023; Hausmann et al., 2018; Ruiz-Frau et al., 2020). Fig. 3B shows a clear trend from the early studies, which were primarily focused on counts of SM data points as proxies for a single CES, towards the analysis of the textual and/or visual content of the posts (N = 160). Though the majority of the studies focus on visual content (N = 85), there is a growing interest in recent years toward the exploration of SM texts, either on their own (N = 57) or in combination with the visual content in a multi-modal setting (N = 17). Video content remains largely unexplored, with only one manual investigation of videos from YouTube (Kikuchi et al., 2022).

Much innovation in ecosystem services research with SM data has come in recent years from increased integration of advanced data analytics techniques (Schirpke et al., 2023). The number of studies performing automated analysis of text and/or visual content has substantially increased over time (Fig. 3D), representing about 41% of all studies in the dataset and the majority (55%) of studies performing content analysis. Despite this, a considerable number of studies remain, also in recent years, that rely on manual content investigation (38 studies since 2021). Although perhaps only the few studies in the dataset with sample sizes in the order of the tens of millions of datapoints can be characterized as "big data" studies (Havinga et al., 2024, 2023, 2021; Linder and Lusseau, 2024), studies with automated content analysis rely on an approximately tenfold larger sample size (median = 24,961; N = 88) than studies with manual content analysis (median = 2290; N = 68). The Kruskal-Wallis ($H(2) = 53.5$, $p < 0.001$, $\eta^2 = 0.264$, indicating a large effect size) and Dunn tests reveal a statistically significant difference between the sample sizes of manual content analyses compared to automated analyses ($z = 6.70$, $p < 0.001$) and studies investigating metadata only ($z = -5.71$, $p < 0.001$) (Fig. 4 *left*). The Kruskal-Wallis test also reveals significant differences in sample sizes according to the analyzed media type ($H(2) = 14.7$, $p < 0.001$, $\eta^2 = 0.083$, indicating a moderate effect size) (Fig. 4 *right*), notably between photo content analyses and both text only ($z = -3.49$, $p < 0.01$) and combined text and

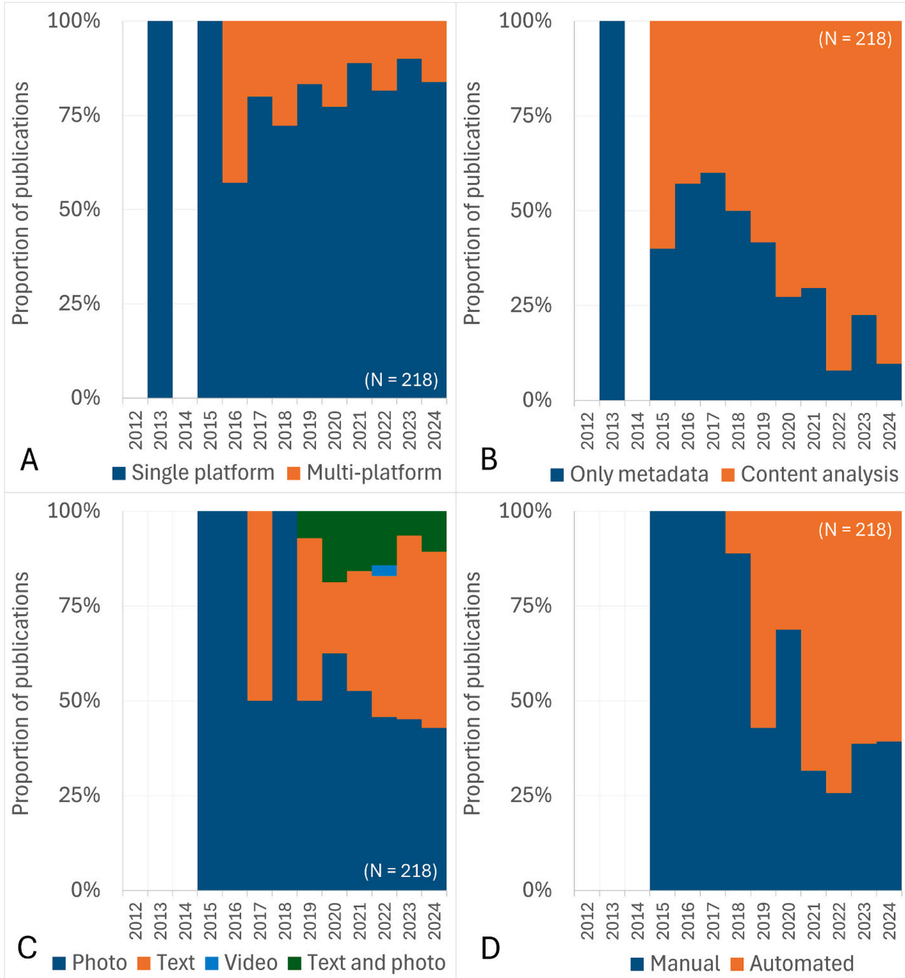

Fig. 3. Trends in studies by number of social media platforms analyzed (A), metadata vs. content analysis (B), analyzed content type (C), and manual vs. automated content analysis (D). The horizontal axis represents the year of publication.

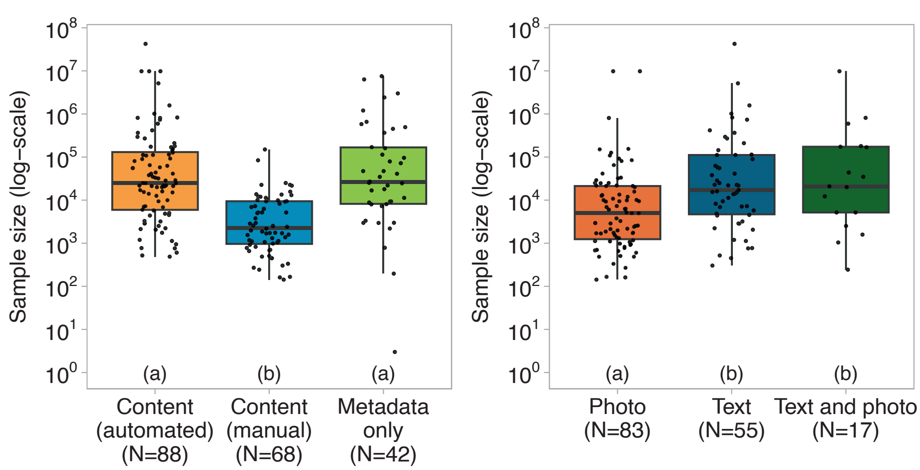

Fig. 4. Distribution of usable sample sizes in studies performing only metadata analysis or also social media content analysis (left) and between different types of media content analysis (right). Note: Separately for each chart, different letters denote a statistically significant difference at p-level < 0.01 between the categories.

photo analyses ($z = -2.43$, $p < 0.05$), but these can be largely attributed to a larger fraction of studies performing manual analysis of photographic content compared to texts (Fig. 5). The median usable sample size for the entire dataset is 11,308 (N = 198).

3.2. Methods for automated content analysis

3.2.1. Photo analysis

Table 1 and Table 2 provide an overview of the tools used in the analyzed studies for the automated analysis of SM photos and texts. A fairly large number of studies use commercial, pre-trained image

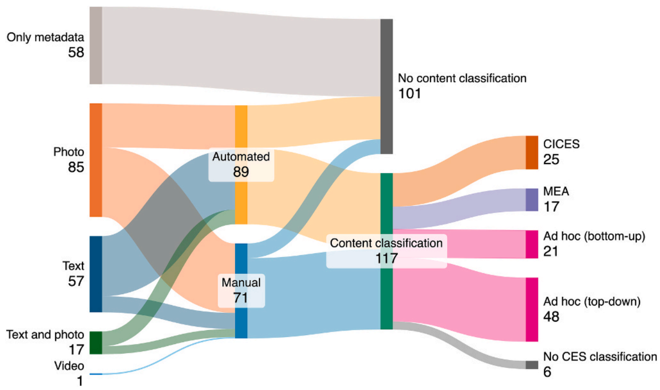

Fig. 5. Distribution of the studies according to investigated data type, methodology, and content classification type. The diagram was created using SankeyMATIC (https://sankeymatic.com/).

Table 1
Overview of tools used for automated analysis of social media photographs in ecosystem services research.

Objective	Analytical tool	Studies	Examples
Image labeling	Clarifai	7	Depietri et al., 2021; Egarter Vigl et al., 2021; Karasov et al., 2020; Lee et al., 2019
	Google Cloud Vision	17	Fox et al., 2021; Ghermandi et al., 2020; Gosal et al., 2019; Richards and Tunçer, 2018
	Microsoft Azure	4	Ruiz-Frau et al., 2020; Spalding et al., 2023; Yee and Carrasco, 2024
CNN-based classification	Pre-trained	6	Chen et al., 2024; Havinga et al., 2021; Huai et al., 2022; Matasov et al., 2023; Wang et al., 2022
	Transfer learning	6	Cardoso et al., 2022; Havinga et al., 2021; Lingua et al., 2022; Winder et al., 2022
	Trained from scratch	2	Mouttaki et al., 2022; Santana et al., 2024
Facial expression recognition	FireFACE	3	Li et al., 2022; Wang and Zhou, 2024; Zheng et al., 2023
	Microsoft Cognitive Services	1	Do, 2019

Notes: CV = computer vision; CNN = convolutional neural network.

labeling tools such as Google Cloud Vision, Clarifai and Microsoft Azure to characterize the visual content of photographs. Such software associates each photograph with a series of machine tags (e.g., "tree", "sky", "hiking"), each with an estimated confidence level. These can then be subject to further investigation using, for instance, cluster analysis (Kaiser et al., 2021), latent semantic analysis (Gosal et al., 2019), or visual sentiment analysis (Ghermandi et al., 2020b). Ghermandi et al. (2022) compare the performance of these three tools for the analysis of human-nature interactions in urban green and blue infrastructure.

Recent studies have increasingly relied on Convolutional Neural Networks (CNN) to classify photographs into categories reflecting different CES aspects. Several studies build on an existing CNN architecture (e.g., ResNet152, InceptionResNetV2, VGG16, YOLOv5), previously trained on image databases such as ImageNet, Places365, or Google OpenImages, to filter for outdoor images (Havinga et al., 2021; Huai et al., 2022) or to extract image features that can then be directly associated to CES (Chen et al., 2024; Matasov et al., 2023) or further analyzed using techniques such as cluster analysis (Huai et al., 2022; Wang et al., 2022).

Alternatively, pre-existing CNNs can be adapted and retrained with an *ad hoc* training set, in a process known as transfer learning, to give researchers freedom in choosing the model output, such as for instance CES-related classes (Cardoso et al., 2022; Havinga et al., 2023; Lingua et al., 2022a, 2023; Winder et al., 2022). Finally, CNN can be trained from scratch for the purposes of the studies (Mouttaki et al., 2022; Santana et al., 2024). Cardoso et al. (2022) suggest that transfer learning of pre-existing CNNs may outperform training from scratch.

An additional option for photo content analysis consists in the analysis of the emotions demonstrated by visitors through facial expression recognition software such as FireFACE (Li et al., 2024; Wang and Zhou, 2024; Zheng et al., 2023) or Microsoft Cognition Services (Do, 2019).

Table 2
Overview of tools used for automated analysis of social media texts in ecosystem services research.

Objective	Analytical tool	Studies	Examples
Text classification	Keyword-based filtering	25	Egorova, 2021; Hale et al., 2019; Komossa et al., 2023; Spalding and Parrett, 2019; You et al., 2022
	Static and contextual word embeddings	6	Chai-allah et al., 2023; Gugulica and Burghardt, 2023; Wang et al., 2021; Zheng et al., 2024
	Other classification algorithms	2	Dang and Li, 2023; Spalding et al., 2023
Topic ranking	Keyword frequency	14	Bi et al., 2024; Wang et al., 2021; Zhang et al., 2024; Zhao et al., 2023; Zhu et al., 2023
	Network analysis	5	De Juan et al., 2021; Ishida et al., 2023; Kong and Sarmiento, 2022; Ruiz-Frau et al., 2020
	TF-IDF	2	Gugulica and Burghardt, 2023; Havinga et al., 2024
Opinion mining	Sentiment analysis	19	Erskine et al., 2021; Fox et al., 2022; Havinga et al., 2024; Tyner and Scott Graham, 2022
	Emotion analysis	1	Teles Da Mota and Pickering, 2021
Relationships between CES	In-text proximity analysis	1	Busch et al., 2024

Notes: NLP = Natural Language Processing; TF-IDF = Term Frequency – Inverse Document Frequency.

3.2.2. *Text analysis*

SM texts analyses employ various text mining techniques to classify content into categories and topics, which may or may not directly correspond to CES types, assess the significance of specific CES-related aspects, extract user sentiments and emotions, or explore relationships between different CES and their components.

Many studies (Table 2) use simple keyword-based filtering to classify texts. Lists of keywords may be derived from the analysis of the entire texts (Linder and Lusseau, 2024) or from hashtags only (De Juan et al., 2021; Grzyb et al., 2021; Mancini et al., 2019; Ruiz-Frau et al., 2020). Themes and keywords used in the analysis can be used in a fully automated way (i.e., based on a pre-determined vocabulary) (Graham and Eigenbrod, 2019; Knoble and Yu, 2023; Zhang et al., 2022b) or in a semi-automated fashion. The latter derives keywords from manual investigation of a subset of the data (Benati et al., 2024; Tyner and Scott Graham, 2022), or a from curated list of unique or frequent keywords (Chen et al., 2024; Komossa et al., 2023; Li et al., 2024; Mancini et al., 2019; Zhang et al., 2022a), bi-grams (Bruzzese et al., 2022; Zhao et al., 2023), or n-grams (Kong et al., 2023; Kong and Sarmiento, 2022; Marchi et al., 2022). This process may be assisted by integration of Natural Language Processing (NLP) techniques for text annotation such as Part-of-Speech (POS) identification (Chen et al., 2024; Kong and Sarmiento, 2022; Linder and Lusseau, 2024) and Named Entity Recognition (Kong et al., 2023). In semi-automated approaches, manual classification can be conducted by one or more authors, with or without intercoder agreement (Benati et al., 2024), or through crowdsourced platforms like Amazon Mechanical Turk (Kong and Sarmiento, 2022). Although computationally efficient and scalable, these approaches require exhaustive keyword lists and overlook the semantic context in which the keywords appear (Gugulica and Burghardt, 2023).

As an alternative to keyword-based filtering, both supervised (Dang and Li, 2023; Spalding et al., 2023) and unsupervised semantic clustering techniques have been employed. These include static word embeddings like word2vec (Chai-allah et al., 2023; Gugulica and Burghardt, 2023; Wang et al., 2021a; Zhang et al., 2024) and GloVe (Zheng et al., 2024), as well as contextual embeddings such as Bidirectional Encoder Representations from Transformers (BERT) and variations of BERT (Zhao et al., 2024; Zheng et al., 2024). None of the reviewed studies utilized contextual embeddings with Generative Pretrained Transformer (GPT) architecture (e.g., ChatGPT), though these are expected to play a significant role in future research (Depietri et al., 2025; Luo et al., 2025).

The relative importance of different themes within the overall corpus of SM texts are assessed through frequency of occurrence of keywords (Yang and Duan, 2024; Zhu et al., 2023), measures of centrality from graph theory (De Juan et al., 2021; Ishida et al., 2023), or using NLP techniques for text mining such as TF-IDF (Gugulica and Burghardt, 2023).

Opinion mining through sentiment (Erskine et al., 2021; Fox et al., 2022; Li et al., 2024; Liao et al., 2023; Tyner and Scott Graham, 2022) or emotion analysis can be implemented alone or in combination with the results of text classification and topic ranking to analyze discourse communities. Cluster analysis techniques such as Self-Organizing Maps (Kong et al., 2023) are also used after text analysis for grouping multiple study sites based on the content of SM texts (Li et al., 2024).

3.3. Characterizing cultural ecosystem services via social media data

Fig. 5 shows the cumulative distribution of the reviewed studies by data category, type of content analysis, and use of classification techniques for the SM data content. Studies that analyzed only SM metadata (N = 58) as well as a subset of those performing visual or textual content analysis (N = 43) did not distinguish between different CES types. Instead, all analyzed SM data were attributed to a single CES, sometimes following keyword- or content-based filtering (e.g., selecting only panoramic photographs to investigate landscape aesthetics; see Tenerelli et al., 2017; Langemeyer et al., 2018). Most of these studies focused on nature-based recreation (N = 66), including nine studies that applied the InVEST Recreation model (https://naturalcapitalproject.stanford.edu/invest/recreation; accessed 26 October 2025). Within this group of nature-based recreation studies, there is an increasing interest in integrating SM data with economic valuation techniques—particularly the travel cost model (Azevedo, 2021; Ghermandi, 2018; Lingua et al., 2022b; Nyelele et al., 2023; Sinclair et al., 2020, 2018) and benefit transfer techniques (Lingua et al., 2022a).

Most of the studies performing content analysis (117 out of 160) used classification techniques to discriminate between SM posts; of these 117, 111 considered two or more different types of CES. Only 42 studies explicitly referred to one of the internationally recognized ecosystem services classification systems (CICES in 25 studies; MEA in 17 studies). Most of the studies instead relied on alternative classifications, either derived from previous SM data studies (e.g., Retka et al., 2019), integrating multiple classification systems, or developing ad hoc frameworks. The latter followed either a top-down approach (using predetermined categories that were deemed relevant by the authors) or a bottom-up approach (e.g., derived from cluster analyses of SM posts). Some studies went as far as explicitly stating that they found leading CES classification systems unsuitable for application to SM data (Yee and Carrasco, 2024).

Of the different CES-related groups identified by using the AI tool, the most frequently assessed were physical recreation, aesthetic and sensory experience, and cultural heritage (Fig. 6). Existence and bequest values were the least commonly mentioned in the reviewed studies. For most CES groups, identification was primarily based on specific visual elements in photographs, with relatively few studies integrating both textual and visual information. Manual inspection of visual or textual content was the predominant approach, with automated methods prevailing only for social interaction, observational recreation, and health and wellbeing. In the majority of cases, CES were identified through activities or elements of the environment, while only a limited number of studies considered abstract concepts or affective states—typically expressed in texts—as a basis for classification. Notably, in 16% of the cases criteria for identifying a specific CES were not clearly provided in the studies. Because the original categories from individual studies were grouped using an AI-based procedure, the resulting CES groups are often somewhat heterogeneous and may not align clearly with established classifications such as CICES, MEA, or TEEB. Each CES group is described in greater detail in the following subsections.

A considerable number of classification schemes included categories that did not attempt to assign specific aspects of the observed content to specific CES but rather associated them with elements of the natural or built environment. These included studies identifying natural elements (N = 43) (e.g., water bodies, geological formations, meteorological phenomena), wildlife and biodiversity (N = 27) (e.g., flora and fauna), and agricultural and rural land (N = 8). Elements of the built environment included infrastructure and facilities (N = 15), built environment (N = 10) (e.g., man-made structures, monuments), and transportation (N = 12). Finally, 12 studies considered in their classification categories that could not be easily associated with any of the above-mentioned themes (e.g., economic, social industries, livelihood).

3.3.1. Physical recreation

Physical recreation concentrates on active interactions with the natural environment (CICES 3.1.1.1). Accordingly, there is high agreement across studies in referring to different types of recreational activities, either combining them into a single CES class (Chen et al., 2020a; Lenormand et al., 2018; Schirpke et al., 2021; Van Berkel et al., 2018), or singling out specific activities such as hiking (Lingua et al., 2023; Spalding and Parrett, 2019), biking (Lingua et al., 2023; Roberts et al., 2017), or fishing (Daymond et al., 2023; Richards and Friess, 2015; Spalding and Parrett, 2019). This CES is usually identified through photographs (Fig. 6), depicting people engaged in recreational activities (Angradi et al., 2018; Huang et al., 2024; Rossi et al., 2020; Zapata-Caldas et al., 2022), while less studies also include recreational facilities or equipment (Depietri et al., 2021; Keleş Özgenç et al., 2024; Lingua et al., 2023). However, studies often do not explore the role of the natural environment or specific natural features in supporting the provision of benefits, and effects on well-being have been rarely assessed through textual analysis (Egorova, 2021; Zhang et al., 2024). Best practice for comprehensively assessing this CES would combine the identification of recreational activities carried out in natural settings in photos or texts with clear indications of well-being benefits or the importance of natural features as derived from text analysis (Zhang et al., 2024).

3.3.2. Aesthetic and sensory experience

This group largely aligns with the CES category related to aesthetic experiences (3.2.1.4) in CICES v5.2 (Haines-Young, 2023). It also encompasses related concepts such as scenery (Chang and Olafsson, 2022a), landscape appreciation (Santana et al., 2024), nature appreciation (Santos Vieira et al., 2021), and what various authors—in line with MEA (2005)—describe as inspiration (Johnson et al., 2019), specifically the inspiration drawn from nature for art, folklore, national symbols, architecture, and advertising. While the assessment of inspiration is relative straightforward—typically requiring the representation of

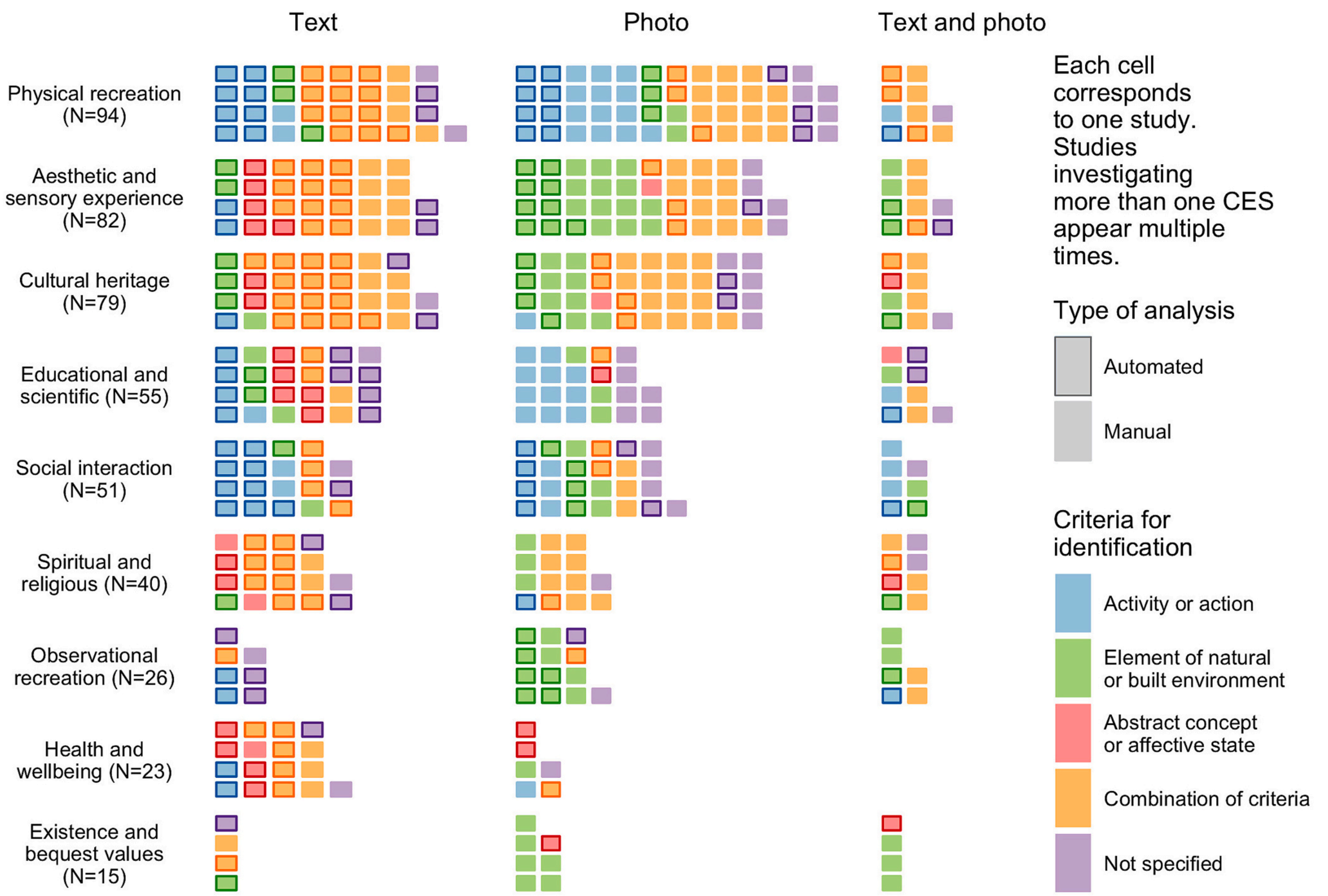

Fig. 6. Groups of cultural ecosystem services examined in the reviewed studies, categorized by type of media analyzed, analytical approach, and classification criteria used.

natural elements in human artworks and symbols (Keleş Özgenç et al., 2024; Li et al., 2022)—the assessment of aesthetics can be broadly divided into two main approaches: one based on the identification of specific abiotic and biotic elements (Ebner et al., 2022), and the other on cognitive interpretations (Chen et al., 2024). The first typically relies on observable features such as scenic, landscape, or panoramic views, or on specific ecological elements to identify this CES (Keleş Özgenç et al., 2024; Vidal-Llamas et al., 2024; Zapata-Caldas et al., 2022). The second approach may be based either on the researchers' subjective judgment of what is deemed beautiful or aesthetically pleasing (e.g., landscape photographs) or on a specific mention of keywords such as "beauty" or "stunning" (Chai-allah et al., 2023; Zhao et al., 2023) in the analyzed texts. While the former arguably raises concerns regarding scientific robustness of the analyses, the latter represents a more rigorous form of cognitive-based assessment. Unlike more universalized or researcher-driven assessments, this user-cognition-based approach can accommodate pluralistic and culturally diverse understandings of aesthetics (Cao et al., 2022).

3.3.3. *Cultural heritage*

Cultural heritage is assessed using social media text and photo indiscriminately (Fig. 6), both through manual and automated analysis, the latter mostly applied to text data. This group roughly corresponds to CES 3.2.1.3 of CICES v5.2, which refers to the "characteristics of living systems that are resonant in terms of culture or heritage". Accordingly, terms like "culture," "heritage," and "history" appear most frequently in the descriptions and examples of the criteria employed by studies in this group. Some studies nevertheless consider a variety of additional aspects, which overlap with other CES in the CICES classification. These include sacred and/or religious values (CICES 3.4.1.2), as identified both through religious activities (Moreno-Llorca et al., 2020) or elements of the natural or built environment such as religious buildings (Chai-allah et al., 2023; Ghermandi et al., 2022), symbolic values (CICES 3.4.1.1) (Ebner et al., 2022; Tian et al., 2021), artistic inspiration and entertainment (CICES 3.3.1.1) (Linder and Lusseau, 2024; Santana et al., 2024). This group also includes aspects that are not clearly aligned with existing classifications, for example,: "identity", whether personal (Gan et al., 2024; Zhu et al., 2023) or collective (Wahler et al., 2023), and whether associated to place uniqueness (Kong and Sarmiento, 2022), folklore and traditions (Li et al., 2023), or local economic activities (Martínez Pastur et al., 2016); "sense of place", associated either with recognised environmental features (Zhao et al., 2023) or with personal memories and routines (Wang et al., 2023); and "gastronomy", experienced in the wild (Moreno-Llorca et al., 2020) or at restaurants (Ros-Candeira et al., 2020).

Overall, cultural heritage is most commonly identified in the reviewed studies through natural or built environments (Calcagni et al., 2022), animal and plant species (Arslan and Örücü, 2021; Egarter Vigl et al., 2021), or artefacts, both tangible and intangible (Keleş Özgenç et al., 2024; Li et al., 2023), and across urban (Chen et al., 2024; Yee and Carrasco, 2024) and non-urban (Clemente et al., 2019) contexts. In contrast, classifications based on activities (Retka et al., 2019; Ruiz-Frau et al., 2020) or cognitive dimensions (Thiagarajah et al., 2015; Wahler et al., 2023) are less frequently employed.

3.3.4. *Educational and scientific*

This group combines the two categories from CICES v5.2 that refer to "elements of living systems that enable scientific investigation or the creation of traditional ecological knowledge," (CICES 3.2.1.1) and to "elements of living systems that enable education and training" (CICES 3.2.1.2). These are also referred to as cognitive values (Calcagni et al., 2022), which encompass intellectual interactions with the natural environment that foster scientific investigation, the creation of traditional ecological knowledge, and education or training—essentially, the in-situ research and study of nature. The identification is primarily based on activity-related criteria such as learning, reading, studying, teaching, and writing (Linder and Lusseau, 2024), as embedded in text or image content (Fig. 6). For example, photographs depicting people learning in natural environments or conducting scientific research in nature, including activities on research vessels (Angradi et al., 2018; Hale et al., 2019), are used for identification. Some studies also consider specific elements and contextual features, such as the presence of explanatory signs, visitor centers, and interpretive trails (Rossi et al., 2020), or the use of Latin names for plant species (Calcagni et al., 2022). When possible, it is good practice to analyze both image and text content together, as their integration is often crucial for proper understanding the cognitive value being conveyed (Busch et al., 2024; Calcagni et al., 2022; Schirpke et al., 2021).

3.3.5. Social interaction

The creation and maintenance of social relations are excluded from the CES identified by CICES because considered to relate to outcomes within the social system and not exclusively to cultural aspects (Haines-Young and Potschin, 2018). They are however acknowledged by MEA (2005) and studies frequently refer to the influence of nature in shaping social interactions among CES. Classes such as "social relations" and "social interactions" are often used to code data that simply portrays groups of people (Richards and Tunçer, 2018; Vaz et al., 2019; Zheng et al., 2024) or individuals interacting both with each other and with the natural environment (Calcagni et al., 2023; Koh et al., 2022; Muñoz et al., 2020). Those interactions can be formal or informal (Santana et al., 2024) and have a political (Amorim Maia et al., 2020), identitarian (Cardoso et al., 2022; Fan et al., 2024), or gastronomic focus (Callau et al., 2019; Kaiser et al., 2021; Wang et al., 2022; Yee and Carrasco, 2024). Social interactions can happen in dedicated touristic settings and making use of recreational equipment (Chang and Olafsson, 2022; Fan et al., 2024), which leads to some overlap with physical recreation (CICES 3.1.1.1). Criteria for identification mainly focus on activities and environmental elements (including the presence of other people), especially in photographs, and only in minor part on affective states and emotions (Hale et al., 2019).

3.3.6. Spiritual and religious

This group broadly aligns with CES derived from the spiritual, sacred, or religious significance of nature and ecosystems (CICES 3.4.1.2). Some inconsistencies in definition emerge however across studies, with most combining spiritual and religious aspects into a single class, but others treating them as distinct (Azevedo, 2023; Gan et al., 2024). Potential conflation with other CES also occurs when states like "pleasurable mood" (Bi et al., 2024; Dai et al., 2019), "relaxation" (Chen et al., 2020b), and "forgetting worries" (Chen et al., 2024) are categorized as spiritual experiences. Attribution ranges between specific ecosystem components (Arslan and Örücü, 2021) and landscapes (Cao et al., 2022; Gan et al., 2024; Keleş Özgenç et al., 2024). Identification criteria also show substantial variation. Criteria based on the mere presence of religious structures like mosques (Arslan and Örücü, 2021; Keleş Özgenç et al., 2024), churches (Clemente et al., 2019), or temples (Guo et al., 2023) in photographs or textual references (Li et al., 2022; Liao et al., 2023), or ambiguous emotional terminology such as "spectacular", "cozy", "enjoy" (Bi et al., 2024), or "love" (Hale et al., 2019) arguably lack sufficient specificity for the reliable identification of spiritual or religious CES. Best practices for identification may instead focus on activities clearly demonstrating spiritual engagement with nature such as "people meditating or religious ceremonies in natural settings" (Clemente et al., 2019) for photographic analysis, or explicit references to "refuge, solitude, and spiritual and religious experiences" (Johnson et al., 2019) in textual analysis.

3.3.7. Observational recreation

This group includes studies that refer to passive or observational interactions with living systems that enable activities promoting health, recuperation or enjoyment or that are used for entertainment or representation (CICES 3.1.1.2 and 3.3.1.1). The classification of this CES usually relies on the assumption that pictures depicting specific plants or animals or tags indicating names of species can be understood as observational recreation (Santana et al., 2024; Yee and Carrasco, 2024). However, indications on related activities, such as boat trips (Spalding et al., 2023), or associated benefits, such as health improvement or enjoyment, are often lacking. When solely based on the identification of natural or built environment elements in photographs or texts, the attribution of such photos or texts to specific CES appears at least questionable. Inconsistencies may also arise when entire landscapes are included (Karasov et al., 2022; Yang and Duan, 2024), since this potentially conflates with aesthetic experiences. To clearly identify this CES, best practices would comprise a notion of activities during which the photographs have been taken (Spalding et al., 2023), a reference to the required equipment (Lingua et al 2023), or an indication of associated emotions or benefits extracted through textual analysis (Calcagni et al 2022).

3.3.8. Health and wellbeing

This group aligns most closely with the CICES categories comprising physical and experiential interactions with the natural environment through active or immersive as well as passive or observational interactions (CICES 3.1.1.1 and 3.1.1.2). The focus of the studies is specifically on the health and well-being benefits that arise from such interactions. This includes, for example, relaxation (Gan et al., 2024; Koh et al., 2022), positive emotions (Chai-allah et al., 2023; Egorova, 2021; Ghermandi et al., 2022; Grzyb et al., 2021), therapeutic effects (Chen et al., 2020b; Wahler et al., 2023; Wang et al., 2021b), and notions of self-care (Linder and Lusseau, 2024). Definitions are often vague and identification criteria highly heterogeneous across studies. For example, studies rely on words indicating emotions and judgements such as "nice, enjoy, magic, fun, peaceful, relax, happy, spectacular, or exciting" (Chai-allah et al., 2023; Egorova, 2021), refer to activities such as "chilling, daydreaming, reflecting, or strolling" (Linder and Lusseau, 2024), or focus on recreational activities indirectly relating these to well-being benefits (Amorim Maia et al., 2020; Meng et al., 2020; Zhang et al., 2024b). Natural assets are rarely indicated, sometimes generically referring to the place or study area in general (Gan et al., 2024; Koh et al., 2022) or more specifically as "gorgeous bays and views" or "beautiful beech forest next to river" (Egorova, 2021). The identification of health and well-being benefits requires clear definition, a careful selection of appropriate terms that can be used in textual analysis and that may indicate relationships between place or environmental characteristics and benefits.

3.3.9. Existence and bequest values

This group combines CES coded by CICES as existence (CICES 3.4.2.1) and bequest (CICES 3.4.2.2), jointly defined as "biotic characteristics that have a non-use value". Existence and bequest are often inferred in the investigated studies based on the implicit, and arguably questionable, assumption by the researchers that the species and landmarks depicted in SM photographs are worth protecting, regardless of their direct utility (Chivulescu et al., 2024; Rossi et al., 2020)—whether for their diversity (Vidal-Llamas et al., 2024) or their charisma (Zapata-Caldas et al., 2022)—or for the benefit of future generations (Calcagni et al., 2022; Chen et al., 2020b). Lee et al. (2019) used seasons and weather as criteria for identifying existence and bequest value. Some of the category definitions included in this group appear to align more closely with supporting ecosystem services (e.g., "life sustaining" in Chen et al., 2020) or with concepts such as "sense of place" or belonging (Chen et al., 2024). Manual analysis of visual data is more frequent for studies in this group than text-based or automated approaches.

4. Discussion and conclusion

SM data has been an important driver of innovation in CES research in the past decade (Schirpke et al., 2023). With a growing fraction of CES studies overall and with half of the 218 retrieved studies published in 2022 or later, interest in this novel data source appears to be still firmly on the rise. While SM data-based research has already played a key role in introducing innovative data analytics into the broader field of ecosystem services research, many of the issues raised in its early stages remain unresolved (Ghermandi and Sinclair, 2019). These include concerns around data biases and uncertainty regarding the long-term viability of this research field, especially in light of the evolving nature of SM platforms and their shifting policies and Terms of Service (Otero et al., 2025). These persistent challenges are likely to create barriers for early-career researchers and to limit the use of these techniques by practitioners. The absence of consensus regarding conceptual frameworks and CES classifications, coupled with the lack of standardized methods for analyzing CES-related SM content, constitutes an additional barrier to the adoption of these approaches outside academia. As a result, the field has yet to fully realize its potential for large-scale application (both in terms of geographic scope and big data analysis), near real-time and continuous monitoring, and meaningful uptake in regions (e.g., Africa, Middle East, and South-East Asia) and for biomes (e.g., mountain and desert ecosystems) that have traditionally been suffering from data scarcity for ecosystem researchers and managers (Fig. 1; Ghermandi et al., 2023). The following sub-sections further discuss our findings concerning data sources, analytical methods, classification systems and classification criteria, and conclude with a forward-looking glance at critical issues to be considered and addressed by future researchers.

4.1. Shifting data sources

Flickr remains by far the dominant SM platform used in ecosystem services research (Fig. 2), in spite of the fluctuations in the popularity of this platform over time and biases in user base (Leppämäki et al., 2025). Such dominance is only challenged by the rapid growth of studies relying on Chinese platforms such as Weibo, Dianping, and Ctrip, which mirrors the rise of (SM data-based) CES research in China (Wang et al., 2021). The persistent widespread use of Flickr data is likely largely driven by convenience of data sampling—enabled by the platform's longstanding commitment to relatively open access data policies—, availability of spatially explicit information, and by its integration into the InVEST Recreation model, although its popularity among nature photographers may have also played a role (Oteros-Rozas et al., 2018). For comparison, changes in data accessibility to researchers from platforms such as Instagram and Twitter/X, have severely limited their use in CES research over time. Some researchers have responded to such changes by expanding the range of platforms used in the analysis. The studies we reviewed in this paper used data from 28 different SM platforms, compared to 14 SM platforms found in a review of studies in the broader field of environmental research by Ghermandi and Sinclair (2019). Whether growing restrictions in data accessibility will lead to a shift toward more ethically and legally ambiguous practices involving web scraping tools remains to be determined. Coupled with the trend toward a decrease in the fraction of studies using data from multiple SM sources (Fig. 3A)—contrary to the recommendations of multiple studies (Ghermandi, 2022; Otero et al., 2025; Tenkanen et al., 2017)—increasing restrictions on data accessibility raise concerns about the applicability of findings to real-world management decisions, due to a potential for platform-specific biases in the analyzed data and temporal instability of data sources (Ghermandi et al., 2026). This underscores the need for studies that critically compare the socio-demographic profile of users and differences in the content shared across platforms. Promising developments and novel options of data access for researchers, emerging particularly in Europe under the Union's "Digital Service Act" article 40 (European Union, 2022; Selling et al., 2025), seem are not yet widely reflected in the CES literature analyzed here.

4.2. Methodological developments

The trends observed in the literature also testify to rapid changes in the scope of analysis and in the methodologies implemented to investigate the data. While early studies focused on metadata (e.g., geotags and timestamps) to, for instance, assess spatial and temporal distribution of visits to natural areas (Wood et al., 2013), more recently interest has shifted towards the analysis of the actual content of photos and texts (Fig. 3B; Schirpke et al., 2023). More specifically, automated content analysis applying machine learning techniques is rapidly gaining ground, although manual analysis still remains important. Automated techniques applied primarily to texts (e.g., NLP for sentiment/emotion analysis, etc.) and images (for labeling, CNN-based classification, and for facial expression recognition) vary over a broad range of complexity, reflecting rapid changes in data analytics techniques over the investigated period (see Tables 1 and 2). Such focus on methodological innovation—rather than on the practical applicability of study results to real-world ecosystem management—may arguably also partially explain the use of data from a single platform. This trend will likely continue with the uptake of large language and visual language models in CES research (Liao et al., 2025; Luo et al., 2025; Zhao et al., 2026; Zheng et al., 2026). There remains significant untapped potential—as well as critical methodological and ethical considerations, including environmental implications and human involvement—that will require careful attention as more complex models and assessment pipelines will be employed to identify CES from textual and visual content, as well as so far widely untapped video and soundscape sources (Manley et al., 2022).

4.3. CES classifications

Slightly less than half of all studies (42%), and a majority of those published since 2022 (51%), rely on the analysis of SM content to distinguish between multiple CES (Fig. 5). To date, however, there is little agreement regarding the different classes of services to be investigated and their definitions. The challenge of CES classification is not specific to SM data analysis and rather reflects a broader tension between culturally specific, locally adapted, and often qualitative approaches to CES assessment, and generalized, universal classification systems that prioritize broad applicability and comparability across sites and spatial scales—often at the expense of capturing the complexity deriving from local perceptions and worldviews (Chan et al., 2016; Christie et al., 2019; Fish et al., 2016; Nowak-Olejnik et al., 2022). Most of the studies reviewed do not directly apply CES classifications from leading international frameworks but instead adapt these classifications to the specific case study. This may be due to the perceived relevance of only certain CES classes, the practicality of extracting those classes from the available data, the view that generalized frameworks are not well suited for SM data analysis (Yee and Carrasco, 2024), or a preference for bottom-up content analysis without reliance on predefined categories (De Juan et al., 2021). While the AI-based grouping into nine CES classes in this study does nevertheless suggest the presence of some general patterns, we caution against interpreting this synthesis as a step toward a new or more broadly accepted CES classification, which is beyond the scope of this work. On the contrary, the considerable heterogeneity in CES definitions and interpretations across several groups seems to preclude such an interpretation of our findings. The current lack of agreement regarding classifications and definitions of CES (Gould and Satterfield, 2025) remains a barrier for the comparability and interoperability of studies (*sensu* Bagstad et al., 2025).

4.4. Criteria for CES identification: reflections and future directions

A central focus of the present study is the examination of criteria used to identify specific CES within textual and visual SM content (Sections 3.3.1–3.3.9). What emerges from the analysis is a lack of consistency across approaches and interpretations, with many studies relying on assumptions that are either implicit or weakly justified. In this context, we highlight below five key aspects that, in our opinion, warrant careful consideration in future studies within this field:

- *Distinguishing between user-expressed benefits and those inferred through researcher interpretation*: A critical distinction exists between assigning a CES category based on an explicit, user-generated expression of a benefit and doing so based on a researcher's interpretation of some specific content (see Section 3.3.2). For instance, a post containing the phrase "beautiful flower" signals an aesthetic experience on the part of the user who generated this content. In contrast, inferring an aesthetic value from a close-up photograph of a flower requires an additional, and potentially unwarranted, assumption by the researcher (e.g., could the photograph instead reflect appreciation of the scientific significance of a rare species or convey a symbolic meaning?). The latter represents a key entry point for bias, especially when researchers or computational models lack sensitivity to local and cultural contexts, including those shaped by specific social groups (Tasser et al., 2025). At a minimum, studies should explicitly acknowledge the assumptions involved and the potential limitations they introduce.
- *Differentiating between ecosystem services and the benefits they generate*: Some user-generated content may indicate the enjoyment of a benefit derived from an interaction with nature without explicitly referencing the type(s) of ecosystem service(s) that produced it (see, for instance, Section 3.3.7). For example, textual expressions such as "tranquility," "happiness," or "excitement" reflect perceived benefits, but do not necessarily reveal whether they stem from recreational, aesthetic, or other cultural experiences (Ebner et al., 2022). Clearly distinguishing between these two conceptually distinct stages of the ecosystem services "cascade model" (Haines-Young and Potschin, 2010) would enhance the analytical rigor and replicability of studies, while still capturing valuable insights into the benefits people derive from interactions with nature (Nowak-Olejnik et al., 2022; Stålhammar and Pedersen, 2017).
- *Ensuring that both the "ecological" and "use" clauses are met*: The "ecological" and "use" clauses are foundational components of the CICES classification (Haines-Young and Potschin, 2018), yet they have received only limited attention in SM data-based CES research (Busch et al., 2024). The ecological clause requires demonstrable links to biophysical or landscape features that provide the service, while the use clause requires evidence of human perception, interaction, or benefit. Although inferring the ecological clause from content geotagged within natural settings (e.g., national parks) may serve as a pragmatic solution, it remains a second-best approach and should be explicitly acknowledged as such. Likewise, assuming the use clause based solely on the presence of certain elements (e.g., birds or scenic views) or keywords (e.g., "beautiful") risks introducing bias unless supported by contextual cues that indicate meaningful engagement with the natural element. This concern is particularly acute for text analyses that rely on simple keyword-based methods rather than context-aware NLP techniques. Clear articulation of how both clauses are operationalized and validated will improve transparency, comparability, and interpretability across future studies.
- *Engaging with neighboring fields of research:* Research on the use of SM data in CES assessments is rapidly consolidating into a field of its own. While this specialization has clear benefits, it also risks overlooking important developments in adjacent areas. In particular, we observe a widening gap between SM data-based CES research and advances in more place-based and qualitative CES scholarship (Brill et al., 2022; Himes and Muraca, 2018). This concerns not only empirical insights, but also conceptual debates including epistemic justice, whose perspectives and values are considered, and the importance of understanding CES within diverse local and cultural contexts (Gould and Satterfield, 2025; Hoelting et al., 2024b). Addressing this gap requires future research to more critically reflect on the scope and limits of universal assessment approaches that lack local validations. Integrating SM data analyses with survey-based or participatory methods can provide more holistic and complementary insights into people's perceptions and values of CES (Ebner et al., 2022).
- *Dealing with hybrid nature experiences:* In the digital age, the boundary between social-ecological and digital systems is increasingly blurred. While the benefits of indirect, screen-mediated nature experiences have received some attention (Browning et al., 2020), SM are actively shaping the quality and type of such experiences, creating a "digital ecosystem" in which the appreciation of CES and their values are negotiated (Calcagni et al., 2019). To date the "seeding" experiences that drive CES expressions in digital spaces have largely been nature-based (Langemeyer and Calcagni, 2022). However, the rapid rise of artificial and AI-generated nature content raises important questions for SM-based CES research. Some are technical—how to identify and filter content rooted in real-world nature experiences—while others are conceptual: what implications do digital or hybrid nature experiences have for both human wellbeing and nature conservation?

In conclusion, despite the shifting landscape of platforms and data accessibility, research on SM data-based assessments of CES is thriving, as evidenced by a steady growth in publications and methodological innovation. Persistent issues—such as unresolved biases, fragmented methodologies, and occasional reliance on tenuous assumptions—continue to challenge the field's scientific rigor and reproducibility. Advancing toward greater coherence, standardization, and methodological robustness will be key to fostering the maturation of this promising yet still evolving area of inquiry.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT to improve readability and language in some sections of the manuscript. The authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

CRediT authorship contribution statement

Andrea Ghermandi: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Fulvia Calcagni:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Johannes Langemeyer:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Uta Schirpke:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Given their role as editors of Ecosystem Services, AG, JL and US had no involvement in the peer review of this article and had no access to information regarding its peer review. Full responsibility for the editorial process for this article was delegated to another journal editor. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecoser.2026.101839.

Data availability

Data will be made available on request.

References

Amorim Maia, A.T., Calcagni, F., Connolly, J.J.T., Anguelovski, I., Langemeyer, J., 2020. Hidden drivers of social injustice: uncovering unequal cultural ecosystem services behind green gentrification. Environ Sci Policy 112, 254–263. https://doi.org/10.1016/j.envsci.2020.05.021.

Andersson, E., Tengö, M., McPhearson, T., Kremer, P., 2015. Cultural ecosystem services as a gateway for improving urban sustainability. Ecosyst. Serv. 12, 165–168. https://doi.org/10.1016/j.ecoser.2014.08.002.

Angradi, T.R., Launspach, J.J., Debbout, R., 2018. Determining preferences for ecosystem benefits in Great Lakes areas of concern from photographs posted to social media. J. Gt. Lakes Res. 44, 340–351. https://doi.org/10.1016/j.jglr.2017.12.007.

Arslan, E.S., Örücü, Ö.K., 2021. MaxEnt modelling of the potential distribution areas of cultural ecosystem services using social media data and GIS. Environ. Dev. Sustain. 23, 2655–2667. https://doi.org/10.1007/s10668-020-00692-3.

Arts, K., van der Wal, R., Adams, W.M., 2015. Digital technology and the conservation of nature. Ambio 44, 661–673. https://doi.org/10.1007/s13280-015-0705-1.

Azevedo, A., 2023. Pull and push drivers of giant-wave spectators in Nazaré, Portugal: a cultural ecosystem services assessment based on geo-tagged photos. Land 12, 360. https://doi.org/10.3390/land12020360.

Azevedo, A., 2021. Using social media photos as a proxy to estimate the recreational value of (im)movable heritage: the Rubjerg Knude (Denmark) lighthouse. Int. J. Contemp. Hosp. Manag. 33, 2283–2303. https://doi.org/10.1108/IJCHM-04-2020-0365.

Baas, J., Schotten, M., Plume, A., Côté, G., Karimi, R., 2020. Scopus as a curated, high-quality bibliometric data source for academic research in quantitative science studies. Quant. Sci. Stud. 1, 377–386. https://doi.org/10.1162/qss_a_00019.

Bagstad, K.J., Balbi, S., Adamo, G., Athanasiadis, I.N., Affinito, F., Willcock, S., Magrach, A., Hayashi, K., Harmáčková, Z.V., Niamir, A., 2025. Interoperability for ecosystem service assessments: why, how, who, and for whom? Ecosyst. Serv.

Benati, G., Calcagni, F., Martellozzo, F., Ghermandi, A., Langemeyer, J., 2024. Unequal access to cultural ecosystem services of green spaces within the city of Rome – a spatial social media-based analysis. Ecosyst. Serv. 66, 101594. https://doi.org/10.1016/j.ecoser.2023.101594.

Bi, X., Gan, X., Jiang, Z., Li, Z., Li, J., 2024. How do landscape patterns in urban parks affect multiple cultural ecosystem services perceived by residents? Sci. Total Environ. 946, 174255. https://doi.org/10.1016/j.scitotenv.2024.174255.

Bieling, C., Plieninger, T., Pirker, H., Vogl, C.R., 2014. Linkages between landscapes and human well-being: An empirical exploration with short interviews, Ecological Economics. Elsevier.

Brill, G.C., Anderson, P.M.L., O'Farrell, P., 2022. Relational values of cultural ecosystem services in an urban conservation area: the case of Table Mountain National Park, South Africa. Land 11, 603. https://doi.org/10.3390/land11050603.

Browning, M.H.E.M., Mimnaugh, K.J., van Riper, C.J., Laurent, H.K., LaValle, S.M., 2020. Can simulated nature support mental health? Comparing short, single-doses of 360-degree nature videos in virtual reality with the outdoors. Front. Psychol. 10, 2667. https://doi.org/10.3389/fpsyg.2019.02667.

Bruzzese, S., Ahmed, W., Blanc, S., Brun, F., 2022. Ecosystem services: a social and semantic network analysis of public opinion on Twitter. Int. J. Environ. Res. Public Health 19, 15012. https://doi.org/10.3390/ijerph192215012.

Busch, C., Specht, K., Inostroza, L., Falke, M., Zepp, H., 2024. Disentangling cultural ecosystem services co-production in urban green spaces through social media reviews. Ecosyst. Serv. 70, 101675. https://doi.org/10.1016/j.ecoser.2024.101675.

Calcagni, F., Amorim Maia, A.T., Connolly, J.J.T., Langemeyer, J., 2019. Digital co-construction of relational values: understanding the role of social media for sustainability. Sustain. Sci. 14, 1309–1321. https://doi.org/10.1007/s11625-019-00672-1.

Calcagni, F., Connolly, J.J.T., Langemeyer, J., 2023. Plural relational green space values for whom, when, and where? – A social media approach. Digit. Geogr. Soc. 5, 100065. https://doi.org/10.1016/j.diggeo.2023.100065.

Calcagni, F., Nogué Batallé, J., Baró, F., Langemeyer, J., 2022. A tag is worth a thousand pictures: a framework for an empirically grounded typology of relational values through social media. Ecosyst. Serv. 58, 101495. https://doi.org/10.1016/j.ecoser.2022.101495.

Callau, A.À., Albert, M.Y.P., Rota, J.J., Giné, D.S., 2019. Landscape characterization using photographs from crowdsourced platforms: content analysis of social media photographs. Open Geosci. 11, 558–571. https://doi.org/10.1515/geo-2019-0046.

Cao, H., Wang, M., Su, S., Kang, M., 2022. Explicit quantification of coastal cultural ecosystem services: a novel approach based on the content and sentimental analysis of social media. Ecol. Ind. 137, 108756. https://doi.org/10.1016/j.ecolind.2022.108756.

Cardoso, A.S., Renna, F., Moreno-Llorca, R., Alcaraz-Segura, D., Tabik, S., Ladle, R.J., Vaz, A.S., 2022. Classifying the content of social media images to support cultural ecosystem service assessments using deep learning models. Ecosyst. Serv. 54, 101410. https://doi.org/10.1016/j.ecoser.2022.101410.

Casalegno, S., Inger, R., DeSilvey, C., Gaston, K.J., 2013. Spatial covariance between aesthetic value and other ecosystem services. PLoS One 8, e68437. https://doi.org/10.1371/journal.pone.0068437.

Chai-allah, A., Fox, N., Günther, F., Bentayeb, F., Brunschwig, G., Bimonte, S., Joly, F., 2023. Mining crowdsourced text to capture hikers' perceptions associated with landscape features and outdoor physical activities. Ecol. Inform. 78, 102332. https://doi.org/10.1016/j.ecoinf.2023.102332.

Chan, K.M., Guerry, A.D., Balvanera, P., Klain, S., Satterfield, T., Basurto, X., Bostrom, A., Chuenpagdee, R., Gould, R., Halpern, B.S., 2012. Where are cultural and social in ecosystem services? A framework for constructive engagement. Bioscience 62, 744–756.

Chan, K.M.A., Balvanera, P., Benessaiah, K., Chapman, M., Díaz, S., Gómez-Baggethun, E., Gould, R., Hannahs, N., Jax, K., Klain, S., Luck, G.W., Martín-López, B., Muraca, B., Norton, B., Ott, K., Pascual, U., Satterfield, T., Tadaki, M., Taggart, J., Turner, N., 2016. Why protect nature? Rethinking values and the environment. Proc. Natl. Acad. Sci. 113, 1462–1465. https://doi.org/10.1073/pnas.1525002113.

Chang, P., Olafsson, A.S., 2022. The scale effects of landscape variables on landscape experiences: a multi-scale spatial analysis of social media data in an urban nature park context. Landsc. Ecol. 37, 1271–1291. https://doi.org/10.1007/s10980-022-01402-2.

Chen, Y., Caesemaecker, C., Rahman, H.T., Sherren, K., 2020a. Comparing cultural ecosystem service delivery in dykelands and marshes using Instagram: a case of the Cornwallis (Jijuktu'kwejk) River, Nova Scotia, Canada. Ocean Coast. Manag. 193, 105254. https://doi.org/10.1016/j.ocecoaman.2020.105254.

Chen, Y., Hong, C., Yang, Y., Li, J., Wang, Y., Zheng, T., Zhang, Y., Shao, F., 2024. Mining social media data to capture urban park visitors' perception of cultural ecosystem services and landscape factors. Forests 15, 213. https://doi.org/10.3390/f15010213.

Chen, Y., Ke, X., Min, M., Cheng, P., 2020b. Disparity in perceptions of social values for ecosystem services of urban green space: a case study in the East Lake Scenic Area. Wuhan. Front. Public Health 8, 370. https://doi.org/10.3389/fpubh.2020.00370.

Cheng, X., Van Damme, S., Li, L., Uyttenhove, P., 2019. Evaluation of cultural ecosystem services: a review of methods. Ecosyst. Serv. 37, 100925. https://doi.org/10.1016/j.ecoser.2019.100925.

Chivulescu, S., Hapa, M., Pitar, D., Lorenţ, A., Marmureanu, L., Leca, S., Radu, R., Cazacu, R., Dobre, A.C., Pascu, I.S., Marcu, C., Verghelet, M., Vezeanu, C., Racoviceanu, T., Badea, O., 2024. Integrating monetary and non-monetary valuation for ecosystem services in Piatra Craiului national park, Southern Carpathians: a comprehensive approach to sustainability and conservation. Front. for. Glob. Change 7, 1280793. https://doi.org/10.3389/ffgc.2024.1280793.

Christie, M., Martín-López, B., Church, A., Siwicka, E., Szymonczyk, P., Mena Sauterel, J., 2019. Understanding the diversity of values of "Nature's contributions to people": insights from the IPBES Assessment of Europe and Central Asia. Sustain. Sci. 14, 1267–1282. https://doi.org/10.1007/s11625-019-00716-6.

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. https://doi.org/10.1016/j.ecolind.2018.08.043.

Cohen, J., 2013. Statistical Power Analysis for the Behavioral Sciences, 2nd ed. Routledge, New York. https://doi.org/10.4324/9780203771587.

Dai, P., Zhang, S., Chen, Z., Gong, Y., Hou, H., 2019. Perceptions of cultural ecosystem services in Urban Parks Based on Social Network Data. Sustainability 11, 5386. https://doi.org/10.3390/su11195386.

Dang, H., Li, J., 2023. Supply-demand relationship and spatial flow of urban cultural ecosystem services: the case of Shenzhen, China. J. Clean. Prod. 423, 138765. https://doi.org/10.1016/j.jclepro.2023.138765.

Daymond, T., Andrew, M.E., Kobryn, H.T., 2023. Crowdsourcing social values data: Flickr and public participation GIS provide different perspectives of ecosystem services in a remote coastal region. Ecosyst. Serv. 64, 101566. https://doi.org/10.1016/j.ecoser.2023.101566.

De Juan, S., Ospina-Álvarez, A., Villasante, S., Ruiz-Frau, A., 2021. A Graph Theory approach to assess nature's contribution to people at a global scale. Sci. Rep. 11, 9118. https://doi.org/10.1038/s41598-021-88745-z.

Depietri, Y., Ghermandi, A., Campisi-Pinto, S., Orenstein, D.E., 2021. Public participation GIS versus geolocated social media data to assess urban cultural ecosystem services: Instances of complementarity. Ecosyst. Serv. 50, 101277. https://doi.org/10.1016/j.ecoser.2021.101277.

Depietri, Y., Ghermandi, A., Hadar, L., Orenstein, D.E., 2025. Leveraging AI and social media for actionable insights for nature park management. J. Outdoor Recreat. Tour. 52, 100923. https://doi.org/10.1016/j.jort.2025.100923.

Díaz, S., Pascual, U., Stenseke, M., Martín-López, B., Watson, R.T., Molnár, Z., Hill, R., Chan, K.M.A., Baste, I.A., Brauman, K.A., Polasky, S., Church, A., Lonsdale, M., Larigauderie, A., Leadley, P.W., Van Oudenhoven, A.P.E., Van Der Plaat, F., Schröter, M., Lavorel, S., Aumeeruddy-Thomas, Y., Bukvareva, E., Davies, K., Demissew, S., Erpul, G., Failler, P., Guerra, C.A., Hewitt, C.L., Keune, H., Lindley, S., Shirayama, Y., 2018. Assessing nature's contributions to people. Science 359, 270–272. https://doi.org/10.1126/science.aap8826.

Do, Y., 2019. Valuating aesthetic benefits of cultural ecosystem services using conservation culturomics. Ecosyst. Serv. 36, 100894. https://doi.org/10.1016/j.ecoser.2019.100894.

Ebner, M., Schirpke, U., Tappeiner, U., 2022. Combining multiple socio-cultural approaches – deeper insights into cultural ecosystem services of mountain lakes? Landsc. Urban Plan. 228, 104549. https://doi.org/10.1016/j.landurbplan.2022.104549.

Egarter Vigl, L., Marsoner, T., Giombini, V., Pecher, C., Simion, H., Stemle, E., Tasser, E., Depellegrin, D., 2021. Harnessing artificial intelligence technology and social media data to support Cultural Ecosystem Service assessments. People Nat. 3, 673–685. https://doi.org/10.1002/pan3.10199.

Egorova, E., 2021. Using textual volunteered geographic information to model nature-based activities: a case study from Aotearoa New Zealand. J. Spat. Inf. Sci. 25–63. https://doi.org/10.5311/JOSIS.2021.23.157.

Erskine, E., Baillie, R., Lusseau, D., 2021. Marine protected areas provide more cultural ecosystem services than other adjacent coastal areas. One Earth 4, 1175–1185. https://doi.org/10.1016/j.oneear.2021.07.014.

European Union, 2022. Regulation - 2022/2065 - EN - DSA - EUR-Lex [WWW Document]. URL https://eur-lex.europa.eu/eli/reg/2022/2065/oj/eng (accessed 2.23.26).

Fan, Y., Mandal, M.S.H., Nakabayashi, M., Hosaka, T., 2024. Visitor experience with biodiversity in tropical rainforests: a global-scale assessment using social media data. Biol. Conserv. 293, 110590. https://doi.org/10.1016/j.biocon.2024.110590.

Fish, R., Church, A., Winter, M., 2016. Conceptualising cultural ecosystem services: A novel framework for research and critical engagement, Ecosystem Services. Elsevier.

Fox, N., Chamberlain, B., Lindquist, M., Van Berkel, D., 2022. Understanding landscape aesthetics using a Novel Viewshed Assessment of social media locations within the Troodos UNESCO Global Geopark. Cyprus. Front. Environ. Sci. 10, 884115. https://doi.org/10.3389/fenvs.2022.884115.

Fox, N., Graham, L.J., Eigenbrod, F., Bullock, J.M., Parks, K.E., 2021. Enriching social media data allows a more robust representation of cultural ecosystem services. Ecosyst. Serv. 50, 101328. https://doi.org/10.1016/j.ecoser.2021.101328.

Gan, Q., Liao, L., Kang, X., Xu, Z., Fu, T., Cao, Y., Feng, Y., Dong, J., Lan, S., 2024. Cultural ecosystem services and disservices in protected areas: Hotspots and influencing factors based on tourists' digital footprints. Ecosyst. Serv. 70, 101680. https://doi.org/10.1016/j.ecoser.2024.101680.

Ghermandi, A., 2022. Geolocated social media data counts as a proxy for recreational visits in natural areas: a meta-analysis. J. Environ. Manage. 317, 115325. https://doi.org/10.1016/j.jenvman.2022.115325.

Ghermandi, A., 2018. Integrating social media analysis and revealed preference methods to value the recreation services of ecologically engineered wetlands. Ecosyst. Serv Assess. Valuat. Recreat. Ecosyst. Serv. 31, 351–357. https://doi.org/10.1016/j.ecoser.2017.12.012.

Ghermandi, A., Camacho-Valdez, V., Trejo-Espinosa, H., 2020a. Social media-based analysis of cultural ecosystem services and heritage tourism in a coastal region of Mexico. Tour. Manag. 77, 104002. https://doi.org/10.1016/j.tourman.2019.104002.

Ghermandi, A., Depietri, Y., Orenstein, D.E., 2026. Human-nature interactions through a digital prism: Heterogeneity in user socio-demographics and content across social media platforms. Landsc. Urban Plan. 268, 105568. https://doi.org/10.1016/j.landurbplan.2025.105568.

Ghermandi, A., Depietri, Y., Sinclair, M., 2022. In the AI of the beholder: a comparative analysis of computer vision-assisted characterizations of human-nature interactions in urban green spaces. Landsc. Urban Plan. 217, 104261. https://doi.org/10.1016/j.landurbplan.2021.104261.

Ghermandi, A., Langemeyer, J., Van Berkel, D., Calcagni, F., Depietri, Y., Egarter Vigl, L., Fox, N., Havinga, I., Jäger, H., Kaiser, N., Karasov, O., McPhearson, T., Podschun, S., Ruiz-Frau, A., Sinclair, M., Venohr, M., Wood, S.A., 2023. Social media data for environmental sustainability: a critical review of opportunities, threats, and ethical use. One Earth 6, 236–250. https://doi.org/10.1016/j.oneear.2023.02.008.

Ghermandi, A., Sinclair, M., 2019. Passive crowdsourcing of social media in environmental research: a systematic map. Glob. Environ. Change 55, 36–47. https://doi.org/10.1016/j.gloenvcha.2019.02.003.

Ghermandi, A., Sinclair, M., Fichtman, E., Gish, M., 2020b. Novel insights on intensity and typology of direct human-nature interactions in protected areas through passive crowdsourcing. Glob. Environ. Change 65, 102189. https://doi.org/10.1016/j.gloenvcha.2020.102189.

Gosal, A.S., Geijzendorffer, I.R., Václavík, T., Poulin, B., Ziv, G., 2019. Using social media, machine learning and natural language processing to map multiple recreational beneficiaries. Ecosyst. Serv. 38, 100958. https://doi.org/10.1016/j.ecoser.2019.100958.

Gould, R.K., Satterfield, T., 2025. Critiques of cultural ecosystem services, and ways forward that minimize them. The Routledge Handbook of Cultural Ecosystem Services. Routledge.

Graham, L.J., Eigenbrod, F., 2019. Scale dependency in drivers of outdoor recreation in England. People Nat. 1, 406–416. https://doi.org/10.1002/pan3.10042.

Grzyb, T., Kulczyk, S., Derek, M., Woźniak, E., 2021. Using social media to assess recreation across urban green spaces in times of abrupt change. Ecosyst. Serv. 49, 101297. https://doi.org/10.1016/j.ecoser.2021.101297.

Gugulica, M., Burghardt, D., 2023. Mapping indicators of cultural ecosystem services use in urban green spaces based on text classification of geosocial media data. Ecosyst. Serv. 60, 101508. https://doi.org/10.1016/j.ecoser.2022.101508.

Guo, R.-Z., Lin, L., Xu, J.-F., Dai, W.-H., Song, Y.-B., Dong, M., 2023. Spatio-temporal characteristics of cultural ecosystem services and their relations to landscape factors in Hangzhou Xixi National Wetland Park, China. Ecol. Indic. 154, 110910. https://doi.org/10.1016/j.ecolind.2023.110910.

Haines-Young, R., 2023. Common International Classification of Ecosystem Services (CICES) V5. 2 and Guidance on the Application of the Revised Structure.

Haines-Young, R., Potschin, M., 2010. The links between biodiversity, ecosystem services and human well-being. In: Frid, C.L.J., Raffaelli, D.G (Eds.), Ecosystem Ecology: A New Synthesis, Ecological Reviews. Cambridge University Press, Cambridge, pp. 110–139. https://doi.org/10.1017/CBO9780511750458.007.

Haines-Young, R., Potschin, M.B., 2018. Common international classification of ecosystem services (CICES) V5. 1 and guidance on the application of the revised structure. Eur. Environ. Agency 53.

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. Indic. 107, 105580. https://doi.org/10.1016/j.ecolind.2019.105580.

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, e12343. https://doi.org/10.1111/conl.12343.

Havinga, I., Marcos, D., Bogaart, P., Massimino, D., Hein, L., Tuia, D., 2023. Social media and deep learning reveal specific cultural preferences for biodiversity. People Nat. 5, 981–998. https://doi.org/10.1002/pan3.10466.

Havinga, I., Marcos, D., Bogaart, P., Tuia, D., Hein, L., 2024. Understanding the sentiment associated with cultural ecosystem services using images and text from social media. Ecosyst. Serv. 65, 101581. https://doi.org/10.1016/j.ecoser.2023.101581.

Havinga, I., Marcos, D., Bogaart, P.W., Hein, L., Tuia, D., 2021. Social media and deep learning capture the aesthetic quality of the landscape. Sci. Rep. 11, 20000. https://doi.org/10.1038/s41598-021-99282-0.

Heikinheimo, V., Minin, E.D., Tenkanen, H., Hausmann, A., Erkkonen, J., Toivonen, T., 2017. User-generated geographic information for visitor monitoring in a national park: a comparison of social media data and visitor survey. ISPRS Int. J. Geo-Inf. 6, 85. https://doi.org/10.3390/ijgi6030085.

Himes, A., Muraca, B., 2018. Relational values: the key to pluralistic valuation of ecosystem services. Curr. Opin. Environ. Sustain Sustainability Challenges: Relational Values 35, 1–7. https://doi.org/10.1016/j.cosust.2018.09.005.

Hoelting, K.R., Martinez, D.E., Schuster, R.M., Gavin, M.C., 2024a. Advancing knowledge pluralism and cultural benefits in ecosystem services theory and application. Ecosyst. Serv. 65, 101583. https://doi.org/10.1016/j.ecoser.2023.101583.

Hoelting, K.R., Morse, J.W., Gould, R.K., Martinez, D.E., Hauptfeld, R.S., Cravens, A.E., Breslow, S.J., Bair, L.S., Schuster, R.M., Gavin, M.C., 2024b. Opportunities for improved consideration of cultural benefits in environmental decision-making. Ecosyst. Serv. 65, 101587. https://doi.org/10.1016/j.ecoser.2023.101587.

Huai, S., Chen, F., Liu, S., Canters, F., Van De Voorde, T., 2022. Using social media photos and computer vision to assess cultural ecosystem services and landscape features in urban parks. Ecosyst. Serv. 57, 101475. https://doi.org/10.1016/j.ecoser.2022.101475.

Huang, S., Xiao, X., Tian, T., Che, Y., 2024. Seasonal influences on preferences for urban blue-green spaces: Integrating land surface temperature into the assessment of cultural ecosystem service value. Sustain. Cities Soc. 102, 105237. https://doi.org/10.1016/j.scs.2024.105237.

Ishida, S., Matsui, T., Haga, C., Hori, K., Hashimoto, S., Saito, O., 2023. Twitter mining for detecting interest trends on biodiversity: messages from seven language communities. Sustainability 15, 12893. https://doi.org/10.3390/su151712893.

Johnson, M., Campbell, L., Svendsen, E., McMillen, H., 2019. Mapping urban park cultural ecosystem services: a Comparison of Twitter and semi-structured interview methods. Sustainability 11, 6137. https://doi.org/10.3390/su11216137.

Kaiser, N.N., Ghermandi, A., Feld, C.K., Hershkovitz, Y., Palt, M., Stoll, S., 2021. Societal benefits of river restoration – Implications from social media analysis. Ecosyst. Serv. 50, 101317. https://doi.org/10.1016/j.ecoser.2021.101317.

Karasov, O., Heremans, S., Külvik, M., Domnich, A., Burdun, I., Kull, A., Helm, A., Uuemaa, E., 2022. Beyond land cover: how integrated remote sensing and social media data analysis facilitates assessment of cultural ecosystem services. Ecosyst. Serv. 53, 101391. https://doi.org/10.1016/j.ecoser.2021.101391.

Karasov, O., Heremans, S., Külvik, M., Domnich, A., Chervanyov, I., 2020. On how crowdsourced data and landscape organisation metrics can facilitate the mapping of cultural ecosystem services: an Estonian Case Study. Land 9, 158. https://doi.org/10.3390/land9050158.

Kassambara, A., 2019. rstatix: Pipe-friendly framework for basic statistical tests. CRAN Contrib Packag.

Keleş Özgenç, E., Dönmez, A.H., Özgenç, E., 2024. Evaluating cultural ecosystem services through geospatial social media data: a study of Edirne City. J. Geovisualization Spat. Anal. 8, 30. https://doi.org/10.1007/s41651-024-00193-1.

Kikuchi, Y., Nishimura, I., Sasaki, T., 2022. Wild birds in YouTube videos: presence of specific species contributes to increased views. Ecol. Inform. 71, 101767. https://doi.org/10.1016/j.ecoinf.2022.101767.

Knoble, C., Yu, D., 2023. Bridging the Gap: analyzing the relationship between environmental justice awareness on Twitter and socio-environmental factors using remote sensing and big data. Remote Sens. 15, 5510. https://doi.org/10.3390/rs15235510.

Koh, Y.F., Loc, H.H., Park, E., 2022. Towards a “City in Nature”: evaluating the cultural ecosystem services approach using online public participation GIS to support urban green space management. Sustainability 14, 1499. https://doi.org/10.3390/su14031499.

Komossa, F., Mariño, D., Michel, A.H., Purves, R.S., 2023. Find the one you like! Profiling Swiss parks with user generated content. J. Outdoor Recreat. Tour. 44, 100673. https://doi.org/10.1016/j.jort.2023.100673.

Kong, I., Sarmiento, F.O., 2022. Utilizing a crowdsourced phrasal lexicon to identify cultural ecosystem services in El Cajas National Park. Ecuador. Ecosyst. Serv. 56, 101441. https://doi.org/10.1016/j.ecoser.2022.101441.

Kong, I., Sarmiento, F.O., Mu, L., 2023. Crowdsourced text analysis to characterize the U. S. National Parks based on cultural ecosystem services. Landsc. Urban Plan. 233, 104692. https://doi.org/10.1016/j.landurbplan.2023.104692.

Kosanic, A., Petzold, J., 2020. A systematic review of cultural ecosystem services and human wellbeing, Ecosystem Services. Elsevier.

Langemeyer, J., Calcagni, F., 2022. Virtual spill-over effects: what social media has to do with relational values and global environmental stewardship. Ecosyst. Serv. 53, 101400. https://doi.org/10.1016/j.ecoser.2021.101400.

Langemeyer, J., Calcagni, F., Baró, F., 2018. Mapping the intangible: using geolocated social media data to examine landscape aesthetics. Land Use Policy 77, 542–552. https://doi.org/10.1016/j.landusepol.2018.05.049.

Langemeyer, J., Connolly, J.J., 2020. Weaving notions of justice into urban ecosystem services research and practice, Environmental science & policy. Elsevier.

Langemeyer, J., Ghermandi, A., Keeler, B., Van Berkel, D., 2023. The future of crowd-sourced cultural ecosystem services assessments. Ecosyst. Serv. 60, 101518. https://doi.org/10.1016/j.ecoser.2023.101518.

Lee, H., Seo, B., Koellner, T., Lautenbach, S., 2019. Mapping cultural ecosystem services 2.0 – potential and shortcomings from unlabeled crowd sourced images. Ecol. Indic. 96, 505–515. https://doi.org/10.1016/j.ecolind.2018.08.035.

Lenormand, M., Luque, S., Langemeyer, J., Tenerelli, P., Zulian, G., Aalders, I., Chivulescu, S., Clemente, P., Dick, J., Van Dijk, J., Van Eupen, M., Giuca, R.C., Kopperoinen, L., Lellei-Kovács, E., Leone, M., Lieskovský, J., Schirpke, U., Smith, A. C., Tappeiner, U., Woods, H., 2018. Multiscale socio-ecological networks in the age of information. PLoS ONE 13, e0206672. https://doi.org/10.1371/journal.pone.0206672.

Leppämäki, T., Heikinheimo, V., Eklund, J., Hausmann, A., Toivonen, T., 2025. The rise and fall of the social media platform Flickr: Implications for nature recreation research. Journal of Outdoor Recreation and Tourism. Elsevier.

Li, C., Liang, Q., Lin, B., Zhai, J., 2023. Landscape management and planning as a spatial organization method connecting CES supply-demand assessment and sustainable tourism development. J. Outdoor Recreat. Tour. 44, 100705. https://doi.org/10.1016/j.jort.2023.100705.

Li, H., Peng, J., Jiao, Y., Ai, S., 2022a. Experiencing urban green and blue spaces in urban wetlands as a nature-based solution to promote positive emotions. Forests 13, 473. https://doi.org/10.3390/f13030473.

Li, J., Gao, J., Zhang, Z., Fu, J., Shao, G., Zhao, Z., Yang, P., 2024a. Insights into citizens' experiences of cultural ecosystem services in urban green spaces based on social media analytics. Landsc. Urban Plan. 244, 104999. https://doi.org/10.1016/j.landurbplan.2023.104999.

Li, T., Xiang, Z., Li, Y., 2024b. POIs-based public preferences mapping on imbalanced supply-demand of recreation services can support sustainable coastal beach management. Front. Mar. Sci. 11, 1288112. https://doi.org/10.3389/fmars.2024.1288112.

Li, Y., Xie, L., Zhang, L., Huang, L., Lin, Y., Su, Y., AmirReza, S., He, S., Zhu, C., Li, S., Gan, M., Huang, Lu., Wang, K., Zhang, J., Chen, X., 2022b. Understanding different cultural ecosystem services: an exploration of rural landscape preferences based on geographic and social media data. J. Environ. Manage. 317, 115487. https://doi.org/10.1016/j.jenvman.2022.115487.

Liao, H.-Y., Zhao, C., Koylu, C., Cao, H., Qiu, J., Callaghan, C.T., Song, J., Shao, W., 2025. Mapping cultural ecosystem service flows from social media imagery with Vision–Language Models: A zero-shot CLIP framework. https://doi.org/10.32942/X29S8C.

Liao, J., Liao, Q., Wang, W., Shen, S., Sun, Y., Xiao, P., Cao, Y., Chen, J., 2023. Quantifying and mapping landscape value using online texts: a deep learning approach. Appl. Geogr. 154, 102950. https://doi.org/10.1016/j.apgeog.2023.102950.

Linder, A.C., Lusseau, D., 2024. Resilience of human-nature interaction network to pandemic conditions. Sci. Total Environ. 931, 172813. https://doi.org/10.1016/j.scitotenv.2024.172813.

Lingua, F., Coops, N.C., Griess, V.C., 2023. Assessing forest recreational potential from social media data and remote sensing technologies data. Ecol. Indic. 149, 110165. https://doi.org/10.1016/j.ecolind.2023.110165.

Lingua, F., Coops, N.C., Griess, V.C., 2022a. Valuing cultural ecosystem services combining deep learning and benefit transfer approach. Ecosyst. Serv. 58, 101487. https://doi.org/10.1016/j.ecoser.2022.101487.

Lingua, F., Coops, N.C., Lafond, V., Gaston, C., Griess, V.C., 2022b. Characterizing, mapping and valuing the demand for forest recreation using crowdsourced social media data. PLoS ONE 17, e0272406. https://doi.org/10.1371/journal.pone.0272406.

Luo, H., Zhang, Z., Zhu, Q., Ameur, N.E.H.B., Liu, X., Ding, F., Cai, Y., 2025. Using large language models to investigate cultural ecosystem services perceptions: a few-shot and prompt method. Landsc. Urban Plan. 258, 105323.

Mancini, F., Coghill, G.M., Lusseau, D., 2019. Quantifying wildlife watchers' preferences to investigate the overlap between recreational and conservation value of natural areas. J. Appl. Ecol. 56, 387–397. https://doi.org/10.1111/1365-2664.13274.

Manley, K., Nyelele, C., Egoh, B.N., 2022. A review of machine learning and big data applications in addressing ecosystem service research gaps. Ecosyst. Serv. 57, 101478. https://doi.org/10.1016/j.ecoser.2022.101478.

Marchi, V., Speak, A., Ugolini, F., Sanesi, G., Carrus, G., Salbitano, F., 2022. Attitudes towards urban green during the COVID-19 pandemic via Twitter. Cities 126, 103707. https://doi.org/10.1016/j.cities.2022.103707.

Martínez Pastur, G., Peri, P.L., Lencinas, M.V., García-Llorente, M., Martín-López, B., 2016. Spatial patterns of cultural ecosystem services provision in Southern Patagonia. Landsc. Ecol. 31, 383–399. https://doi.org/10.1007/s10980-015-0254-9.

Matasov, V., Vasenev, V., Matasov, D., Dvornikov, Y., Filyushkina, A., Bubalo, M., Nakhaev, M., Konstantinova, A., 2023. COVID-19 pandemic changes the recreational use of Moscow parks in space and time: Outcomes from crowd-sourcing and machine learning. Urban for. Urban Green. 83, 127911. https://doi.org/10.1016/j.ufug.2023.127911.

McDonough, K., Hutchinson, S., Moore, T., Hutchinson, J.M.S., 2017. Analysis of publication trends in ecosystem services research. Ecosyst. Serv. 25, 82–88. https://doi.org/10.1016/j.ecoser.2017.03.022.

MEA, 2005. Millennium Ecosystem Assessment - Ecosystems and human well-being: Synthesis. Island Press, Washington, DC.

Meikle, G., 2024. Social Media: The Convergence of Public and Personal Communication, 2nd ed. Routledge, New York. https://doi.org/10.4324/9781003021100.

Meng, S., Huang, Q., Zhang, L., He, C., Inostroza, L., Bai, Y., Yin, D., 2020. Matches and mismatches between the supply of and demand for cultural ecosystem services in rapidly urbanizing watersheds: a case study in the Guanting Reservoir basin, China. Ecosyst. Serv. 45, 101156. https://doi.org/10.1016/j.ecoser.2020.101156.

Moreno-Llorca, R., F. Méndez, P., Ros-Candeira, A., Alcaraz-Segura, D., Santamaría, L., Ramos-Ridao, Á.F., Revilla, E., Bonet-García, F.J., Vaz, A.S., 2020. Evaluating tourist profiles and nature-based experiences in Biosphere Reserves using Flickr: Matches and mismatches between online social surveys and photo content analysis. Sci. Total Environ. 737, 140067. https://doi.org/10.1016/j.scitotenv.2020.140067.

Mouttaki, I., Bagdanavičiūtė, I., Maanan, M., Erraiss, M., Rhinane, H., Maanan, M., 2022. Classifying and mapping cultural ecosystem services using artificial intelligence and social media data. Wetlands 42, 86. https://doi.org/10.1007/s13157-022-01616-9.

Muñoz, L., Hausner, V.H., Runge, C., Brown, G., Daigle, R., 2020. Using crowdsourced spatial data from Flickr vs. PPGIS for understanding nature's contribution to people in Southern Norway. People Nat. 2, 437–449. https://doi.org/10.1002/pan3.10083.

Nowak-Olejnik, A., Schirpke, U., Tappeiner, U., 2022. A systematic review on subjective well-being benefits associated with cultural ecosystem services. Ecosyst. Serv. 57, 101467. https://doi.org/10.1016/j.ecoser.2022.101467.

Nyelele, C., Keske, C., Gon Chung, M., Guo, H., Egoh, B.N., 2023. Using social media data to estimate recreational travel costs: a case study from California. Ecol. Indic. 154, 110638. https://doi.org/10.1016/j.ecolind.2023.110638.

Otero, P., Menéndez-Blázquez, J., March, D., 2025. Challenges of passive citizen science in ecology within a shifting social media landscape. Ecol. Inform. 90, 103278. https://doi.org/10.1016/j.ecoinf.2025.103278.

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. Indic., Landscape Indicators – Monitoring of Biodiversity and Ecosystem Services at Landscape Level 94, 74–86. https://doi.org/10.1016/j.ecolind.2017.02.009.

Page, M.J., McKenzie, J.E., Bossuyt, P.M., Boutron, I., Hoffmann, T.C., Mulrow, C.D., Shamseer, L., Tetzlaff, J.M., Akl, E.A., Brennan, S.E., Chou, R., Glanville, J., Grimshaw, J.M., Hróbjartsson, A., Lalu, M.M., Li, T., Loder, E.W., Mayo-Wilson, E., McDonald, S., McGuinness, L.A., Stewart, L.A., Thomas, J., Tricco, A.C., Welch, V.A., Whiting, P., Moher, D., 2021. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ 372, n71. https://doi.org/10.1136/bmj.n71.

Retka, J., Jepson, P., Ladle, R.J., Malhado, A.C.M., Vieira, F.A.S., Normande, I.C., Souza, C.N., Bragagnolo, C., Correia, R.A., 2019. Assessing cultural ecosystem services of a large marine protected area through social media photographs. Ocean Coast. Manag. 176, 40–48. https://doi.org/10.1016/j.ocecoaman.2019.04.018.

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. Indic. 53, 187–195. https://doi.org/10.1016/j.ecolind.2015.01.034.

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. https://doi.org/10.1016/j.ecoser.2017.09.004.

Roberts, H., Sadler, J., Chapman, L., 2017. Using Twitter to investigate seasonal variation in physical activity in urban green space. Geo Geogr. Environ. 4, e00041. https://doi.org/10.1002/geo2.41.

Ros-Candeira, A., Moreno-Llorca, R., Alcaraz-Segura, D., Bonet-García, F.J., Vaz, A.S., 2020. Social media photo content for Sierra Nevada: a dataset to support the assessment of cultural ecosystem services in protected areas. Nat. Conserv. 38, 1–12. https://doi.org/10.3897/neobiota.38.38325.

Rossi, S.D., Barros, A., Walden-Schreiner, C., Pickering, C., 2020. Using social media images to assess ecosystem services in a remote protected area in the Argentinean Andes. Ambio 49, 1146–1160. https://doi.org/10.1007/s13280-019-01268-w.

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. https://doi.org/10.1016/j.ecoser.2020.101176.

Santana, M.V.A., Oliveira, D.V.B., Albuquerque, U., 2024. Investigating cultural ecosystem services of the Caatinga on Flickr. Ethnobiol. Conserv. 14. https://doi.org/10.15451/ec2024-10-14.08-1-9.

Santos Vieira, F.A., Vinhas Santos, D.T., Bragagnolo, C., Campos-Silva, J.V., Henriques Correia, R.A., Jepson, P., Mendes Malhado, A.C., Ladle, R.J., 2021. Social media data reveals multiple cultural services along the 8.500 kilometers of Brazilian coastline. Ocean Coast. Manag. 214, 105918. https://doi.org/10.1016/j.ocecoaman.2021.105918.

Schirpke, U., Ghermandi, A., Sinclair, M., Van Berkel, D., Fox, N., Vargas, L., Willemen, L., 2023. Emerging technologies for assessing ecosystem services: a synthesis of opportunities and challenges. Ecosyst. Serv. 63, 101558. https://doi.org/10.1016/j.ecoser.2023.101558.
Schirpke, U., Tasser, E., Ebner, M., Tappeiner, U., 2021. What can geotagged photographs tell us about cultural ecosystem services of lakes? Ecosyst. Serv. 51, 101354. https://doi.org/10.1016/j.ecoser.2021.101354.
Scowen, M., Athanasiadis, I.N., Bullock, J.M., Eigenbrod, F., Willcock, S., 2021. The current and future uses of machine learning in ecosystem service research, Science of the Total Environment. Elsevier.
Selling, L.K., Iglesias Keller, C., Ohme, J., Klinger, U., de Vreese, C., 2025. Data access for researchers under the Digital Services Act: from policy to practice. Weizenbaum Policy Papers, Weizenbaum Institute, Berlin https://doi.org/10.34669/WI.PP/14.
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. https://doi.org/10.1016/j.scitotenv.2018.06.056.
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. https://doi.org/10.1016/j.ecoser.2020.101165.
Spalding, M., Parrett, C.L., 2019. Global patterns in mangrove recreation and tourism. Mar. Policy 110, 103540. https://doi.org/10.1016/j.marpol.2019.103540.
Spalding, M.D., Longley-Wood, K., McNulty, V.P., Constantine, S., Acosta-Morel, M., Anthony, V., Cole, A.D., Hall, G., Nickel, B.A., Schill, S.R., Schuhmann, P.W., Tanner, D., 2023. Nature dependent tourism – Combining big data and local knowledge. J. Environ. Manage. 337, 117696. https://doi.org/10.1016/j.jenvman.2023.117696.
Stålhammar, S., Pedersen, E., 2017. Recreational cultural ecosystem services: how do people describe the value? Ecosyst. Serv. 26, 1–9. https://doi.org/10.1016/j.ecoser.2017.05.010.
Tasser, E., Kuhlmann, K., Mwanza, M.W., Schermer, M., Tappeiner, U., Tembo, G., Zoderer, B.M., Schirpke, U., 2025. A comparative analysis of ecosystem services perceptions across two regions in Eastern Africa and Central Europe. Ecosyst. Serv. 74, 101747. https://doi.org/10.1016/j.ecoser.2025.101747.
Teeb, 2010. The Economics of Ecosystems and Biodiversity: Ecological and economic foundations, Pushpam Kumar. ed. Earthscan, London and Washington.
Teles Da Mota, V., Pickering, C., 2021. Geography of Discourse about a European Natural Park: Insights from a Multilingual Analysis of Tweets. Soc. Nat. Resour. 34, 1492–1509. https://doi.org/10.1080/08941920.2021.1971809.
Tenerelli, P., Demšar, U., Luque, S., 2016. Crowdsourcing indicators for cultural ecosystem services: a geographically weighted approach for mountain landscapes. Ecol. Indic. 64, 237–248. https://doi.org/10.1016/j.ecolind.2015.12.042.
Tenerelli, P., Püffel, C., Luque, S., 2017. Spatial assessment of aesthetic services in a complex mountain region: combining visual landscape properties with crowdsourced geographic information. Landsc. Ecol. 32, 1097–1115. https://doi.org/10.1007/s10980-017-0498-7.
Tenkanen, H., Di Minin, E., Heikinheimo, V., Hausmann, A., Herbst, M., Kajala, L., Toivonen, T., 2017. Instagram, Flickr, or Twitter: Assessing the usability of social media data for visitor monitoring in protected areas. Sci. Rep. 7, 17615. https://doi.org/10.1038/s41598-017-18007-4.
Thiagarajah, J., Wong, S.K.M., Richards, D.R., Friess, D.A., 2015. Historical and contemporary cultural ecosystem service values in the rapidly urbanizing city state of Singapore. Ambio 44, 666–677. https://doi.org/10.1007/s13280-015-0647-7.
Tian, T., Sun, L., Peng, S., Sun, F., Che, Y., 2021. Understanding the process from perception to cultural ecosystem services assessment by comparing valuation methods. Urban for. Urban Green. 57, 126945. https://doi.org/10.1016/j.ufug.2020.126945.
Tyner, E.H., Scott Graham, S., 2022. Tweeting the Laurentian Great Lakes: a community opinion analysis about Great Lakes areas as assessed through mentions on Twitter. J. Gt. Lakes Res. 48, 1444–1453. https://doi.org/10.1016/j.jglr.2022.03.013.
Van Berkel, D.B., Tabrizian, P., Dorning, M.A., Smart, L., Newcomb, D., Mehaffey, M., Neale, A., Meentemeyer, R.K., 2018. Quantifying the visual-sensory landscape qualities that contribute to cultural ecosystem services using social media and LiDAR. Ecosyst. Serv. 31, 326–335. https://doi.org/10.1016/j.ecoser.2018.03.022.
Van Raemdonck, N., Picone, I., Pierson, J., 2025. Affordances-in-practice: how social norm dynamics in climate change publics are shaped on Instagram and Twitter. Soc. Media Soc. 11, 20563051251319066. https://doi.org/10.1177/20563051251319066.
Van Zanten, B.T., Van Berkel, D.B., Meentemeyer, R.K., Smith, J.W., Tieskens, K.F., Verburg, P.H., 2016. Continental-scale quantification of landscape values using social media data. Proc. Natl. Acad. Sci. 113, 12974–12979. https://doi.org/10.1073/pnas.1614158113.
Vaz, A.S., Gonçalves, J.F., Pereira, P., Santarém, F., Vicente, J.R., Honrado, J.P., 2019. Earth observation and social media: evaluating the spatiotemporal contribution of non-native trees to cultural ecosystem services. Remote Sens. Environ. 230, 111193. https://doi.org/10.1016/j.rse.2019.05.012.
Vidal-Llamas, A., Nicolás-Ruiz, N., Suárez Alonso, M.L., Vidal-Abarca Gutiérrez, M.R., 2024. Exploring the cultural ecosystem services of arid watersheds: a social media analysis. J. Arid Environ. 221, 105141. https://doi.org/10.1016/j.jaridenv.2024.105141.
Wahler, H., Fanini, L., Riechers, M., 2023. Valuing beaches for beauty and recreation only? Uncovering perception bias through a hashtag analysis. Mar. Policy 155, 105707. https://doi.org/10.1016/j.marpol.2023.105707.
Wang, B., Zhang, Q., Cui, F., 2021a. Scientific research on ecosystem services and human well-being: a bibliometric analysis. Ecol. Indic. 125, 107449. https://doi.org/10.1016/j.ecolind.2021.107449.
Wang, L., Zhou, C., 2024. Evaluation of perceptions using facial expression scores on ecological service value of blue and green spaces in 61 Parks in Guizhou. Sustainability 16, 4108. https://doi.org/10.3390/su16104108.
Wang, W., Wu, C., Fang, Q., Harrison, O.I., 2023. Cultural ecosystem services evaluation in a coastal city of China using social media data. Ocean Coast. Manag. 242, 106693. https://doi.org/10.1016/j.ocecoaman.2023.106693.
Wang, Y., Shi, X., Cheng, K., Zhang, J., Chang, Q., 2022a. How do urban park features affect cultural ecosystem services: Quantified evidence for design practices. Urban for. Urban Green. 76, 127713. https://doi.org/10.1016/j.ufug.2022.127713.
Wang, Z., Fu, H., Jian, Y., Qureshi, S., Jie, H., Wang, L., 2022b. On the comparative use of social media data and survey data in prioritizing ecosystem services for cost-effective governance. Ecosyst. Serv. 56, 101446. https://doi.org/10.1016/j.ecoser.2022.101446.
Wang, Z., Miao, Y., Xu, M., Zhu, Z., Qureshi, S., Chang, Q., 2021. Revealing the differences of urban parks' services to human wellbeing based upon social media data. Urban for. Urban Green. 63, 127233. https://doi.org/10.1016/j.ufug.2021.127233.
Winder, S.G., Lee, H., Seo, B., Lia, E.H., Wood, S.A., 2022. An open-source image classifier for characterizing recreational activities across landscapes. People Nat. 4, 1249–1262. https://doi.org/10.1002/pan3.10382.
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, 1–7.
Yang, Y., Duan, W., 2024. An interpretation of landscape preferences based on geographic and social media data to understand different cultural ecosystem services. Land 13, 125. https://doi.org/10.3390/land13020125.
Yee, T.B.L., Carrasco, L.R., 2024. Applying deep learning on social media to investigate cultural ecosystem services in protected areas worldwide. Sci. Rep. 14, 13700. https://doi.org/10.1038/s41598-024-64115-3.
You, S., Zheng, Q., Chen, B., Xu, Z., Lin, Y., Gan, M., Zhu, C., Deng, J., Wang, K., 2022. Identifying the spatiotemporal dynamics of forest ecotourism values with remotely sensed images and social media data: a perspective of public preferences. J. Clean. Prod. 341, 130715. https://doi.org/10.1016/j.jclepro.2022.130715.
Zapata-Caldas, E., Calcagni, F., Baró, F., Langemeyer, J., 2022. Using crowdsourced imagery to assess cultural ecosystem services in data-scarce urban contexts: the case of the metropolitan area of Cali, Colombia. Ecosyst. Serv. 56, 101445. https://doi.org/10.1016/j.ecoser.2022.101445.
Zhang, H., Huang, R., Zhang, Y., Buhalis, D., 2020. Cultural ecosystem services evaluation using geolocated social media data: a review. Tour. Geogr. 1–23. https://doi.org/10.1080/14616688.2020.1801828.
Zhang, H., Yu, J., Dong, X., Zhai, X., Shen, J., 2024a. Rethinking cultural ecosystem services in urban forest parks: an analysis of citizens' physical activities based on social media data. Forests 15, 1633. https://doi.org/10.3390/f15091633.
Zhang, J., Cheng, Y., Mao, Y., Cai, W., Zhao, B., 2022a. What are the factors influencing recreational visits to national forest parks in China? Experiments using crowdsourced geospatial data. Urban for. Urban Green. 72, 127570. https://doi.org/10.1016/j.ufug.2022.127570.
Zhang, J., He, C., Huang, Q., Li, J., Qi, T., 2022b. Evaluating the supply and demand of cultural ecosystem services in the Tibetan Plateau of China. Landsc. Ecol. 37, 2131–2148. https://doi.org/10.1007/s10980-022-01467-z.
Zhang, J., Luo, Y., Cao, H., Su, S., 2024b. Scrutinizing the cultural ecosystem services of Chinese Classical Gardens: a novel deep learning approach based on online reviews from a multisensory perspective. Appl. Geogr. 172, 103404. https://doi.org/10.1016/j.apgeog.2024.103404.
Zhao, Q., Chen, Y., Gone, K.P., Wells, E., Margeson, K., Sherren, K., 2023. Modelling cultural ecosystem services in agricultural dykelands and tidal wetlands to inform coastal infrastructure decisions: a social media data approach. Mar. Policy 150, 105533. https://doi.org/10.1016/j.marpol.2023.105533.
Zhao, X., Lu, Y., Huang, W., Lin, G., 2024. Assessing and interpreting perceived park accessibility, usability and attractiveness through texts and images from social media. Sustain. Cities Soc. 112, 105619. https://doi.org/10.1016/j.scs.2024.105619.
Zhao, Z., Ma, Z., Chen, B., Li, P., Yu, W., Hu, W., Zhang, D., Liao, J., 2026. Understanding public perceptions of cultural ecosystem services in urban coastal wetland ecological restoration areas: a social media-based large language model approach. J. Environ. Manage. 401, 128816. https://doi.org/10.1016/j.jenvman.2026.128816.
Zheng, S., Ren, Y., Zhu, C., Wang, X., Zhao, M., Wang, S., Wang, J., Yang, T., 2026. Quantifying cultural ecosystem services in urban parks using social media and large language models: Insights for Beijing's Garden City initiative. Urban for. Urban Green. 117, 129263. https://doi.org/10.1016/j.ufug.2026.129263.
Zheng, T., Pan, Q., Zhang, X., Wang, C., Yan, Y., Van De Voorde, T., 2024. Research note: linking sensory perceptions with landscape elements through a combined approach based on prior knowledge and machine learning. Landsc. Urban Plan. 242, 104928. https://doi.org/10.1016/j.landurbplan.2023.104928.
Zheng, Y., Zhu, J., Wang, S., Guo, P., 2023. Perceived Economic Values of Cultural Ecosystem Services in Green and Blue Spaces of 98 Urban Wetland Parks in Jiangxi, China. Forests 14, 273. https://doi.org/10.3390/f14020273.
Zhu, X., Cheng, X., Zhang, B., Mihalko, C., 2023. A user-feedback indicator framework to understand cultural ecosystem services of urban green space. Ecol. Indic. 154, 110642. https://doi.org/10.1016/j.ecolind.2023.110642.