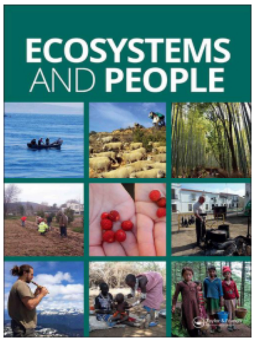

Taylor & Francis
Taylor & Francis Group

Ecosystems and People

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/tbsm22

Extracting sensory experiences and cultural ecosystem services from actively crowdsourced descriptions of everyday lived landscapes

Manuel F. Baer, Flurina Wartmann, Nora Fagerholm & Ross S. Purves

To cite this article: Manuel F. Baer, Flurina Wartmann, Nora Fagerholm & Ross S. Purves (2024) Extracting sensory experiences and cultural ecosystem services from actively crowdsourced descriptions of everyday lived landscapes, Ecosystems and People, 20:1, 2331761, DOI: 10.1080/26395916.2024.2331761

To link to this article: https://doi.org/10.1080/26395916.2024.2331761

Published online: 03 Apr 2024.

ECOSYSTEMS AND PEOPLE
2024, VOL. 20, NO. 1, 2331761
https://doi.org/10.1080/26395916.2024.2331761

Taylor & Francis
Taylor & Francis Group

RESEARCH

OPEN ACCESS Check for updates

Extracting sensory experiences and cultural ecosystem services from actively crowdsourced descriptions of everyday lived landscapes

Manuel F. Baer [a,b,c], Flurina Wartmann [d], Nora Fagerholm [e] and Ross S. Purves [a,b]

[a]Department of Geography, University of Zurich, Zürich, Switzerland; [b]URPP Language and Space, University of Zurich, Zürich, Switzerland; [c]Centre for eResearch, University of Auckland, Auckland, New Zealand; [d]Department of Geography & Environment, School of Geosciences, University of Aberdeen, Aberdeen, UK; [e]Department of Geography and Geology, University of Turku, Turku, Finland

ABSTRACT

What cultural ecosystem services (CES) do people perceive in their immediate surroundings, and what sensory experiences are linked to these ecosystem services? And how are these CES and experiences expressed in natural language? In this study, we used data generated through a gamified application called *Window Expeditions*, where people uploaded short descriptions of landscapes they were able to experience through their windows during the COVID-19 pandemic. We used a combination of annotation, close reading and distant reading using natural language processing and graph analysis to extract CES and sensory experiences and link these to biophysical landscape elements. In total, 272 users contributed 373 descriptions in English across more than 40 countries. Of the cultural ecosystem services, recreation was the most prominently described, followed by heritage, identity and tranquility. Descriptions of sensory experiences focused on the visual but also included auditory experiences and touch and feel. Sensory experiences and cultural ecosystem services varied according to biophysical landscape elements, with, for example, animals being more associated with sound and touch/feel and heritage being more associated with moving objects and the built environment. Sentiments also varied across the senses, with the visual being more strongly associated with positive experiences than other senses. This study showed how a hybrid approach combining manual analysis and natural language processing can be productively applied to landscape descriptions generated by members of the public, and how CES on everyday lived landscapes can be extracted from such data sources.

ARTICLE HISTORY
Received 25 July 2023
Accepted 4 March 2024

EDITED BY
Christian Albert

KEYWORDS
Active crowdsourcing; cultural ecosystem services; everyday lived landscapes; multi-sensory landscape perception; natural language processing; gamification

1. Introduction

Various frameworks exist dividing landscapes into individual natural, social and perceptual dimensions, including the ecosystem service framework (MA 2005; Costanza et al. 2017) and landscape character assessment (Tudor 2014). However, not all of these dimensions are equally easy to measure, since not all aspects of landscapes and our interactions with them lend themselves to assessment and quantification through, for example, sensors measuring biophysical properties of the Earth's surface (Grêt-Regamey et al. 2021). Particularly challenging are intangible dimensions such as inspiration, identity, heritage, tranquility, recreation and religious values which are conceptualised as cultural ecosystem services, or CES (Bieling 2014; Wartmann and Purves 2018; Fagerholm et al. 2020). Although CES are deemed highly important for people, their assessment still lags behind those of other ecosystem services (Chan et al. 2012; Milcu et al. 2013). This, in turn, brings the risk that services that are important to people, but methodologically challenging to investigate, are not properly incorporated in decision-making. In this paper, we present a study aiming to help address this gap by using novel forms of crowdsourced descriptions which include CES.

1.1. Cultural ecosystem services and landscape perception

Cultural ecosystem services form an important part of the ecosystems services framework, which describes and quantifies the various benefits that humans derive from the landscapes they interact with (Shapiro and Báldi 2014; Costanza et al. 2017). Among the CES most commonly assessed are recreation, aesthetics and religious values (Milcu et al. 2013). Studies asking people which CES they most commonly perceive find identity, recreation and tranquility to be among the most reported (Bieling 2014; Fagerholm et al. 2020). These services are closely linked to the concept of landscapes and their properties. Fish et al. (2016), for example, introduce a framework that conceptualises CES as combinations of biophysical elements, environmental spaces, cultural practices and cultural goods as well as cultural ecosystem benefits and the relations and interactions between these. The framework has been widely adopted in landscape and cultural ecosystem services-related literature and explicitly links perceived biophysical elements of landscapes with perceived cultural

CONTACT Manuel F. Baer manuel.baer@uzh.ch

ecosystem services (Bryce et al. 2016). It also provides further opportunities to link the rich tradition of landscape perception research (Zube and Pitt 1981; Zube 1986; Kaplan and Kaplan 1989; Herzog et al. 2000) more closely with cultural ecosystem services (Schaich et al. 2010). The importance of understanding CES through the lens of landscape perception research is reflected in modern, policy-driven, definitions of landscape. Most prominently, the European Landscape Convention (ELC) defines landscape as an 'area, as perceived by people, whose character is the result of the action and interaction of natural and/or human factors' (European Landscape Convention 2000, p. 2), emphasising both perceptual and interactional dimensions of landscapes.

Within the field of landscape perception research, the investigation of visual landscape aesthetics dominates (Daniel 2001; Tveit et al. 2006; Ode et al. 2008; Brabyn 2009). Previous studies on visual landscape perception have shown that specific landscape configurations can invoke certain emotions. For example, water bodies are seen as being aesthetically pleasing and thus beneficial for mental restoration (White et al. 2010), whereas built structures are often perceived as disturbing (Zube and Pitt 1981). Scenicness, most often in a purely visual sense, has been studied extensively (Seresinhe et al. 2018, 2019), whereas work emphasising the importance of other sensory experiences such as '[…] odors, sounds, and tactilities that we know we must have if life is to have any satisfaction at all' (Tuan 1989, p. 235) remains more limited. Exploration of the auditory dimension of landscapes has primarily focused on the soundscapes of urban areas (Aiello et al. 2016), as well as investigating tranquility, often through the absence of disturbing sounds (Watts et al. 2011; Watts and Pheasant 2013). Landscape research on auditory dimensions of landscapes has also explored the negative influence of noise on well-being and health (Goines and Hagler 2007; Vienneau et al. 2022) and the annoyance of sound (Marquis-Favre et al. 2005). Emitters of disturbing sounds often include anthropogenic sources such as traffic, crowds and sounds from wind turbines (Chesnokova and Purves 2018; Mora-Araus et al. 2021). Other senses are underrepresented in landscape perception research – little work has investigated smell, taste or touch and feel. Nonetheless, evidence suggests smellscapes are important in how we perceive landscapes (Lefebvre 1992) and efforts have been made to capture the various smells of our surroundings (Lefebvre 1992; Henshaw 2013; Quercia et al. 2015). Similarly, the haptic dimension – such as sand under your feet or the feel of rain on your skin – influences our perception of landscapes, but has largely been overlooked, with a few exceptions (e.g. Brown 2017).

1.2. Landscape and geographic elements

Instead of partitioning landscape perception into the perceptual dimensions of seeing, hearing, touching and feeling, we can also parcel up landscapes in terms of the elements that people perceive, or in other words, geographic categories, with examples including river, meadow, potato field, soccer court or road. In this sense, we can think of landscapes as populated by biophysical elements or natural features (Fish et al. 2016; La Notte et al. 2017) as well as human constructions and signs of use and occupation. The availability, configuration and layout of these landscape elements influence the possible functions of a landscape resulting in potential services and benefits (La Notte et al. 2017) as well as potential disservices and negative impacts (Shapiro and Báldi 2014). How people parcel up the landscape into different categories when they talk and write about landscape has been shown to be highly variable, and far from universal (Burenhult and Levinson 2008; van Putten et al. 2020). Previous qualitative studies of geographic categories have suggested that biophysical elements such as mountains, forests and water bodies are particularly salient, while trees and animals are less salient (Bieling 2014; Wartmann et al. 2015).

Our work takes as a starting point the observation from Smith and Mark's seminal work on geographic objects, that many 'naive or folk disciplines appear to work exclusively […] with object-based representations of reality' (Smith and Mark 2003, p. 419). One form of such objects is the perceived biophysical elements of a landscape, and their representation in language. Biophysical elements provide the material properties of a given landscape and allow for sociocultural interactions (Fish et al. 2016). They are defined by Fish et al. simply as the 'physical and non-human components' of landscapes (Fish et al. 2016, p. 212); however, here we also include 'environmental features, such as landforms, water bodies and life forms; ecological dimensions (e.g. habitat); ephemeral qualities and dynamic environmental conditions, such as seasonal changes, time of day or cloud; and human-activity elements' (Dakin 2003, p. 192). These biophysical elements are perceived through sensory experiences which guide our actions and interactions within a given landscape (Gibson 1986; Heft 2010). Their importance may vary both individually and culturally, as reflected in language and values (Burenhult and Levinson 2008; van Putten et al. 2020), and in turn influence our behaviour and sociocultural practices.

Recent work also noted the importance of monitoring ecosystem disservices, or potentially negative impacts of environments on human well-being

(Shapiro and Báldi 2014; Torkko et al. 2023). One approach to capturing information about these less easily quantifiable aspects of landscapes is through the lens of perception studies of revealed and stated preferences (Adamowicz et al. 1994; Haab and McConnell 2002). Multiple approaches to collecting data capturing these notions exist, through the use of, for example, surveys, questionnaires and interviews (Swanwick 2009; Bieling 2014; Fagerholm et al. 2020). All have the advantage of allowing carefully chosen samples of participants and questions investigating, typically, a specific region or theme. However, an important disadvantage is that they are essentially top-down, with the results being strongly dependent on both who is asked and the ways in which questions are formulated.

1.3. Crowdsourcing as a data source for studying landscape perception

A new data source, which has recently been the subject of much attention, is the use of passive and active crowdsourcing (See et al. 2016). Crowdsourcing refers to the outsourcing of a task to a large number of participants, commonly through the internet (Rouse 2010). Crowdsourced data have the potential to complement traditional methods by offering a (potentially) large and cost-efficient dataset (See et al. 2016). Many crowdsourcing approaches used in landscape perception to date have focused on passive data collection, for example through the analysis of social media data (Aiello et al. 2016; Chesnokova and Purves 2018; Bubalo et al. 2019; Hausmann et al. 2020; Cui et al. 2021; Grêt-Regamey et al. 2021). However, these data are typically noisy, and contain large volumes of irrelevant data (Ghermandi and Sinclair 2019). Active crowdsourcing can, firstly, minimise irrelevant data, secondly, explicitly involve contributors in science and thirdly, be designed to explicitly collect data in novel forms complementing existing approaches (cf. Salk et al. 2016; Baer et al. 2019; Laso Bayas et al. 2020).

One particularly promising approach is the analysis of natural language describing the ways in which people perceive landscapes and the environment in their own words, data which also captures mentioned stated and revealed preferences. Since natural language is rich and complex, it lends itself to detailed analysis of the relationships between the ways in which landscape is perceived, valued and interacted with, as shown by Bieling (2014) in her exploration of short stories about landscapesor, more generally, with respect to full-text descriptions of landscapes found in newspaper articles, blogs and other sources (Derungs and Purves 2016; Wartmann and Purves 2018; Koblet and Purves 2020). Larger text data sets require associated computational methods for analysis, and the field of computational linguistics has advanced considerably, making the accuracy of some algorithms such as part-of-speech (PoS) tagging, where words in a sentence are tagged according to their part-of-speech (e.g. noun, verb, adjective) on par with human interpretations for individual words, or so-called tokens (Manning 2011). However, the complexity of language makes it hard for computers to understand underlying meanings beyond part-of-speech tagging, particularly in rich natural language contributions. Large language models and machine-learning approaches are rapidly evolving with increasingly impressive results (Kocoń et al. 2023) and slowly permeating into everyday life. More common large language models such as ChatGPT[1] and Google Gemini[2] are increasingly capable of interpreting inputs and generating relevant outputs, at times surpassing the quality of human responses (cf. Herbold et al. 2023). However, for more subjective tasks (such as interpreting natural language landscape descriptions containing cultural ecosystem services and sensory experiences) specific domain knowledge is required, which these models have yet to acquire (Kocoń et al. 2023). Humans, on the other hand, excel at identifying semantics and meaning within written language for specific domains. This calls for the involvement of people to add meaning as metadata to textual datasets to make them machine-readable. This process of adding additional information in a computer-friendly format is known as annotation or qualitative coding (Hsieh and Shannon 2005; Pustejovsky and Stubbs 2013) and, despite the emergence of large language models, remains essential to many machine learning or computational linguistics efforts, especially in domains not likely to be common in large-scale training data, which are dominated by easily available online collections such as Wikipedia, news stories and bulletin boards such as Reddit (Bender et al. 2021).

1.4. The importance of everyday lived landscapes

We aim to further our understanding of the relations between people and landscapes by exploring CES through language and how these are linked with positive and negative sensory experiences. To do so, we developed a gamified, active crowdsourcing platform, *Window Expeditions*, to collect data in three languages (English, French and German) about everyday landscapes at any location on the Earth's surface (Baer and Purves 2022). This work started during the global COVID-19 pandemic, which was later termed as an 'anthropause' (Rutz 2022), a period during which human mobility significantly decreased. This anthropause also emphasised the importance of local landscapes as providers of cultural ecosystem services for citizens restricted to highly local activities or confined to their place of residence (Grima et al. 2020; Beckmann-Wübbelt et al. 2021). In terms of research, this shift reinforced the need to consider how people perceive and appreciate what we term in this paper as everyday lived landscapes.

We understand everyday lived landscapes as the areas in which people spend most of their time, mostly residential areas or places of work. These show many similarities with vernacular landscapes described as the 'meaningful spaces [...] in globalized urban environments' which are inhabited by 'ordinary people living ordinary lives' (Krase and Shortell 2011, p. 371). In this paper, we analyse natural language data about everyday lived landscapes collected through the platform *Window Expeditions* to investigate the two research questions:

(1) What perceived biophysical elements and cultural ecosystem services can be identified in a corpus of in-situ natural language descriptions of everyday lived landscapes?

(2) How are biophysical elements and cultural ecosystem services linked to sensory experiences expressed in natural language landscape descriptions?

2. Data and methods

To explore how biophysical elements of a landscape are perceived through the different senses and how they are linked to perceived cultural ecosystem (dis)services, we combined approaches from geographic information science, landscape perception research, humanities and linguistics (Figure 1). We developed a gamified online application to collect in-situ, natural language descriptions of everyday landscapes (Baer and Purves 2022) and analysed the resulting data using a combination of qualitative methods such as close reading and iterative annotation as well as quantitative measures such as descriptive statistics and network analyses.

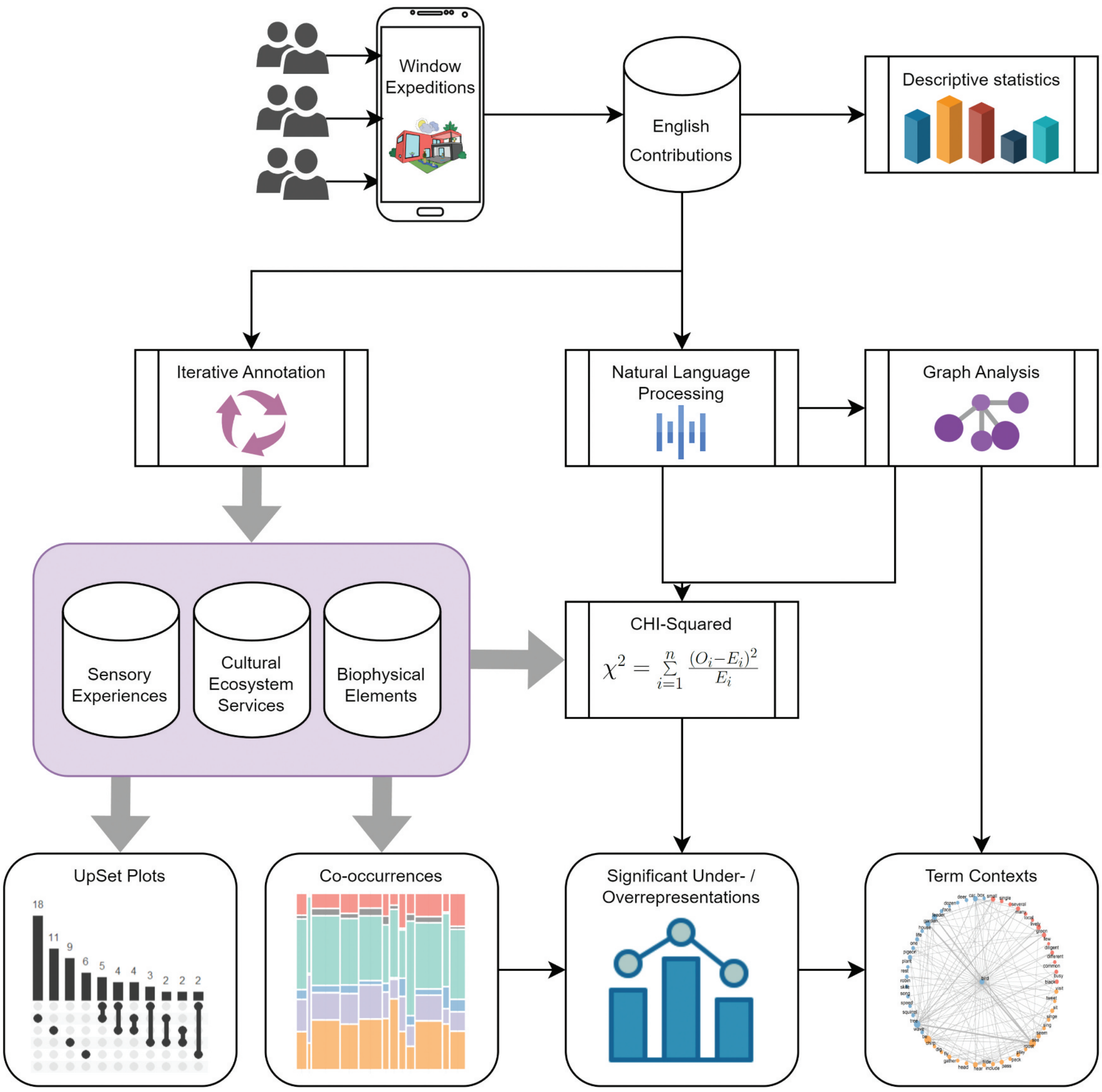

Figure 1. Overview of the methods.

2.1. Data generation

The first wave of the global COVID-19 pandemic led to significant changes in people's everyday mobility (Lee et al. 2020; Lucchini et al. 2021) through interventions such as lockdowns and social distancing (Flaxman et al. 2020). As a result, people started spending significantly more time in and around their homes and, in some countries, were discouraged from frequenting outdoor areas. During the first few months of the global pandemic and the associated first wave of lockdowns, we implemented the active crowdsourcing platform *Window Expeditions* (Baer and Purves 2022) where participants could contribute descriptions of their surroundings safely from home. The application was made available globally and promoted on various citizen science platforms, through Twitter and other social media platforms, and extensive use of e-mails and word of mouth in the networks of colleagues, families and friends. Using their mobile phone or an internet browser, participants could contribute anonymously or as registered users and the application was implemented in three languages: English, French and German. Users interested in contributing were asked to upload a natural language description, through the following question (here in English): 'Type in a description of your surroundings using whole sentences. How would you describe them to a friend?'. In addition, we asked users to report on gender, age and the languages they believed they were fluent in. *Window Expeditions* successfully generated a heterogeneous multilingual corpus of in-situ natural language descriptions of everyday lived landscapes (cf. Example 2.1) including limited demographic information about the contributors.

Example 2.1

Slow and quiet but peaceful.

Full dark with bright moon. Moonlit shadow of fence in the back garden.

When I look out of the window, I see an empty campus. The sidewalks are empty, autumn leaves scattered around. The last rays of autumn sunlight are trickling through the trees onto a well kept (and still green) but empty lawn in front of the Aula.

Beautiful beach! I like to run along this beach with my eyes shut at half tide and listen to the waves and birds. Feels so surreal. Other times we play here with a ball or frisbie on the big open golden sandy space. It's quite flat, not too steep but does have some rocks at the east and west sides which are good to explore with the kids.

Looking out over a fairly typical Dutch neighborhood backyard. 2-storey terraced houses, small gardens and sheds. Houses are quite varied, of mixed sizes and from different time periods. Many of the small gardens don't have lawn but hard surface, but still lots of green (shrubs, trees). Now it's autumn and the sun is shining (for a change), so lots of beautiful colors. Several smaller birds and some pigeons and ravens are around.

There is a big old pine tree next to the window, I can only see part of the trunk and a few branches. A maple tree next to it has fresh leaves and the sunlight of the morning is dotting them. I see the neigboring house and its parking lot with cars and bikes, and a lady walking slowly across the yard. A portion of the blue sky is visible, and so is a tiny glimpse of the quiet road, with cars parked on the side. Pollen and maybe petals from the flowers in a bird cherry tree that I can see in the right corner of my window are floating in the air.

2.2. Descriptive statistics of contributors

Firstly, we calculated descriptive statistics of contributing users. We calculated median and mean age of contributing users as well as number of contributions per user. Using regular expressions (REGEX) we identified which languages each user reported on being fluent in and calculated each language's frequency.

2.3. Annotation

We iteratively annotated the dataset from *Window Expeditions* to identify biophysical elements, sensory experiences and cultural ecosystem services. To do so, we first created annotation guidelines based on definitions identified in the literature. Whilst annotating the descriptions, we refined the guidelines to include new emergent categories and then repeated the annotation. We repeated these iterations of refinement and annotation until no further updates to the guidelines were necessary. We first annotated biophysical elements and completed this annotation step, then followed with annotating sensory experiences and finally cultural ecosystem services. We followed this sequence since we judged that the complexity of the annotation increased in this order, and familiarity with the nature of the texts made annotation easier.

2.3.1. Biophysical elements

To identify biophysical elements (such as tree, bird, or hill) in our dataset, we extracted all nouns, identified through the natural language processing pipeline, and counted their respective frequencies. All nouns present four or more times were annotated as being a biophysical element or not by two authors. The resulting biophysical noun terms were further categorised as belonging to one higher-order biophysical category by one author. The resulting categories of biophysical elements are summarised in Table 1. To tie together the annotated cultural ecosystem services and sensory experiences with the biophysical element categories of everyday lived landscapes, we extracted co-occurrences and checked for significant outliers. Each unique combination of cultural ecosystem service or sensory experience and biophysical category was counted as a co-occurrence. This potentially resulted in multiple co-occurrences per contribution. For example, a contribution referencing to the CES of *recreation* and *tranquility*, the sensory experiences of *sight* and *sound* and the biophysical categories of *vegetation* and *water* would result in four cultural ecosystem services co-occurrences: recreation – vegetation, recreation – water, tranquility – vegetation, tranquility – water and four sensory experiences co-occurrences: sight – vegetation, sight – water, sound – vegetation, sound – water.

2.3.2. Sensory experience

To annotate sensory experiences, all four authors collaboratively created a set of annotation guidelines in an iterative process. We annotated a random sample of contributions using the sensory dimensions found in similar literature: sight, sound, smell/taste and touch/feel (Tudor 2014). To complement the annotations, we added information on attitudes towards sensory experiences (positive, negative or neutral). Using the resulting guidelines, one author annotated all contributions indicating if a sensory experience is present within a contribution and if so what attitude is expressed towards the identified experience. To explore the potential salient features of sensory experiences of landscapes, we calculated which nouns, adjectives and verbs appeared significantly more frequently within each sensory dimension compared to the corpus as a whole using Chi-Square (χ^2) statistics.

2.3.3. Cultural ecosystem services

To annotate cultural ecosystem services, we also iteratively created a set of annotation guidelines. We annotated a random sample of contributions using the cultural ecosystem services of inspiration, identity, heritage, religious values and recreation, common in landscape research (MA 2005; Bieling 2014). The iterative process revealed tranquility as an important category, in line with existing literature (Chesnokova and Purves 2018; Wartmann et al. 2019, 2021), and we therefore added tranquility as a separate cultural ecosystem service. After three cycles of annotation, we found minimal discrepancies in annotations and one author annotated all contributions using the created guidelines. Attitudes towards specific cultural ecosystem services were not annotated since they are not always easy to disentangle (for example, in the following example 'I can see kids playing in the driveway and judging by the racket, they seem to be having fun' - it is not easy to decide whether the author considers this a positive, negative or neutral experience). Following the same approach as for sensory experiences, we identified nouns, adjectives and verbs found significantly more frequently within a specific cultural ecosystem service compared with the whole corpus.

Table 1. Categories of biophysical landscape elements and examples thereof.

Category	Examples
Animal	dog, bird, squirrel
Anthropogenic object	football, chair, turbine
Built environment	house, building, highway
Building part	floor, window, balcony
Land cover	forest, driveway, farm
Material	ground, wood, rock
Moving object	car, boat, train
Natural feature	mountain, sea, hillside
People	people, child, neighbour
Vegetation	tree, flowers, shrub
Water	water, lake, pond
Weather/atmosphere	sky, horizon, breeze

2.4. Natural language processing (NLP)

To analyse our data computationally, we processed each contribution in our collection of descriptions using SpaCy,[3] a natural language processing library, to add linguistic information to contributions. For every contribution, we identified each term's 'part-of-speech', which is the category to which a word is assigned based on its function. In English important parts of speech include nouns, pronouns, adjectives, verbs and adverbs. Furthermore, we also identified syntactic relations between individual terms. For example, in the following sentence 'an old, rusty car spoils the view of the beautiful tree', we associated beautiful with tree but not car. In addition, we lemmatised words, grouping together inflected forms under a single lemma (e.g. 'run' is the lemma of 'runs', 'ran', 'running'). This allowed us to explore the various configurations of parts-of-speech within and between contributions, as well as the frequencies of individual noun, verb and adjective lemmas.

To identify particularly prominent terms within annotated sensory experiences or cultural ecosystem services, we calculated χ^2 statistics. χ^2 is used to identify significant over- or under-representations in one sample compared to another (Kilgarriff 2001; Chen and Chen 2011). We first created a list of terms with frequencies equal to or higher than five within a given sensory experience or cultural ecosystem service, the minimum frequency needed for reliable χ^2 calculations (Kilgarriff 2001). We then compared the frequency of each term within a specific dimension to the frequency of the term within the whole corpus. The results indicate if a term is found significantly more frequently within a specific dimension, and thus, what terms are particularly important for each dimension. In addition, we calculated χ^2 to identify significantly overrepresented biophysical categories within specific dimensions.

To further explore the context in which terms are used, we created graphs where nodes represent term lemmas and edges are syntactic relations connecting terms. We were especially interested in the context of the terms identified through the χ^2 analysis. To explore the context of individual terms in more detail, we consult the generated corpus graph and, for each of the terms we are interested in, identify all other terms connected to the term of interest through at least one or more edges.

2.5. Linking biophysical elements, sensory experiences and cultural ecosystem services

We were also interested in linking biophysical elements, sensory experiences and cultural ecosystem services. Of particular interest were co-occurring elements and dimensions within contributions and what these tell us about how and what people perceive in their everyday lived landscapes. We thus explored co-occurring biophysical elements and sensory experiences as well as cultural ecosystem services and identify outliers. To delve deeper into questions of how sensory experiences are related with cultural ecosystem services, we linked annotated cultural ecosystem services with mentions of sensory experiences segregated by attitude. Further, we counted the number of co-occurring sensory experiences as well as cultural ecosystem services within each contribution and visualised these using Upset plots (Lex et al. 2014; Conway et al. 2017). To explore the ties between sensory experiences and cultural ecosystem services further, we created a graph where the nodes represented a dimension of sensory experience or a cultural ecosystem service and the edges represent the links between these.

3. Results

In the following, we present key findings from analysing our corpus of in-situ natural language everyday lived landscape descriptions. We first give an overview of the general characteristics of the contributions and users before going into more detailed analyses of perceived and reported biophysical elements, sensory experiences and cultural ecosystem services. In the final section, we tie together the mentioned biophysical elements, sensory experiences and cultural ecosystem services.

3.1. User characteristics

During a period of 10 months (16 August 2020 to 18 June 2021) a total of 272 users contributed 373 in-situ English descriptions of everyday lived landscapes to the project. A total of 143 and 26 users contributed descriptions in German and French, respectively. Due to the relatively small number of contributions in these languages, the remainder of our analysis focuses on descriptions contributed by users in English.

Of the users writing English descriptions, 84.6% were aged between the working ages of 18–65 years old (median year of birth was 1987). Users reported the languages they believed to be fluent in as meta-data for each contribution, and English was attributed most prominently ($n = 329$), followed by German ($n = 51$), Spanish ($n = 32$) and French ($n = 19$). Contributions were submitted from 43 unique countries or regions with most in the United Kingdom ($n = 108$) followed by the United States ($n = 76$) and Switzerland ($n = 47$). Of note is the number of descriptions written in English, although their authors also reported being fluent in a language in which the platform was implemented.

3.2. Biophysical elements in landscapes

We first identify biophysical elements and their respective categories in our corpus. The results show the biophysical categories of vegetation, weather/atmosphere and built environment to be most prominent (Table 2). Further categories include building parts and moving objects, reflecting urban infrastructure and motorised transport. In addition, categories associated with more natural features such as animals and land cover are found occasionally. Least common are people, water and anthropogenic objects. Overall, these results reflect people contributing in everyday lived landscapes and reporting on perceived biophysical elements visible from home such as trees, roads and clouds.

3.3. Sensory experiences in landscapes

The data set contained 210 (56%) contributions annotated as containing at least one reference to a sensory experience. Table 3 gives an overview of the distribution of senses across these descriptions. Sight is most common sense, followed by hearing, touch/feel and finally smell. Sight is much more

Table 2. Annotated biophysical element distribution.

Category	Contributions	Lemmas	Unique
Vegetation	222	503	18
Weather/atmosphere	213	410	16
Built environment	185	401	17
Land cover	156	286	17
Building part	129	228	12
Animals	94	149	12
Natural features	81	113	6
Moving objects	79	103	5
Material	76	92	10
People	60	80	5
Water	45	64	6
Anthropogenic object	35	47	8

commonly associated with positive descriptions (80%) than sound (45.6%) or touch/feel (11.8%), where neutral and negative experiences are more common than positive. Descriptions associated with smell are generally rare. Importantly, senses often do not occur in isolation in the descriptions. Thirty-two per cent of descriptions described more than one sense, with Figure 2 describing all combinations of experience. Here, we note that combined experiences of sight and sound are more common than any individual sensory experiences except sight, and that experiences related to touch/feel are twice as common in combination (30) than in isolation (15).

These summaries of the senses annotated in descriptions do not tell us about the context of these sensory experiences. To understand this in more detail, we turn to χ^2 statistics, and identify nouns occurring more frequently in conjunction with specific senses than in the corpus as a whole. Since sight dominates the overall distributions, we concentrate on sound and touch/feel. Smells were too rare to carry out statistical analysis. Table 4 reveals six significant terms, four of which are associated with sounds and two with touch/feel. Of those associated with sound, two relate directly to auditory experiences (hear/sound), one is related to the absence of sound (quiet) and one refers to wildlife, or more specifically bird. In the case of touch/feel one term relates to cold and another to wind. The terms related to touch/feel already suggest why these experiences might be less likely to have been annotated as positive (c.f. Table 3). To illustrate the analysis of the context of terms in more detail, we chose the most common terms (bird) and created a subgraph of co-occurrences with other parts of speech (Figure 3).

Bird shows a large number of connections with a variety of other nouns, adjectives and verbs, underlining the frequent mentioning of birds in our corpora as well as the potential importance of birds in how participants perceive their everyday lived landscapes. Upon further inspection we find 54 contributions to contain the lemma bird, in line with the prominence of the term in the auditory sensory dimension. The network shows many generic bird-related adjectives relating not only to sounds emitted by birds (e.g. chirp, sing, tweet), but also other activities fly, gather, peck and roost) and mentions of quantity (e.g. single, few and many).

Interestingly, the context graph shows participants only mention three types of birds (Pigeon, Robin and Sparrow) that are syntactically connected with the term bird. However, whilst annotating all contributions as to sensory experiences and CES (as described in Sections 2.3.2 and 2.3.3), we noted a large variety of reported bird species. To further investigate this

Table 3. Counts of descriptions associated with different senses and their associated sentiment.

	Count	Positive	Negative	Neutral
Sight	165	132	29	4
Sound	90	42	19	29
Touch/feel	51	6	13	32
Smell	11	6	1	4

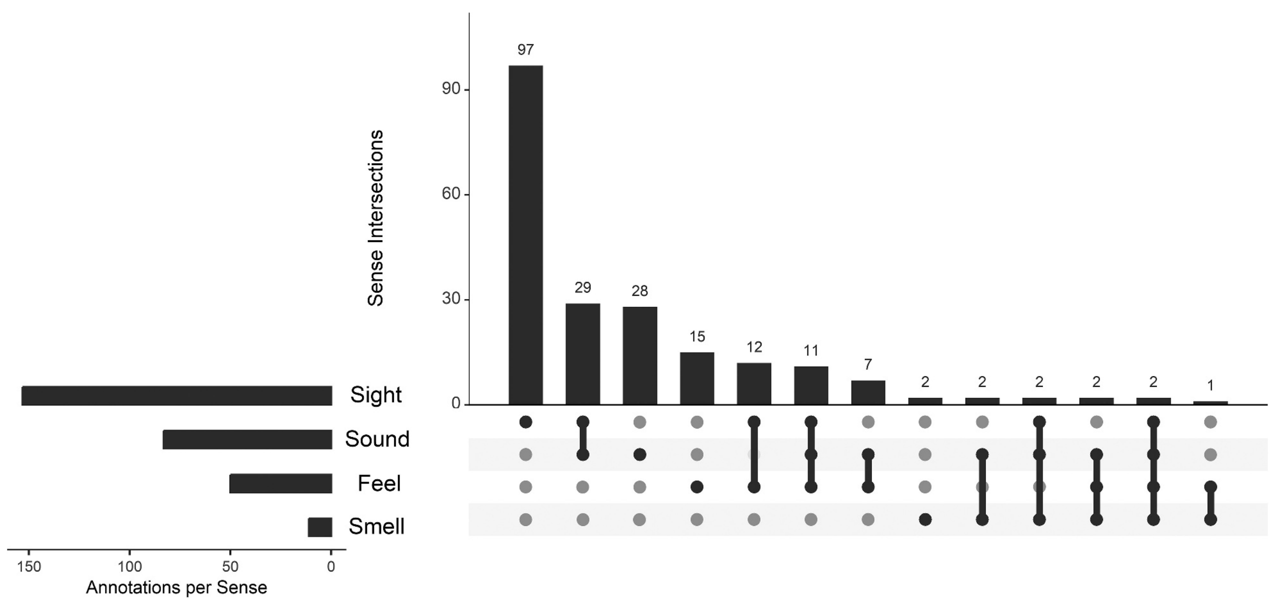

Figure 2. Upset plot (Lex et al. 2014; Conway et al. 2017) of the senses and their respective overlaps. The histograms show the number of contributions annotated as containing sensory experiences. The intersections of sensory experiences are indicated by dots in the respective bars. Reading example: 97 descriptions described only sight and 29 captions included both sight and sound. In total, 153 captions were annotated with some combination of sight (97+29+12+11+2+2).

Table 4. Terms that are significantly more frequent in the auditory and haptic dimensions.

Sense	Term	N	χ^2 (p-value)
Sound	bird	40	7.4 (p = .006)
Sound	hear	39	21.4 (p < .001)
Sound	quiet	26	15.4 (p < .001)
Sound	sound	13	7.6 (p = .006)
Touch/feel	cold	19	31.6 (p < .001)
Touch/feel	wind	18	17.1 (p < .001)

discrepancy between the network (Figure 3) and the large number of specific bird species mentioned within the individual contributions, we created an additional pipeline to computationally identify bird species that contributors mentioned.

To do so, we first downloaded an extensive list of English names for known bird species[4] and iterated through all contributions using the list to extract user-mentioned bird species. We then found 47 contributions containing the lemmas of 50 unique bird species including Acorn Woodpecker, Blue Jay, Goldfinch, House Martin, Green Parakeet and White Tailed Eagle. The most frequent with seven mentions was Magpie followed by Robin ($n = 6$) and Blackbird ($n = 5$), chicken ($n = 5$) and Pigeon ($n = 5$). We discuss the discrepancy between our automated approach and the presence of specific bird species further in the discussion.

3.4. Cultural ecosystem services in landscapes

As well as containing contributions annotated as referring to sensory experiences, the dataset also contained 116 contributions containing at least one cultural ecosystem service (Table 5). However, in contrast to sensory experiences, single CES were much more common (75%) in total, with co-occurrences between CES being uncommon and rather evenly distributed across CES combinations (Figure 4). As suggested by the importance of quiet, tranquillity was a relatively common CES, and we included it as an individual category. As is common in studies of CES, recreation was the most common category identified, and religious values were rarely mentioned. Using the same approach as taken with sensory experiences, we found that old was overrepresented in the CES dimension heritage compared to the corpus as a whole ($\chi^2(df = 1, N = 20) = 25.1$, p<.001) and created a network graph for this term.

The extracted subgraph shows that the term old is frequently mentioned in the context of built structures of potential cultural relevance including church, castle, mill, harbour, dyke and quarry, as well as more generic terms related to everyday lived landscapes such as house, building, garden and town (Figure 5).

Table 5. Summary of cultural ecosystem services.

CES	Count
Recreation	60
Heritage	34
Identity	24
Tranquillity	19
Inspiration	11
Religious	3

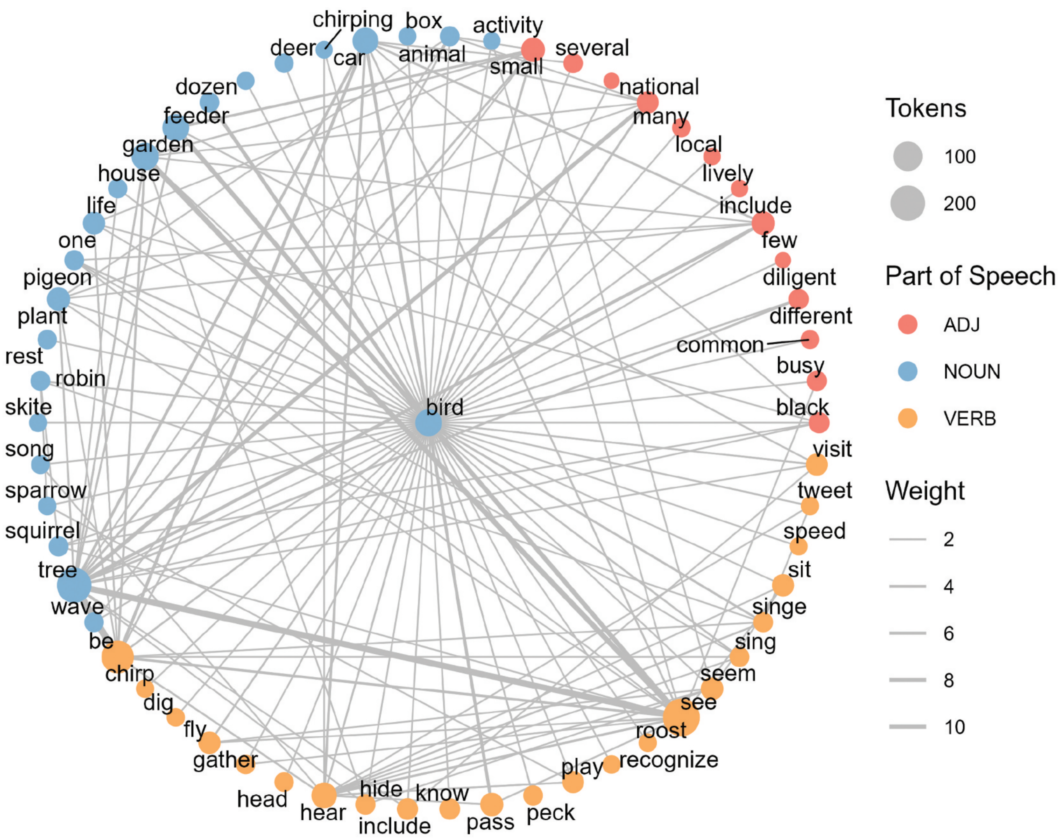

Figure 3. Graph of the context of the term lemma bird.

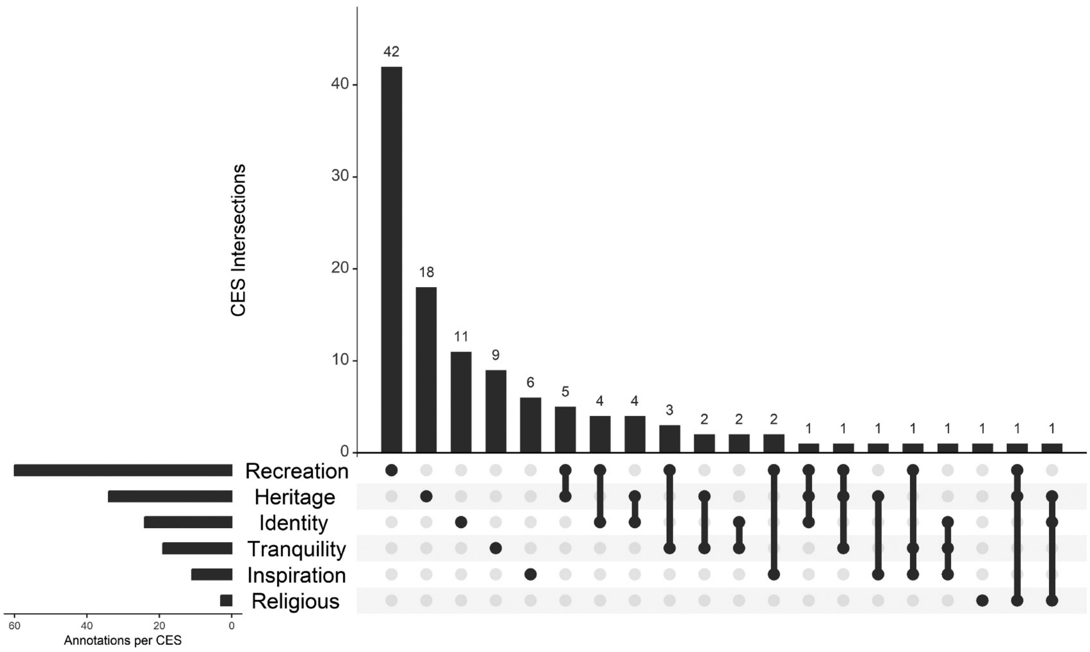

Figure 4. Upset plot (Lex et al. 2014; Conway et al. 2017) of the cultural ecosystem services and their respective overlaps. The histograms show the number of contributions annotated as containing cultural ecosystem services. The intersections of cultural ecosystem services are indicated by dots in the respective bars. Reading example: 42 descriptions described only recreation and 5 captions included both recreation and heritage. In total, 60 captions were annotated with some combination of recreation (42 +5+4+3+2+1+1+1+1).

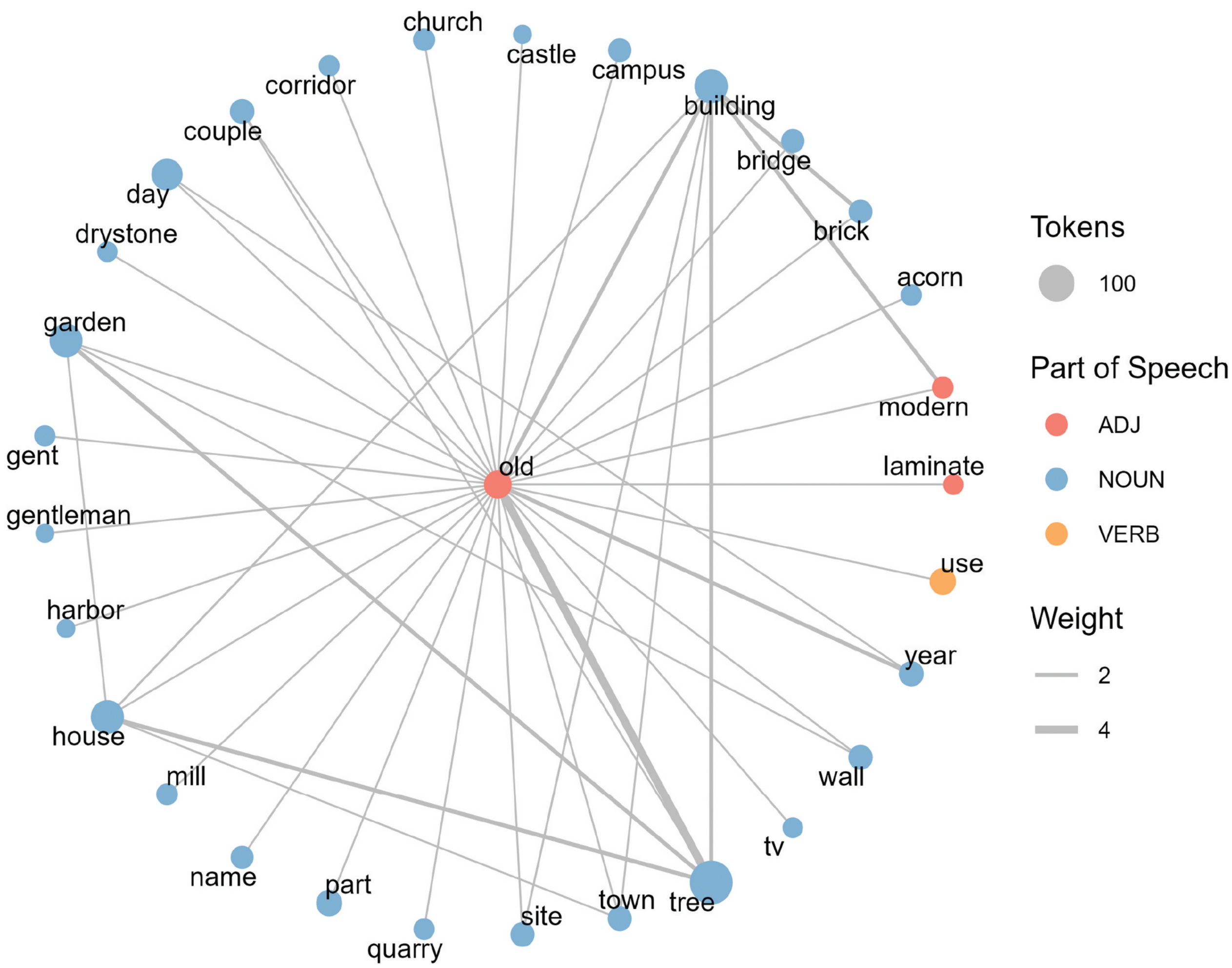

Figure 5. Graph of the context of the term lemma old.

3.5. Linking biophysical elements, sensory experiences and cultural ecosystem services

In our final analysis, we investigated relationships between the three preceding components of our annotations: biophysical elements, sensory experiences and cultural ecosystem services. We use mosaic plots (Jeppson and Hofmann 2023) to quantify the distributions of sensory experiences and CES, respectively, with biophysical elements (Figure 6). Mosaic plots allow us to visualize both proportions (length of bars) and counts (area of bars) in a single representation and to explore qualitative relationships. For example, we observe that animals are more often associated with sound and feeling than most other biophysical categories, while anthropogenic objects are dominated by sight. Similarly, when we explore the relationship between CES and biophysical elements, we observe some notable differences – moving objects, for example, are much more commonly related to heritage than other categories, while natural features and weather appear more likely than other categories to be associated with tranquility. Despite these individual differences, the distribution of categories across biophysical elements is broadly similar for both sensory experiences (χ^2 (df = 33) = 54.6, p = .010) and CES (χ^2 (df = 55) = 47.1, p = .767), with no significant differences in the distributions overall.

4. Discussion

Understanding how people interact with their everyday lived landscapes is of increasing interest,

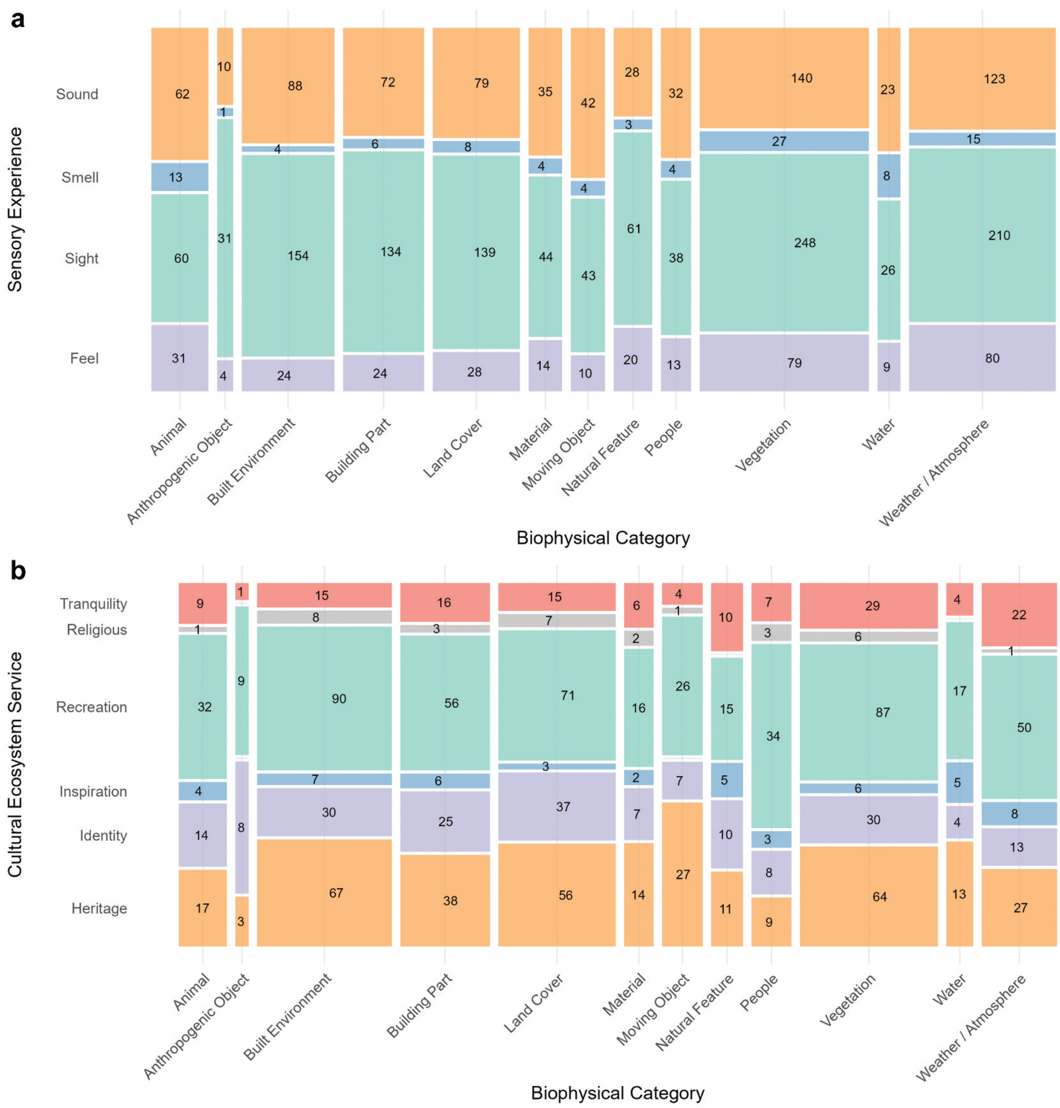

Figure 6. Mosaic plots (Jeppson and Hofmann 2023) showing the distribution of annotated biophysical categories within the annotated dimensions of (a) sensory experiences and (b) cultural ecosystem services. The width of each column indicates the overall relative proportion of the biophysical category compared to the whole dataset. The height of the individual bars within a column indicates the relative proportion of the respective sensory experience or cultural ecosystem service within a biophysical category. The numbers show the absolute number of lemmas annotated within each biophysical category and sensory dimension or cultural ecosystem service.

particularly within the context of the COVID-19 pandemic and the related *anthropause* (Rutz 2022), when people reported visiting (where possible) local areas more, and also valuing those areas more (Grima et al. 2020). Whereas previous studies focused on the overall importance of access to and valuation of nearby green spaces (Grima et al. 2020; Fagerholm et al. 2022; Hansen et al. 2022; Cui et al. 2023). The results of this paper shed light on the elements of everyday lived landscapes considered important by the participating users and the sensory experiences related to cultural ecosystem services.

4.1. Diversity in natural language descriptions of everyday lived landscapes

Biophysical elements constitute an important dimension of landscapes and are argued to aid in integrating cultural aspects in ecosystem services (Daniel et al. 2012). As such, biophysical elements are an important dimension of contemporary cultural ecosystem services frameworks (Fish et al. 2016). Our results suggest that biophysical elements are indeed important perceptual dimensions of landscapes given their frequent mentions. The results show biophysical categories important in everyday lived landscapes such as the surrounding vegetation, the current weather and elements of the built environment to be particularly salient. This contrasts with previous studies in more rural and idealised landscapes where elements such as mountains, forests and water bodies were among the most salient landscape features (Bieling 2014). The difference in the landscape elements found in *Window Expeditions* demonstrates the difference in study locations and the focus on everyday lived landscapes. The rarity of water bodies and natural features likely reflects participants' home locations, but as we did not record exact home locations for privacy reasons, we cannot test this assumption by comparing, e.g. home locations against land use and land cover data. The notable absence of mentions of people in the contributions is likely due to the COVID-19 pandemic, or could also be related to previous observations that people less often describe other people as part of their landscape experience than biophysical elements, even if they are present (Wartmann et al. 2015).

In terms of sensory experiences, we found the visual to be the most commonly mentioned sensory experience, in line with previous work showing the visual dimension to be dominant in landscape perception studies (Daniel 2001). Nonetheless, we also found a number of references to the auditory dimension. Particularly salient is the overrepresentation of the term bird within the auditory dimension, suggesting birds are especially important in the immediate surroundings of our participants. Birds are important inhabitants of lived landscapes, contribute to the soundscape, and have even been found to contribute positively to mental wellbeing (Hammoud et al. 2022). We suggest that this overrepresentation of birds in our data set may be linked to the overall surge in bird observations during the pandemic, particularly of commonly observed garden bird species such as Blackbirds, Blue Tits or Robins in the UK (Barrett and Bott 2020), which fit well with the most mentioned bird species described in this study (Tit, Magpie, Robin and Blackbird).

Our particular focus on the term bird stemmed from the discrepancy between bird being significantly overrepresented in the auditory dimension and the small number of species present in the context graph. By taking a multi-scalar approach (Taylor and Adams 2022), where we combined close and distant reading, we knew that our descriptions did contain many mentions of bird species. We then carried out further computational analysis to quantify which species were present. This approach demonstrates some of the advantages of our multiscalar approach over purely computational analysis. Here, we noted that specific instances of proper nouns were being used, but did not co-occur with the generic noun bird, and then investigated these categories in more depth.

We also note a general potential positivity bias within the contributed natural language landscape descriptions. This inclination towards more positively connotated reports may stem from an underlying positivity bias within language (Dodds et al. 2015), in combination with the tendency of individuals to generally communicate positive rather than negative experiences in landscapes (Taylor et al. 1995). However, not all sensory experiences are as positively connotated as scenic views or melodic bird song. The results also show the auditory dimension commonly co-occurring with the biophysical category of moving objects, primarily transport-related vehicles, which have been identified as disturbing sounds (Stansfeld and Matheson 2003; Watts and Pheasant 2013; Koblet and Purves 2020).

The haptic dimension was frequently found in regard to weather-related phenomena, primarily through 'feeling' the cold air or wind. Although many of the annotated references of the haptic dimension carry a negative connotation, experiencing the weather was still important enough to mention. The literature shows that weather and atmospheric events influence how we experience and perceive landscapes, yet weather is difficult to take into account in models or predictions of CES (Ingold 2005; Półrolniczak and Kolendowicz 2021). This research further highlights the potential link between CES and weather-related phenomena, which should be accounted for in future studies, for example by treating CES as dynamic, especially with respect to weather-related CES such as tranquility.

Cultural ecosystem services encompassing the intangible dimensions of landscapes have gained increasing importance in policy and decision-making contexts. Even though cultural ecosystem services are important dimensions of our environments, their intangible nature makes data collection difficult and participatory approaches become valuable (Brown and Fagerholm 2015; Garcia-Martin et al. 2017; Wartmann and Purves 2018; Bubalo et al. 2019; Depietri et al. 2021). The results of our study once again find recreation, even during the restrictions of the COVID-19 pandemic, to be one of the most salient dimensions described by contributing users (Bieling 2014; Fagerholm et al. 2020). Further important dimensions included heritage, identity and tranquility, suggesting participating users appreciate the historic value of landscapes as well as environments affording solace and respite from the more hectic urban lifestyle (Wartmann et al. 2019; Ugolini et al. 2020; Purves and Wartmann 2023).

4.2. Limitations

Our study has a number of limitations. Firstly, despite the more gamified data collection approach, the underlying corpus that was annotated and analysed was rather small, and thus generalisations are difficult. Even though clear trends were visible as discussed in this paper, a larger corpus could provide more detailed insights into how individuals perceive everyday lived landscapes. This calls for further examination of user motivation and retention in gamified approaches (Kasurinen and Knutas 2018), as well as considering novel methods of landscape-relevant corpus generation from existing text sources (e.g. web corpora such as digitised newspaper archives).

Secondly, we perform our analyses on a collection of English texts and the results may not be transferable to other cultural and linguistic contexts. There is agreement in the literature that landscape perception and language are highly intertwined (Burenhult and Levinson 2008; van Putten et al. 2020). Future data generation efforts should thus strive to generate multilingual collections of landscape-relevant natural language to enable more cross-linguistic analyses (e.g. Feng and Mark 2017). Even where the platform was available in a language in which users were fluent (German or French), many participants still preferred to write English descriptions. Furthermore, though contributions were geographically diverse, they were dominated by a few countries, and we are cautious in claiming that our results are generally applicable. Most obviously, interest in birds is common in the UK, and other landscape elements may emerge if we collect more contributions in different cultural settings.

Lastly, the original descriptions were annotated by human annotators. Even though the annotation guidelines were created in an iterative process to allow for consensus on annotations and reproducibility, all annotators were Western European academics, albeit from different cultural and linguistic backgrounds, who conceptualise human-environment interactions in certain ways, with the annotations reflecting these particular conceptualisations.

5. Implications

As everyday lived landscapes are dynamic areas of interaction, these are prone to change over time. City planners and environmental managers are keen to know about people's preferences and behaviour in these places in order to make informed decisions about sustainable and inclusive planning. With the idea of smart cities based on real-time sensory infrastructure (supported by global passive sensing networks) gaining momentum, there is an increasing need for data gathered with and by people to provide a complementary bottom-up view of what matters to people in their local environment and to help address any biases and gaps in top-down or passively collected information (Miller 2020). Including such public perceptions of everyday lived landscapes can guide policy and decision-making processes and lead to more societally sustainable cities (Bouzguenda et al. 2019).

6. Conclusion

The results of this study show various nuances in how everyday lived landscapes are perceived, and which features people perceive as salient. These findings complement the existing literature on landscape perception twofold. Firstly, the results show salient dimensions and elements of landscapes in everyday lived landscapes revolve around what people see and hear as well as the recreational potential of landscapes, in line with previous findings. However, secondly, important perceived elements of landscapes were found to be natural features such as trees and birds, as well as anthropogenic infrastructures such as houses and buildings. This contrasts with landscape perception studies in more rural landscapes, which frequently mention mountains and water bodies to be the most salient. We argue for a continued shift in the focus of landscape studies to include more urban and particularly the immediate surroundings of lived areas, especially in policy and decision-making contexts that require considering people's everyday environments and experiences that directly link to well-being.

In future work, we plan to a) further gamify the collection of descriptions to increase the cultural diversity of contributions and b) further investigate the use of emerging methods in natural landscape processing to extend our multi-scalar approach to the analysis of larger corpora.

Notes

1. https://chat.openai.com/ (accessed: 26 December 2023).
2. https://deepmind.google/technologies/gemini (accessed: 26 December 2023).
3. https://spacy.io/ (accessed: 18 April 2023).
4. www.worldbirdnames.org/new/ioc-lists/master-list-2/.

Acknowledgements

We would like to thank everyone who took part in *Window Expeditions*, without you this research would not have been possible! We would also like to extend our gratitude to the anonymous reviewers whose helpful comments improved the quality of this paper.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

University Research Priority Program (URPP) – Language and Space & Swiss National Science Foundation Grant [P500PT_214436].

ORCID

Manuel F. Baer http://orcid.org/0000-0002-9474-3299
Flurina Wartmann http://orcid.org/0000-0003-4788-2963
Nora Fagerholm http://orcid.org/0000-0001-5020-0746
Ross S. Purves http://orcid.org/0000-0002-9878-9243

References

Adamowicz W, Louviere J, Williams M. 1994. Combining revealed and stated preference methods for valuing environmental amenities. J Environ Econ Manag. 26 (3):271–292. doi: 10.1006/jeem.1994.1017.

Aiello LM, Schifanella R, Quercia D, Aletta F. 2016. Chatty maps: constructing sound maps of urban areas from social media data. R Soc Open Sci. 3(3):150690. doi: 10.1098/rsos.150690.

Baer MF, Purves RS. 2022. Window expeditions: a playful approach to crowdsourcing natural language descriptions of everyday lived landscapes. Appl Geogr. 148:102802. doi: 10.1016/j.apgeog.2022.102802.

Baer MF, Wartmann FM, Purves RS. 2019. Starborn: towards making in- situ land cover data generation fun with a location-based game. Trans GIS. 23 (5):1008–1028. doi: 10.1111/tgis.12543.

Barrett C, Bott I. 2020. How Britain became a nation of birdwatchers. The pandemic has taught us to take notice of nature — but is it a lasting change?

Beckmann-Wübbelt A, Fricke A, Sebesvari Z, Yakouchenkova IA, Fröhlich K, Saha S. 2021. High public appreciation for the cultural ecosystem services of urban and peri-urban forests during the COVID-19 pandemic. Sustain Cities Soc. 74:103240. doi: 10.1016/j.scs.2021.103240.

Bender EM, Gebru T, McMillan-Major A, Shmitchell S. 2021. On the dangers of stochastic parrots: can language models be too big? Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency. p. 610–623. doi: 10.1145/3442188.3445922.

Bieling C. 2014. Cultural ecosystem services as revealed through short stories from residents of the Swabian Alb (Germany). Ecosyst Serv. 8:207–215. doi: 10.1016/j.ecoser.2014.04.002.

Bouzguenda I, Alalouch C, Fava N. 2019. Towards smart sustainable cities: a review of the role digital citizen participation could play in advancing social sustainability. Sustain Cities Soc. 50:101627. doi: 10.1016/j.scs.2019.101627.

Brabyn L. 2009. Classifying landscape character. Landscape Res. 34(3):299–321. doi: 10.1080/01426390802371202.

Brown KM. 2017. The haptic pleasures of ground-feel: the role of textured terrain in motivating regular exercise. Health Place. 46:307–314. doi: 10.1016/j.healthplace.2016.08.012.

Brown G, Fagerholm N. 2015. Empirical PPGIS/PGIS mapping of ecosystem services: a review and evaluation. Ecosyst Serv. 13:119–133. doi:10.1016/j.ecoser.2014.10.007.

Bryce R, Irvine KN, Church A, Fish R, Ranger S, Kenter JO. 2016. Subjective well-being indicators for large-scale assessment of cultural ecosystem services [shared, plural and cultural values]. Ecosyst Serv. 21:258–269. doi: 10.1016/j.ecoser.2016.07.015.

Bubalo M, Zanten BTV, Verburg PH. 2019. Landscape and urban planning crowdsourcing geo-information on landscape perceptions and preferences: a review. Landsc Urban Plan. 184(January):101–111. doi: 10.1016/j.landurbplan.2019.01.001.

Burenhult N, Levinson SC. 2008. Language and landscape: a cross-linguistic perspective. Lang Sci. 30(2–3):135–150. doi: 10.1016/j.langsci.2006.12.028.

Chan KMA, Guerry AD, Balvanera P, Klain S, Satterfield T, Basurto X, Bostrom A, Chuenpagdee R, Gould R, Halpern BS, et al. 2012. Where are cultural and social in ecosystem services? A framework for constructive engagement. BioScience. 62(8):744–756. doi: 10.1525/bio.2012.62.8.7.

Chen YT, Chen MC. 2011. Using chi-square statistics to measure similarities for text categorization. Expert Syst Appl. 38(4):3085–3090. doi: 10.1016/j.eswa.2010.08.100.

Chesnokova O, Purves RS. 2018. From image descriptions to perceived sounds and sources in landscape: analyzing aural experience through text. Appl Geogr. 93 (February):103–111. doi: 10.1016/j.apgeog.2018.02.014.

Conway JR, Lex A, Gehlenborg N, Hancock J. 2017. Upsetr: an r package for the visualization of intersecting sets and their properties. Bioinformatics. 33 (18):2938–2940. doi: 10.1093/bioinformatics/btx364.

Costanza R, de Groot R, Braat L, Kubiszewski I, Fioramonti L, Sutton P, Farber S, Grasso M. 2017.

Twenty years of ecosystem services: how far have we come and how far do we still need to go? Ecosyst Serv. 28:1–16. doi: 10.1016/j.ecoser.2017.09.008.

Cui N, Malleson N, Houlden V, Comber A. 2021. Using vgi and social media data to understand urban green space: A narrative literature review. ISPRS Int J Geoinf. 10(7):7. doi: 10.3390/ijgi10070425.

Cui N, Malleson N, Houlden V, Comber A. 2023. The impact of the COVID-19 pandemic on the dynamics of topics in urban green space. AGILE GIScience Ser. 4:1–7. doi: 10.5194/agile-giss-4-22-2023.

Dakin S. 2003. There's more to landscape than meets the eye: towards inclusive landscape assessment in resource and environmental management. Can Geogr. 47 (2):185–200. doi: 10.1111/1541-0064.t01-1-00003.

Daniel TC. 2001. Whither scenic beauty? Visual landscape quality assessment in the 21st century. Landsc Urban Plan. 54(1–4):267–281. doi: 10.1016/S0169-2046(01)00141-4.

Daniel TC, Muhar A, Arnberger A, Aznar O, Boyd JW, Chan KM, Costanza R, Elmqvist T, Flint CG, Gobster PH, et al. 2012. Contributions of cultural services to the ecosystem services agenda. Proc Natl Acad Sci USA. 109(23):8812–8819. doi: 10.1073/pnas.1114773109.

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

Derungs C, Purves RS. 2016. Characterising landscape variation through spatial folksonomies. Appl Geogr. 75:60–70. doi: 10.1016/j.apgeog.2016.08.005.

Dodds PS, Clark EM, Desu S, Frank MR, Reagan AJ, Williams JR, Mitchell L, Harris KD, Kloumann IM, Bagrow JP, et al. Human language reveals a universal positivity bias. Proc Natl Acad Sci U S A. 2015;112 (8):2389–2394. doi: 10.1073/pnas.1411678112.

European Landscape Convention. (2000). European Landscape Convention. Report and Convention Florence, ETS No. 17 (176), 8.

Fagerholm N, Martín-López B, Torralba M, Oteros-Rozas E, Lechner AM, Bieling C, Stahl Olafsson A, Albert C, Raymond CM, Garcia-Martin M, et al. 2020. Perceived contributions of multi- functional landscapes to human well-being: evidence from 13 European sites. People Nat. 2(1):217–234. doi: 10.1002/pan3.10067.

Fagerholm N, Samuelsson K, Eilola S, Giusti M, Hasanzadeh K, Kajosaari A, Koch D, Korpilo S, Kyttä M, Legeby A, et al. Analysis of pandemic outdoor recreation and green infrastructure in Nordic cities to enhance urban resilience. NPJ Urban Sustain. 2022;2 (1):25. doi: 10.1038/s42949-022-00068-8.

Feng C-C, Mark DM. 2017. Cross-linguistic research on landscape categories using GEOnet names server data: a case study for Indonesia and Malaysia. Prof Geogr. 69 (4):567–578. doi: 10.1080/00330124.2017.1288575.

Fish R, Church A, Winter M. 2016. Conceptualising cultural ecosystem services: A novel framework for research and critical engagement. Ecosyst Serv. 21 (November):208–217. doi: 10.1016/j.ecoser.2016.09.002.

Flaxman S, Mishra S, Gandy A, Unwin HJT, Mellan TA, Coupland H, Whittaker C, Zhu H, Berah T, Eaton JW, et al. 2020. Estimating the effects of non- pharmaceutical interventions on COVID-19 in Europe. Nature. 584 (7820):257–261. doi: 10.1038/s41586-020-2405-7.

Garcia-Martin M, Fagerholm N, Bieling C, Gounaridis D, Kizos T, Printsmann A, Müller M, Lieskovský J, Plieninger T. 2017. Participatory mapping of landscape values in a pan-European perspective. Landsc Ecol. 32 (11):2133–2150. doi: 10.1007/s10980-017-0531-x.

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

Gibson JJ. 1986. The ecological approach to visual perception. New Jersey (USA): Lawrence Erlbaum Associates.

Goines L, Hagler L. 2007. Noise pollution: a modem plague. South Med J. 100(3):287–294. doi: 10.1097/smj.0b013e3180318be5.

Grêt-Regamey A, Switalski M, Fagerholm N, Korpilo S, Juhola S, Kyttä M, Käyhkö N, McPhearson T, Nollert M, Rinne T, et al. Harnessing sensing systems towards urban sustainability transformation. NPJ Urban Sustain. 2021;1(1):40. doi: 10.1038/s42949-021-00042-w.

Grima N, Corcoran W, Hill-James C, Langton B, Sommer H, Fisher B, Aguilar FX. 2020. The importance of urban natural areas and urban ecosystem services during the COVID-19 pandemic. PLoS One. 15(12): e0243344. doi: 10.1371/journal.pone.0243344.

Haab TC, McConnell KE. 2002. Valuing environmental and natural resources: the econometrics of non-market valuation. Massachusetts (USA): Edward Elgar Publishing, Incorporated.

Hammoud R, Tognin S, Burgess L, Bergou N, Smythe M, Gibbons J, Davidson N, Afifi A, Bakolis I, Mechelli A. 2022. Smartphone-based ecological momentary assessment reveals mental health benefits of birdlife. Sci Rep. 12(1):17589. doi: 10.1038/s41598-022-20207-6.

Hansen AS, Beery T, Fredman P, Wolf-Watz D. 2022. Outdoor recreation in Sweden during and after the covid-19 pandemic–management and policy implications. J Environ Plann Manage. 66(7):1472–1493. doi: 10.1080/09640568.2022.2029736.

Hausmann A, Toivonen T, Fink C, Heikinheimo V, Kulkarni R, Tenkanen H, Di Minin E. 2020. Understanding sentiment of national park visitors from social media data. People Nat. 2(3):750–760. doi: 10.1002/pan3.10130.

Heft H. 2010. Affordances and the perception of landscape and aesthetics. In: Innovative approaches to researching landscape and health. Oxon (UK): Routledge; p. 9–32.

Henshaw V. 2013. Urban smellscapes: understanding and designing city smell environments. Oxon (UK): Routledge.

Herbold S, Hautli-Janisz A, Heuer U, Kikteva Z, Trautsch A. 2023. A large- scale comparison of human-written versus ChatGPT-generated essays. Sci Rep. 13(1):18617. doi: 10.1038/s41598-023-45644-9.

Herzog TR, Herbert EJ, Kaplan R, Crooks CL. 2000. Cultural and developmental comparisons of landscape perceptions and preferences. Environ Behav. 32 (3):323–346. doi: 10.1177/0013916500323002.

Hsieh HF, Shannon SE. 2005. Three approaches to qualitative content analysis. Qual Health Res. 15 (9):1277–1288. doi: 10.1177/1049732305276687.

Ingold T. 2005. The eye of the storm: visual perception and the weather. Vis Stud. 20(2):97–104. doi: 10.1080/14725860500243953.

Jeppson H, Hofmann H. 2023. The r journal: generalized mosaic plots in the gg- plot2 framework [10.32614/RJ-2023-013]. R J. 14(4):50–78. doi: 10.32614/RJ-2023-013.

Kaplan R, Kaplan S. 1989. *The experience of nature: a psychological perspective*. Cambridge (UK): Cambridge University Press.

Kasurinen J, Knutas A. 2018. Publication trends in gamification: a systematic mapping study. Comput Sci Rev. 27:33–44. doi: 10.1016/j.cosrev.2017.10.003.
Kilgarriff A. 2001. Comparing Corpora. Int J Corpus Linguist. 6(1):97–133. doi: 10.1075/ijcl.6.1.05kil.
Koblet O, Purves RS. 2020. From online texts to landscape character assessment: collecting and analysing first-person landscape perception computationally. Landsc Urban Plan. 197(July 2019):103757. doi: 10.1016/j.landurbplan.2020.103757.
Kocoń J, Cichecki I, Kaszyca O, Kochanek M, Szydło D, Baran J, Bielaniewicz J, Gruza M, Janz A, Kanclerz K, et al. 2023. ChatGPT: Jack of all trades, master of none. Inf Fusion. 99(101861):101861. doi: 10.1016/j.inffus.2023.101861.
Krase J, Shortell T. 2011. On the spatial semiotics of vernacular landscapes in global cities. Visual Communic. 10 (3):371–376. doi: 10.1177/1470357211408821.
La Notte A, D'Amato D, Mäkinen H, Paracchini ML, Liquete C, Egoh B, Geneletti D, Crossman ND. 2017. Ecosystem services classification: a systems ecology perspective of the cascade framework. Ecol Indic. 74:392–402. doi: 10.1016/j.ecolind.2016.11.030.
Laso Bayas JC, See L, Bartl H, Sturn T, Karner M, Fraisl D, Moorthy I, Busch M, van der Velde M, Fritz S. 2020. Crowdsourcing Lucas: citizens generating reference land cover and land use data with a mobile app. Land. 9(11). doi: 10.3390/land9110446446.
Lee M, Zhao J, Sun Q, Pan Y, Zhou W, Xiong C, Zhang L, Samy AM. 2020. Human mobility trends during the early stage of the COVID-19 pandemic in the United States. PLoS One. 15(11):1–15. doi: 10.1371/journal.pone.0241468.
Lefebvre H. 1992. The production of space. Vol. 53, Wiley. doi:10.2307/378107.
Lex A, Gehlenborg N, Strobelt H, Vuillemot R, Pfister H. 2014. Upset: visualization of intersecting sets. IEEE Trans Visual Comput Graphics (InfoVis). 20 (12):1983–1992. doi: 10.1109/TVCG.2014.2346248.
Lucchini L, Centellegher S, Pappalardo L, Gallotti R, Privitera F, Lepri B, De Nadai M. 2021. Living in a pandemic: changes in mobility routines, social activity and adherence to COVID-19 protective measures. Sci Rep. 11(1):1–12. doi: 10.1038/s41598-021-04139-1.
MA. 2005. Millennium ecosystem assessment. Ecosystems and human well-being: synthesis. Washington (DC): Island Press.
Manning CD. 2011. Part-of-speech tagging from 97% to 100%: is it time for some linguistics? In: Gelbukh AF, editor. Computational linguistics and intelligent text processing. Berlin Heidelberg: Springer; p. 171–189.
Marquis-Favre C, Premat E, Aubrée D. 2005. Noise and its effects a review on qualitative aspects of sound. part ii: noise and annoyance. Acta Acust United Acust. 91 (4):626–642.
Milcu AI, Hanspach J, Abson D, Fischer J. 2013. Cultural ecosystem services: a literature review and prospects for future research. Ecol Soc. 18(3). doi: 10.5751/ES-05790-180344.
Miller HJ. 2020. Geographic information science iii: giscience, fast and slow – why faster geographic information is not always smarter. Prog Hum Geogr. 44 (1):129–138. doi: 10.1177/0309132518799596.
Mora-Araus M, Velastegui-Montoya A, Jaramillo-Lindao Y, Apolo H. 2021. Mapping the sound landscape during social isolation due to covid-19. 2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS. p. 8340–8343. doi: 10.1109/IGARSS47720.2021.9554530.
Ode Å, Tveit MS, Fry G. 2008. Capturing landscape visual character using indicators: touching base with landscape aesthetic theory. Landscape Res. 33(1):89–117. doi: 10.1080/01426390701773854.
Półrolniczak M, Kolendowicz L. 2021. The influence of weather and level of observer expertise on suburban landscape perception. Build Environ. 202:108016. doi: 10.1016/j.buildenv.2021.108016.
Purves RS, Wartmann FM. 2023. Characterising and mapping potential and experienced tranquillity: from a state of mind to a cultural ecosystem service. Geogr Compass. 17(11):e12726. doi: 10.1111/gec3.12726.
Pustejovsky J, Stubbs A. 2013. Natural language annotation for machine learning – a guide to corpus-building for applications. California (USA): O'Reilly Media, Inc.
Quercia D, Schifanella R, Aiello LM, McLean K. 2015. Smelly maps: the digital life of urban smellscapes. Assoc Adv Artif Intell. 12:3.
Rouse AC. 2010. A preliminary taxonomy of crowdsourcing. ACIS 2010 Proceedings - 21st Australasian Conference on Information Systems.
Rutz C. 2022. Studying pauses and pulses in human mobility and their environmental impacts. Nat Rev Earth Environ. 3(3):157–159. doi: 10.1038/s43017-022-00276-x.
Salk CF, Sturn T, See L, Fritz S, Perger C. 2016. Assessing quality of volunteer crowdsourcing contributions: lessons from the cropland capture game. Int J Digital Earth. 9(4):410–426. doi: 10.1080/17538947.2015.1039609.
Schaich H, Bieling C, Plieninger T. 2010. Linking ecosystem services with cultural landscape research. GAIA - Ecol Perspect Sci Soc. 19(4):269–277. doi: 10.14512/gaia.19.4.9.
See L, Mooney P, Foody G, Bastin L, Comber A, Estima J, Fritz S, Kerle N, Jiang B, Laakso M, et al. 2016. Crowdsourcing, citizen science or volunteered geographic information? The Current state of crowdsourced geographic information. ISPRS Int J Geo-Inf. 5(5):55. doi: 10.3390/ijgi5050055.
Seresinhe CI, Moat HS, Preis T. 2018. Quantifying scenic areas using crowd- sourced data. Environ Plann B: Urban Anal City Sci. 45(3):567–582. doi: 10.1177/0265813516687302.
Seresinhe CI, Preis T, MacKerron G, Moat HS. 2019. Happiness is greater in more scenic locations. Sci Rep. 9(1):1–11. doi: 10.1038/s41598-019-40854-6.
Shapiro J, Báldi A. 2014. Accurate accounting: how to balance ecosystem services and disservices. Ecosyst Serv. 7:201–202. doi: 10.1016/j.ecoser.2014.01.002.
Smith B, Mark DM. 2003. Do mountains exist? towards an ontology of landforms. Environ Plann B Plann Des. 30 (3):411–427. doi: 10.1068/b12821.
Stansfeld SA, Matheson MP. 2003. Noise pollution: non-auditory effects on health. Br Med Bull. 68 (1):243–257. doi: 10.1093/bmb/ldg033.
Swanwick C. 2009. Society's attitudes to and preferences for land and landscape. Land Use Policy. 26(SUPPL. 1):62–75. doi: 10.1016/j.landusepol.2009.08.025.
Taylor JE, Adams B. 2022. The wild process: constructing multi-scalar environmental narratives. In: Environmental narratives. London (UK): Ubiquity Press Ltd.
Taylor JG, Czarnowski KJ, Sexton NR, Flick S. 1995. The importance of water to Rocky Mountain National Park visitors: an adaptation of visitor- employed photography to natural resources management. J Appl Recreat Res. 20 (1):61–85.

Torkko J, Poom A, Willberg E, Toivonen T. 2023. How to best map greenery from a human perspective? comparing computational measurements with human perception. Front Sustain Cities. 10.3389/frsc.2023.11609955

Tuan YF. 1989. Surface phenomena and aesthetic experience. Ann Assoc Am Geogr. 79(2):233–241. doi: 10.1111/j.1467-8306.1989.tb00260.x.

Tudor C. 2014. An approach to landscape character assessment. Nat Engl. 65(October).

Tveit M, Ode Å, Fry G. 2006. Key concepts in a framework for analysing visual landscape character. Landscape Res. 31(3):229–255. doi: 10.1080/01426390600783269.

Ugolini F, Massetti L, Calaza-Martínez P, Cariñanos P, Dobbs C, Ostoic SK, Marin AM, Pearlmutter D, Saaroni H, Šaulienė I, et al. 2020. Effects of the COVID-19 pandemic on the use and perceptions of urban green space: an international exploratory study. Urban For Urban Greening. 56(June):126888. doi: 10.1016/j.ufug.2020.126888.

van Putten S, O'Meara C, Wartmann F, Yager J, Villette J, Mazzuca C, Bieling C, Burenhult N, Purves R, Majid A, et al. 2020. Conceptualisations of landscape differ across European languages. PLoS One. 15(10 October): e0239858. doi:10.1371/journal.pone.0239858.

Vienneau D, Saucy A, Schäffer B, Flückiger B, Tangermann L, Stafoggia M, Wunderli JM, Röösli M, Group SNCS. 2022. Transportation noise exposure and cardiovascular mortality: 15-years of follow-up in a nationwide prospective cohort in Switzerland. Environ Int. 158:106974. doi: 10.1016/j.envint.2021.106974.

Wartmann FM, Baer MF, Hegetschweiler KT, Fischer C, Hunziker M, Purves RS. 2021. Assessing the potential of social media for estimating recreational use of urban and peri-urban forests. Urban For Urban Green. 64 (July):127261. doi: 10.1016/j.ufug.2021.127261.

Wartmann FM, Egorova E, Derungs C, Mark DM, Purves RS. 2015. More than a list: what outdoor free listings of landscape categories reveal about commonsense geographic concepts and memory search strategies. In: Fabrikant SI, Raubal M, Freundschuh S, Bell S, editors. Spatial information theory. lecture notes in computer science. Vol. 9368. Springer; p. 224–243. doi: 10.1007/978-3-319-23374-111.

Wartmann FM, Purves RS. 2018. Investigating sense of place as a cultural ecosystem service in different landscapes through the lens of language. Landsc Urban Plan. 175(March):169–183. doi: 10.1016/j.landurbplan.2018.03.021.

Wartmann FM, Tieskens KF, van Zanten BT, Verburg PH. 2019. Exploring tranquillity experienced in landscapes based on social media. Appl Geogr. 113 (November):102112. doi: 10.1016/j.apgeog.2019.102112.

Watts GR, Pheasant RJ. 2013. Factors affecting tranquillity in the country- side. Appl Acoust. 74(9):1094–1103. doi: 10.1016/j.apacoust.2013.03.007.

Watts GR, Pheasant RJ, Horoshenkov KV. 2011. Predicting perceived tranquillity in urban parks and open spaces. Environ Plann B Plann Des. 38(4):585–594. doi: 10.1068/b36131.

White M, Smith A, Humphryes K, Pahl S, Snelling D, Depledge M. 2010. Blue space: the importance of water for preference, affect, and restorativeness ratings of natural and built scenes. J Environ Psychol. 30(4):482–493. doi: 10.1016/j.jenvp.2010.04.004.

Zube EH. 1986. Local and extra-local perceptions of national parks and protected areas. Landsc Urban Plan. 13:11–17. doi: 10.1016/0169-2046(86)90003-4.

Zube EH, Pitt DG. 1981. Cross-cultural perceptions of scenic and heritage landscapes. Landsc Urban Plan. 8 (1):69–87. doi: 10.1016/0304-3924(81)90041-1.