Crowdsourced data and machine learning to measure cultural ecosystem services

Ilan Havinga

Propositions

1. Employing crowdsourced data helps clarify the cultural ecosystem service concept.

   (this thesis)

2. Machine learning enables a variety of cultural preferences to be linked to specific ecosystem attributes at large-scales.

   (this thesis)

3. Social activities are key to reconnecting people with nature.

4. Model uncertainties should be better communicated to policy-makers and wider society to maintain trust in science.

5. Environmental issues such as climate change are best solved through democratic processes.

6. In a digital world, programming gives you superpowers.

Propositions belonging to the thesis entitled

Crowdsourced data and machine learning to measure cultural ecosystem services

Ilan Havinga

Wageningen, 28 October 2022

Crowdsourced data and machine learning to measure cultural ecosystem services

Ilan Havinga

Crowdsourced data and machine learning to measure cultural ecosystem services

Ilan Havinga

Table of Contents

Chapter 1.

General Introduction

1.1. Background

1.1.1. *Global challenges and policy responses*

Society is facing a variety of complex social and environmental challenges, including rapidly declining levels of biodiversity, climate change and land degradation (Wiedmann et al., 2020). Many of these challenges have emerged as a consequence of the unsustainable use of natural resources by society (Kremen and Merenlender, 2018), with much of the value of nature for human well-being ignored in policy-making (Guerry et al., 2015). For example, as well as providing food and water to support peoples' livelihoods, biogeochemical processes such as carbon sequestration work to regulate the climate (Raupach, 2013). Natural ecosystems also generate a number of important cultural benefits with positive effects on peoples' sense of identity, connection to nature and mental and physical health (Hausmann et al., 2016; Sandifer et al., 2015). The significant cultural value of nature is often the main motivator behind conservation policies aimed at restricting extractive activities such as mining and other unstainable practices (Ladle et al., 2016). This value, however, is not easily captured within standard reporting frameworks that track socioeconomic development (Hein et al., 2015; TEEB, 2010a). As a result, natural ecosystems are often overlooked in land use planning, accelerating a global "extinction of experience" of nature as peoples' contact with nature becomes increasingly limited (Miller, 2005; Soga and Gaston, 2016).

The increasing impact of issues such as land degradation and biodiversity decline has highlighted the need to properly measure and conserve the value generated by nature (Carpenter et al., 2009). These complex challenges and monitoring requirements have led to an emphasis on integrated policy responses which can account for both the ecological and societal processes involved in addressing these challenges (Farrell et al., 2021). This requires both values compatible with current socioeconomic reporting frameworks and a broadening of many of the indicators used by policy-makers in relation to these frameworks (Díaz et al., 2015; Obst et al., 2016). Ultimately, public and private decision-makers need regular and standardised information in relation to the value of nature (Boyd et al., 2018). Because of the spatial nature of natural systems in relation to people, this information must also be spatially-explicit (Hein et al., 2006). This is especially challenging considering the more intangible, cultural contributions of nature to human well-being such as peoples' aesthetic enjoyment of the landscape or their appreciation of individual species (Hernández-Morcillo et al., 2013). However, accounting for this cultural value has been

identified as crucial in developing effective policy responses to the complex issues faced by society (Daniel et al., 2012; Díaz et al., 2018).

1.1.2. Ecosystem service assessments

In this context, the ecosystem service concept has emerged as a science-policy interface through which the contributions of nature to human well-being can be measured to achieve sustainable policy goals (Gómez-Baggethun et al., 2010). Generally, ecosystem services can be defined as the contributions of ecosystems to the benefits that are used in economic and other human activity (United Nations et al., 2021). With roots going back as far as the late 19th century (Missemer, 2018), the concept has rapidly evolved to become a standard feature within global science and policy arenas (Reyers et al., 2013). Its prominence was first established with the Millennium ecosystem Assessment (MA). This structured, global assessment provided an overall framework through which to measure the value generated by ecosystems (MA, 2005). The concept was then further formalised in The Economics of Ecosystem services and Biodiversity (TEEB) report, where the economic and social values of nature were further explored in an ecosystem service context to better inform decision-making and planning (TEEB, 2010a).

Building on these structured formulations, two recent international efforts have sought to further integrate the ecosystems services concept into decision-making: the System of Environmental-Economic Accounting Ecosystem Accounting (SEEA EA) and the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES) (IPBES, 2019; United Nations et al., 2021). The SEEA EA is an internationally agreed statistical framework that accounts for ecosystems and the services they provide to people in a way consistent with the System of National Accounts (SNA) which tracks countries' economic activity (Edens et al., 2022). The framework allows for various indicators, both monetary and non-monetary, to track the contributions of ecosystems to the economy and well-being with a strong spatial underpinning (Hein et al., 2020a). Similarly, the IPBES also provides a framework through which to value the contributions of nature to peoples' well-being, including alternative valuation approaches based on indigenous and local knowledge (IPBES, 2022). In doing so, it seeks to further complement the information available to decision-makers at both local, regional and global levels in a broad ecosystem service context (Díaz et al., 2018).

The IPBES and SEEA EA frameworks build upon the conceptual basis established by the MA and TEEB reports. These earlier conceptual framings put forward the idea of "cultural ecosystem services" (CES) to measure the cultural contributions of ecosystems to human well-being as a distinct category alongside other contributions such as the provisioning or regulating services of nature. The MA first defined CES as "the nonmaterial benefits people obtain from ecosystems through spiritual enrichment, cognitive development, reflection, recreation, and aesthetic experiences" (MA, 2005, p. 40). Nevertheless, such definitions have been the subject of continued debate, not least because these benefits are difficult to measure using either biophysical and monetary indicators but also due to the difficulty of conceptualising CES in quantitative terms (Daniel et al., 2012; Gould et al., 2020a). This debate has only intensified with the introduction of the IPBES framework which introduced the concept of "nature's contributions to people" (NCP) alongside ecosystem services. This removes the CES category entirely and instead makes it a feature of all ecosystem contributions to human well-being, although it retains a set of more culture-specific NCP categories for large-scale assessments (Díaz et al., 2018; Kadykalo et al., 2019). This is in contrast to the SEEA EA which has so far kept CES as a distinct, universal category through which ecosystems generate cultural value (United Nations et al., 2021).

The conceptual debates surrounding CES have largely been driven by the difficulties in measuring CES. These services are generally intangible, context-specific and spatially ambiguous (Milcu et al., 2013; Satz et al., 2013). For example, two individuals walking through the same landscape may benefit in different ways from the nature around them and through the presence of multiple natural elements (Hernández-Morcillo et al., 2013). Identifying these benefits based on individual preferences and then spatially assigning these to biophysical features is a key challenge in CES assessment (Gould et al., 2019a). Many studies have focused on the use of surveys to measure CES, asking participants to recall their interactions with nature (La Rosa et al., 2016). Some survey-based studies have then spatially assigned CES but rarely go beyond broad land cover categories or general points of interest (Eigenbrod et al., 2010; Plieninger et al., 2013). Survey-based approaches are also costly and labour-intensive which mainly restrict their use to local scales (Norton et al., 2012; Peña et al., 2015). As a consequence, there is a much more limited amount of spatial information on CES for use in large-scale ecosystem service assessments versus other types of ecosystem services (Daniel et al., 2012; Russell et al., 2013).

1.1.4. *Crowdsourced data*

The widespread adoption of smartphones coupled with the rapid rise of global internet connectivity now provides a new opportunity to spatially measure CES. The total number of people now using the internet has risen to at least 3.4 billion people or roughly 50% of the world's population (Roser et al., 2015). Mobile phone use has also seen huge increases over the last 20 years, with 90% of the world's population now living within range of a high-quality mobile internet connection (International Telecommunication Union, 2018). As part of this rise in connectivity, social media platform have seen a rapid expansion in the number of users, with one in three people in the world now using some form of social media (Roser et al., 2015). Platforms such as Flickr, Twitter, Facebook, Instagram and Weibo provide opportunities for people to share their interactions with nature in real-time using their smartphones (Ghermandi and Sinclair, 2019). At the same time, dedicated platforms such as iNaturalist and eBird have enabled millions of people to share their interactions with individual species through large-scale citizen science efforts, with the number of species observations on iNaturalist now totalling over 56 million (Di Cecco et al., 2021). Broadly defined as "crowdsourced data" (Calcagni et al., 2019; Ghermandi and Sinclair, 2019), these new digital records of human-nature interactions have generated a wealth of geo-referenced, content-rich data for use in CES assessments (Ilieva and McPhearson, 2018; Ladle et al., 2016; Willemen et al., 2015).

Nevertheless, the use of crowdsourced data has not yet been fully explored and its integration in CES assessments faces a number of challenges. One potential issue is the demographic and geographic representativeness of the data as well as the quality of the geo-located data but validation exercises in the context of ecosystem service assessments are rare (Englund et al., 2017; Oteros-Rozas et al., 2018). As a novel source of data, the nature of the CES captured through platforms such as Flickr or iNaturalist has also not yet been fully explored (Ghermandi et al., 2020b). For example, biodiversity has a great cultural value but it is not clear the extent to which this would be represented through CES indicators based on crowdsourced data (Dallimer et al., 2012; Schröter et al., 2017). However, one of the most pressing challenges has been the sheer size of the datasets involved. The digital records of millions of individuals sharing their interactions with their environments has created new sources of "big data" that are difficult to process and interpret in large quantities (Miller and Goodchild, 2015). This includes images, text, community structure and interactions. Currently, most studies employing crowdsourced data have used only the number of interactions as a generic indicator for CES (van Zanten et al., 2016; Wood et al., 2013).

However, each interaction represents a unique contribution of nature to an individual's experience made apparent through different media such as images and text and this is often not addressed in studies employing crowdsourced data to generate CES indicators (Fox et al., 2021a; Richards and Tunçer, 2018).

1.1.5. Machine learning

In response to these challenges, machine learning has been identified as a powerful new technique to measure the CES of nature using crowdsourced data (Egarter Vigl et al., 2021). Machine learning is a methodological framework that leverages data to construct models and generate predictions across a set of tasks (Jordan and Mitchell, 2015). These models learn data-responsive relationships from observations without a pre-defined set of rules related to the phenomena being modelled. Machine learning is especially effective on large datasets, including "big data", using efficient learning techniques and large computational resources (L. Zhou et al., 2017). This has produced a number of breakthroughs in a wide variety of commercial, technical and scientific fields including natural language processing (NLP) (Hirschberg and Manning, 2015), social science (Hu et al., 2020), ecology (Tuia et al., 2022) and earth system science (Lary et al., 2016).

A great amount of this progress has been driven by deep learning, a particularly successful class of machine learning techniques which uses artificial neural networks to generate predictions (LeCun et al., 2015). Deep learning models automatically learn highly complex representations of the input data through ensembles of filters applied to the data. This enables tasks using multi-dimensional data inputs, such as the RGB layers of an image, to generate predictions of advanced concepts, such as scene classification, object detection or even landscape attractiveness ratings based on crowdsourced perceptions (Cordts et al., 2016; Seresinhe et al., 2017b). Deep learning has also seen significant success in the NLP field. NLP is broadly concerned with processing and analysing large amounts of human language data. Through the application of deep learning techniques, a greater understanding of language has been demonstrated including sarcasm and cultural contexts. This has enabled superior results on common tasks such as translation (Otter et al., 2021).

As a consequence, the application of machine learning to large crowdsourced datasets such as social media data has seen considerable growth in recent years (Balaji et al., 2021). However, its application in a CES context has so far been limited (Egarter Vigl et al., 2021; Richards and Tunçer, 2018). When applied to social media, machine learning has a great amount of potential for CES assessments because models can be trained to generate

predictions of peoples' cultural enjoyment as specific semantic concepts such as landscape attractiveness (Lothian, 1999; Marcos, 2020). These predictions can be spatially mapped using the geo-located records available and, in doing so, enable measurements of peoples' revealed preferences for the environment based on actual human-nature interactions. This important methodological aspect is currently lacking in most spatial CES models which usually rely on proxies such as land cover or landscape features to represent CES supply (de Groot et al., 2010; Hernández-Morcillo et al., 2013). Especially relevant are landscape aesthetics as a key feature of outdoor recreation (Daniel et al., 2012) and peoples' appreciation of biodiversity in terms of their direct interactions with individual species (Hevia et al., 2017). Moreover, machine learning advances in NLP enable an examination of the sentiment generated by human-nature interactions via the text shared by people online. This means a clearer connection can be established between CES and the resulting benefits in terms of peoples' positive experiences, another feature of CES indicators that is generally lacking (Fox et al., 2021a).

1.2. Knowledge gaps

Ecosystems generate a large amount of cultural value for human well-being and this value is a key motivation for sustainable ecosystem management (Plieninger et al., 2013). However, CES are the most difficult to measure and therefore receive insufficient consideration in policy-making (Milcu et al., 2013). For large-scale assessments, spatial data on CES is particularly important to allow a level of generalisation (Norton et al., 2012). Such data is rare and existing methods rarely incorporate the revealed preferences of individuals, an important methodological factor in CES assessment (de Groot et al., 2010). Now, crowdsourced data offers a new opportunity to develop explicit spatial measures of CES for use in large-scale ecosystem service assessments (Ghermandi and Sinclair, 2019). Nevertheless, the conceptual debate surrounding CES leaves a considerable amount of conceptual uncertainty in the spatial quantification of CES and **a definition of CES in the context of crowdsourced data is needed (KG 1).**

The use of crowdsourced data in developing indicators for CES assessments is also rarely validated using other data sources such as survey data. A lack of validation means CES indicators based on crowdsourced data such as social media may not reflect the preferences of the wider population or the heterogeneity of different landscapes (Oteros-Rozas et al., 2018). For example, Flickr has been found to mostly consist of 40 to 60 year old males (Lenormand et al., 2018). At the same time, indicators developed in one geographic

context may not be relevant to another. In the case of landscape aesthetics, this might mean the importance of some landscape features may change such as the uniqueness of natural features in urban versus rural contexts (Jessel, 2006; Uuemaa et al., 2013). **More research is therefore needed to determine whether the preferences reflected in crowdsourced data sources such as Flickr match those reflected in large-scale surveys (KG 2).**

Assessing individual preferences in relation to the natural environment is a central aspect to CES assessment (Milcu et al., 2013). As most platforms are likely to have different sets of active users, a greater understanding of the types of preferences reflected in each source of crowdsourced data is also needed. For example, citizen science is a key source of data on peoples' cultural interactions with biodiversity because it reflects peoples' naturalist interest in biodiversity (Di Cecco et al., 2021). However, a large number of interactions are also shared on social media platforms such as Flickr. For example, many people share wildlife photography on Flickr (Hausmann et al., 2018) or during casual recreation in local green spaces (Lopez et al., 2020). Because of these differences, more work is needed on comparing the preferences available through different platforms and, ultimately, enable their integration in CES assessments (Fox et al., 2021b; Scowen et al., 2021). **A better understanding of the differences in user activity between platforms can therefore support a greater diversity of preferences in CES assessments (KG 3).**

Another unexplored area of research in CES assessment is determining which ecosystem features contribute to cultural benefits (Gould et al., 2020b). Understanding the specific contributions of ecosystems to human well-being at large-scales can provide more relevant data to land use planning or other policy processes (Mandle et al., 2021). For example, biodiversity can be considered a cultural service but it is not clear how peoples' direct interactions with biodiversity compare with actual measures of biodiversity (Dallimer et al., 2012). Similarly, the quality of the natural environment in terms of an ecosystem's condition will affect the supply of ecosystem services (Grizzetti et al., 2019). However, CES indicators generally lack this level of detail versus other ecosystem service measures due to the use of proxies and coarse indicators such as land cover (Hernández-Morcillo et al., 2013). This means that the full effects of land use planning decisions on CES cannot be fully understood (Daniel et al., 2012). Therefore, **more research is needed to identify which ecosystem features generate CES (KG 4).**

Currently, the application of machine learning, especially deep learning, to produce CES indicators is also limited (Scowen et al., 2021). Most present applications of deep learning in a CES context have used objects or scene classifications of images on social

media as proxies for CES (Lee et al., 2019; Richards and Tunçer, 2018). Applications also rely on a limited groups of experts or researchers to categorise CES according to the objects or scenes found in the images (Gosal et al., 2019; Winder et al., 2022). On the other hand, despite their availability, models trained to predict complete semantic representations of CES are lacking. Exploring these more advanced applications therefore constitutes an important knowledge gap when considering the subjectiveness of cultural concepts such as landscape aesthetics (Daniel, 2001). For these purposes, large, crowdsourced datasets, such as those related to aesthetics, can be utilised using machine learning to generate predictions. This would mean a wider set of revealed preferences would be included in CES measures versus only expert judgement (Seresinhe et al., 2017a). Consequently, **more machine learning applications using large, crowdsourced datasets are needed in the context of CES to fully understand its potential (KG 5).**

Finally, CES indicators that do utilise crowdsourced data such as social media do not usually explicitly consider the link to human well-being through peoples' positive experiences of nature (Fox et al., 2021a). For example, CES assessments using social media generally rely on generic indicators such as the number of images with an implied uniform value (Wood et al., 2013). However, one interaction with nature may hold more weight than another or some images may not even relate to a cultural interaction with nature (Gould et al., 2019a). Nevertheless, users of social media share a large amount of data on how they are potentially benefiting from their cultural interactions with nature. For example, the titles, tags and descriptions associated with images on Flickr can reveal how and to what degree people gained a positive experience of nature (Ghermandi et al., 2020a). Now, NLP approaches including machine learning-based sentiment analysis offer a promising set of techniques to estimate the affective states in this text (Gandomi and Haider, 2015). Thus, **more research is needed to explore the potential of NLP in connecting CES indicators to peoples' positive experiences of nature (KG 6).**

1.3. Research questions and outline of the thesis

The full potential of machine learning and crowdsourced data in the development of CES measures has not been fully realised. As outlined in this chapter, many knowledge gaps still exist and demonstrating the use of these novel techniques can help better integrate the ES concept into decision-making, especially at large-scales. Therefore, this thesis aims to explore the potential of crowdsourced data and machine learning to measure CES. This overall objective is addressed through the following research questions:

RQ1. How can CES be defined and spatially modelled in the context of crowdsourced data?

RQ2. How can social media and deep learning capture the aesthetic quality of the landscape in support of aesthetic ecosystem service models?

RQ3. What do social media and deep learning-based indicators of biodiversity-related CES capture in comparison to citizen science and ecological measures?

RQ4. How can social media and NLP capture the positive experiences associated with different CES measures?

These research questions are addressed in this thesis through a series of chapters compiled as independent research papers. The first research question seeks to cover KG 1 and is addressed in Chapter 2 of this thesis, where the current conceptual thinking on CES is considered alongside sources of crowdsourced data to propose a definition to spatially model CES. The second research question is addressed in Chapter 3 and seeks to cover KG2, KG4, KG5 and KG6, with a focus on landscape aesthetics as a key source of cultural value. To do this, deep learning-based predictions of landscape aesthetic quality are generated at national scale using Flickr data and a crowdsourced, geographically-representative survey of Great Britain.

In Chapter 4, research question three is addressed. Deep learning models are trained and applied to predict human-species interactions in Flickr images and these predictions are then used to map biodiversity-related CES in Great Britain. These human-species distributions are then compared with those generated through citizen science as well as ecological measures of bird biodiversity. In doing so, this chapter seeks to address KG3, KG4 and KG5. Following this, Chapter 5 addresses research question 4 with a focus on KG2 and KG 6. Here, a number of sentiment analysis models using NLP are applied to the textual data associated with Flickr images to estimate the positive experiences associated with different CES measures. In particular, the aesthetic and biodiversity-related interactions predicted

using deep learning in the previous two chapters are considered. Sentiment levels are also compared with a national well-being survey on outdoor recreation in Great Britain. Finally, in Chapter 6, the methods and results are discussed in relation to the research questions with a synthesis of the key research findings.

Chapter 2.

Defining and spatially modelling cultural ecosystem services using crowdsourced data

Abstract. Cultural ecosystem services (CES) are some of the most valuable contributions of ecosystems to human well-being. Nevertheless, these services are often underrepresented in ecosystem service assessments. Defining CES for the purposes of spatial quantification has been challenging because it has been difficult to spatially model CES. However, rapid increases in mobile network connectivity and the use of social media have generated huge amounts of crowdsourced data. This offers an opportunity to define and spatially quantify CES. We inventoried established CES conceptualisations and sources of crowdsourced data to propose a CES definition and typology for spatial quantification. Furthermore, we present the results of three spatial models employing crowdsourced data to measure CES on Texel, a coastal island in the Netherlands. Defining CES as information-flows best enables service quantification. A general typology of eight services is proposed. The spatial models produced distributions consistent with known areas of cultural importance on Texel. However, user representativeness and measurement uncertainties affect our results. Ethical considerations must also be taken into account. Still, crowdsourced data is a valuable source of information to define and model CES due to the level of detail available. This can encourage the representation of CES in ecosystem service assessments.

2.1.   Introduction

Ecosystem services (ES) have emerged as a concept to help us better understand, value and manage the contributions of ecosystems to human well-being (Gómez-Baggethun et al., 2010). Cultural ecosystem services (CES) generate a large amount of value for society (Milcu et al., 2013). Culture plays a pervasive role in all human-nature interactions (Díaz et al., 2018) and ecosystems contribute to many intellectual and recreational benefits for human well-being (de Groot et al., 2010). CES are largely without substitutes and, once destroyed, many are irreplaceable (Plieninger et al., 2013). In industrialised societies, CES are often valued over ES that contribute to commodity production (Hernández-Morcillo et al., 2013) while in many indigenous communities CES are essential to cultural identity (Milcu et al., 2013).

Despite the value of CES to human well-being, these services remain some of the most underrepresented in ES assessments (Hernández-Morcillo et al., 2013). CES are generated through combinations of individual activities, preferences and worldviews (Milcu et al., 2013). The subjective nature of CES has meant that operational definitions for the purposes of spatial quantification are rare (Daniel et al., 2012). In this respect, established ES assessment frameworks have been criticised for providing overly generic definitions that can make practical measurement difficult (Boyd and Banzhaf, 2007). Most established assessment frameworks are based on or are influenced by the cascade framework proposed by Haines-Young and Potschin (2010). This tracks the contributions of ecosystems to human well-being in a linear fashion from biological structures and processes to benefits of different value. ES are the contributing factor between the ecosystem and the resulting benefits. The distinction between services and benefits is important because it avoids double counting the contributions of ecosystems to human well-being. However, in providing generic definitions for CES, ES assessment frameworks have tended to conflate CES with both cultural benefits and values (Milcu et al., 2013; Satz et al., 2013).

In part, the ambiguity of CES definitions in established ES assessment frameworks exists because it has been difficult to spatially model the cultural interactions between people and ecosystems (Daniel et al., 2012). Spatially attributing CES remains a key challenge (Hernández-Morcillo et al., 2013; Norton et al., 2012; Schröter et al., 2015) and spatial models have tended to rely on proxies such as land cover (Chan et al., 2011; Eigenbrod et al., 2010; J. Maes et al., 2013). As a result, many studies have focused on qualitative methods such as surveys, interviews and focus groups within small study areas (Plieninger et al., 2013). This has also led to the argument that CES generally defy quantitative measurement as

individual services (Chan et al., 2012b; Fish et al., 2016). Nevertheless, spatial quantification methods applicable to large scales are necessary if the ES concept is to effectively inform land-use and marine policies (Barbier, 2011; Hein et al., 2006; J. Maes et al., 2013). In these cases, the cascade framework proposed by Haines-Young and Potschin (2010) has generally proven to be a useful concept for the spatial quantification of ES (de Groot et al., 2010; Maes et al., 2012; Potschin-Young et al., 2018).

Now, the global rise of mobile internet connectivity and online social media provide new opportunities to spatially model CES. Some 90 percent of the global population now live within range of a high-quality mobile internet connection (International Telecommunication Union, 2018). In developing countries, rapid increases in internet connectivity have been driven by the widespread adoption of smartphones. This widespread adoption is leisure-oriented, providing greater opportunities to socialise and engage with the wider world (Arora, 2012). As a result, social media platforms such as Facebook, Instagram, Twitter, and Weibo have amassed hundreds of millions to billions of active users (Kemp, 2019). On these platforms, users provide a wealth of geo-referenced information about their feelings, preferences and physical interactions with the natural environment (Di Minin et al., 2015; Ilieva and McPhearson, 2018). Internet connectivity has also generated new forms of citizen engagement with biodiversity through citizen science portals such as eBird and iNaturalist (Barve, 2014).
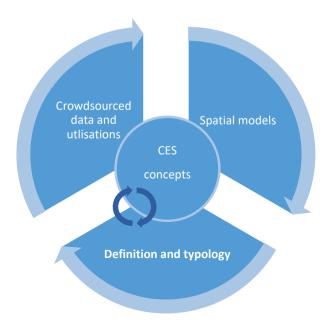
A range of terms have emerged to describe these new data sources. These include 'volunteered geographic information', the 'geoweb', 'user-generated content' and 'big data' (Crampton et al., 2013; Elwood et al., 2012; Elwood and Leszczynski, 2011). In line with the terminology used in recent studies (Calcagni et al., 2019; Ghermandi and Sinclair, 2019; Gliozzo et al., 2016; See et al., 2016; Sinclair et al., 2018; Tenerelli et al., 2016), we refer to these new data sources as crowdsourced data. In this paper, we define this as geo-referenced records of *in situ* human-environment interactions, both voluntarily and passively collected. Compared to the general use of the term 'crowdsourcing', this is a narrower utilisation, excluding *ex situ* crowdsourcing projects such as OpenStreetMap, but broader in also considering passive contributions (See et al., 2016). It also does not limit itself to online sources of data such as with the terms 'geoweb and 'user-generated content' (Elwood and Leszczynski, 2011).

Researchers are beginning to harness the potential of crowdsourced data to examine human-nature interactions and measure CES. Specific services have been assessed using the location and content of images on Flickr, a photo-sharing site (Martínez Pastur et al.,

2016; Richards and Friess, 2015; Willemen et al., 2015). In one case, landscape preferences across the whole of Europe were measured using location data from social media (van Zanten et al., 2016). InVEST, a popular ES modelling tool, integrates Flickr photos in its recreation model (InVEST, 2017). At the same time, Twitter, a micro-blogging platform, has been used to gauge sentiments towards the environment (Wilson et al., 2019) and mobile exercise apps such as Strava have been drawn upon to examine cycling preferences in the urban environment (Griffin and Jiao, 2015; Sun et al., 2017). Mobile signal data has also been used to examine peoples' interactions with natural areas (Pei et al., 2014; Xiao et al., 2019).

Despite the increasing use of crowdsourced data to measure CES, these remain isolated efforts and a structured conceptualisation of CES in this context is still missing. This can partly be attributed to the lack of operational definitions for spatial CES modelling in established ES frameworks. These definitions, in turn, have historically been constrained by a lack of spatial data on the cultural interactions between people and ecosystems. The considerable spatial insights now being generated in the form of crowdsourced data offers a lens through which to examine the CES concept not previously applied in the established conceptual thinking on CES. In doing so, this conceptual thinking can be refined to support the spatial quantification of CES using crowdsourced data, a rich and expansive new source of information which enables CES assessments outside the scope of traditional survey methods.

The objective of this study is to define CES in the context of crowdsourced data and demonstrate the use of this definition in the spatial quantification of CES. We follow an iterative process, developing a definition and typology which considers established conceptual thinking, sources of crowdsourced data, and our own experiences in developing spatial CES models using crowdsourced data (Figure 1). In Section 2.2, CES concepts and sources of crowdsourced data are considered in an inventory of ES assessment frameworks and utilisations of crowdsourced data. In Section 2.3 and 2.4, we outline our CES definition and suggest a general typology of eight services. In Section 2.5, we show the use of the definition and typology in practice with three spatial CES models measuring activity, aesthetic and naturalist services using crowdsourced data on Texel, an island in the Northwest of the Netherlands. In Section 2.6, we discuss our conceptualisation of CES, taking into account the representativeness of the data, measurement uncertainties and ethical considerations. Section 2.7 summarises the main conclusions of the chapter.

Figure 1. Conceptual process followed to develop the CES definition and typology. The proposed definition and typology were developed following an iterative process which considered crowdsourced data and utilisations, the authors' experience developing CES models using these sources as well as established CES concepts, represented by five influential ecosystem service assessment frameworks. In turn, the CES definition and typology seeks to inform the current conceptual thinking reflected in these assessment frameworks.

2.2. Inventories of established CES concepts and crowdsourced data

2.2.1. Methods

2.2.1.1. CES concepts in ES assessment frameworks

In order to include the most established conceptual thinking on CES in our conceptual process, an inventory was compiled of CES conceptualisations in five leading ecosystem assessment frameworks. The frameworks selected include the Millennium Ecosystem Assessment (MA), The Economics of Ecosystems and Biodiversity (TEEB), the System of Environmental Economic Accounting – Experimental Ecosystem Accounting (SEEA EEA), the Common International Classification of Ecosystem Services (CICES) and the Inter-governmental Panel on Biodiversity and Ecosystem Services (IPBES). These were identified as the most established and influential international ES assessment frameworks which are based on a process of consensus building between a large number of public, private and scientific institutions (Díaz et al., 2018; Gómez-Baggethun et al., 2010; Hein et al., 2020a; La Notte et al., 2017). In addition, the Global Ecological Model (GEM) developed by the Dutch Regional and Spatial Planning Office (van der Maarel and Dauvellier, 1978) was included as

an early interpretation of the ES concept which had an influence in its subsequent development (Braat and de Groot, 2012).

2.2.1.2. *Crowdsourced data*

To further inform the conceptual process, an inventory of crowdsourced data utilisations was compiled to better understand the information and forms of data available on human-nature interaction. To do this, we conducted a literature search limited to articles and reviews in the citation database Scopus. A systematic review was then undertaken of the studies returned by this literature search.

A broad range of terms are used to describe crowdsourced data and it is difficult to capture all relevant studies. Thus, a number of search terms were employed to capture as many studies as possible. A search of the CES literature using the term "cultural ecosystem services" was first performed as an initial review found it to return a large number of relevant studies. In addition, the search terms "crowdsourced data", "volunteered geographic information" and "mobile phone data" were entered. We used 'volunteered geographic information' as well as 'crowdsourced data' because it captures a large amount of related studies. In its broadest interpretation, Volunteered Geographic Information (VGI) refers to geo-referenced data from social media and citizen science portals, both voluntarily and passively collected (Connors et al., 2012; Goodchild, 2007). "mobile phone data" was used to broaden the search to include studies using passively-produced mobile signal data.

Following this, the title and abstract of each search result were reviewed and studies (and respective sources) were included based on four criteria: (i) a focus on human-nature interactions, (ii) the use of geo-located records, (iii) the source was still operational, and (iv) the source was of international relevance. In order to check sources against criteria (iii) and (iv), an internet search was performed to evaluate data access, user statistics and the information available. This also helped determine the type of data available. 42 studies were included in the inventory following this process. Article reference lists were again consulted to include studies (and sources) that may have been missed in the initial searches. This added 16 studies to the inventory. A more detailed overview of the literature selection process can be found in Supplementary Figure S1.

2.2.2. Results

2.2.2.1. CES concepts in ES assessment frameworks

For the five ES assessment frameworks reviewed, the CES conceptualisations and related categories are given in Table 1. There are some key differences and similarities between the assessment frameworks. The GEM is unique in its definition of CES as the use and availability of information. On the other hand, the MA and TEEB both define CES in terms of the non-material benefits people gain through nature-related experiences. The SEEA EEA and CICES define CES in terms of physical settings, locations or situations that give rise to intellectual benefits. The definition of CICES also emphasises the physical effects of CES. IPBES has taken a different approach and the CES category has been removed. Instead, cultural benefits arise through regulating, material and non-material ecosystem contributions, termed Nature's Contributions to People (NCP), rather than in terms of services (Díaz et al., 2018).

Still, the IPBES assessment framework retains three culture-specific reporting categories for large-scale assessments: learning and inspiration, physical and psychological experiences, and supporting identities. These are in line with the categories proposed by the four other assessment frameworks which, among others, share categories related to recreation, aesthetics, artistic inspiration, appreciation of biodiversity, cultural heritage, education and spiritual contributions. The GEM is the most unique with its wording regarding some of these categories. In the GEM, orientation functions relate to our sense of identity while signal functions to the health indications ecosystems transmit. The wording also varies further between assessment frameworks. The MA and CICES refer to value in some categories, the TEEB defines categories broadly in terms of benefits, while the SEEA EEA refers to these in terms of experiences and activities.

The variation in the wording of CES categories highlight some differences in the fundamental qualities of the concepts in each of the frameworks. The MA does not make a distinction between services, benefits and values while TEEB considers these as separate concepts. This distinction helps account for the existence of intermediate services, their spatial delineation and economic valuation (TEEB, 2010b). However, it does not make this distinction explicit in its conceptualisation of CES. The SEEA EEA also makes a distinction between services and benefits in its conceptualisation of ES. This distinction is reflected in the SEEA EEA and CICES definitions. Services are contributions to benefits used in economic activity and other human activity. This recognises the joint-production of goods

Table 1. Conceptualisations of CES.

Assessment framework	Acronym	Conceptualisation	Categories
Global Ecological Model (van der Maarel and Dauvellier, 1978, p. 155)	GEM	"*the use and availability of information*"	Orientation function; research function; education function; signal function
Millennium Ecosystem Assessment (MA, 2005, p. 40)	MA	"*the non-material benefits people obtain from ecosystems through spiritual enrichment, cognitive development, reflection, recreation, and aesthetic experiences*"	Cultural diversity; spiritual and religious values; knowledge systems; educational values; inspiration; aesthetic values; social relations; sense of place; cultural heritage values; recreation and ecotourism
The Economics of Ecosystems and Biodiversity (TEEB, 2010a, p. 40)	TEEB	"*the non-material benefits people obtain from contact with ecosystems*"	Recreation and mental and physical health; tourism; aesthetic appreciation and inspiration for culture, art and design; spiritual experience and sense of place
System of Environmental Economic Accounting – Experimental Ecosystem Accounting (UN, 2017; UN et al., 2014, p. 42)	SEEA EEA	"*the physical settings, locations or situations that give rise to intellectual and symbolic benefits obtained by people from ecosystems through recreation, knowledge development, relaxation and spiritual reflection*"	Tourism; recreation; education and learning; religious and spiritual experiences; artistic and other human activities
Common International Classification of Ecosystem Services (Haines-Young and Potschin, 2018, p. 10)	CICES	"*the environmental settings, locations or situations that give rise to changes in the physical or mental states of people*"	Active or immersive interactions; passive or observational interactions; scientific investigation or the creation of traditional ecological knowledge; education and training; culture or heritage; aesthetic experiences; symbolic meaning; sacred or religious meaning; entertainment or representation; existence value; bequest value; other
Inter-governmental Panel on Biodiversity and Ecosystem Services (Díaz et al., 2018)	IPBES	"*culture mediates the relationship between people and all NCP*"	Learning and inspiration; physical and psychological experiences; supporting identities

and services which makes the ES concept compatible with national economic accounting principles (UN et al., 2014). The NCPs proposed by IPBES generally follows the MA's conceptualisation of services as benefits (Díaz et al., 2018).

2.2.2.2. *Crowdsourced data*

The search of the literature highlighted four types of crowdsourced data which enable an examination of human-nature interactions:

    i.   Social media platforms including Flickr, Foursquare, Instagram, Tencent QQ, Twitter and Weibo.

    ii.   Outdoor activity-sharing platforms including Condoon, Geocaching, GPSies, MapMyFitness, Strava and Wikiloc.

    iii.   Citizen science portals including eBird and iNaturalist.

    iv.   Mobile signal data from telecommunications companies.

The different types and sources of crowdsourced data are shown in Table 2 along with the studies utilising these sources.

(i) *Social media platforms*. Flickr is the most popular source of social media data. It has been extensively used in the literature to examine the provision of CES. Flickr is a photo-sharing platform for amateur and professional photographers. It has been estimated to have over 71 million users who have uploaded approximately 197 million geo-tagged photographs (Wood et al., 2013). Its API provides access to the metadata of all publicly-posted photos including their title, tags, image url, associated user profile and location, accurate up to street level. Among other applications, researchers have established measures of CES provision using the locations of photographs (Kim et al., 2019; Tenerelli et al., 2016; van Zanten et al., 2016; Yoshimura and Hiura, 2017) and the content of the images (Richards and Friess, 2015; Richards and Tunçer, 2018; Thiagarajah et al., 2015), measured preferences for biodiversity (Mancini et al., 2019) and used user activity as a proxy to infer visitation rates to parks and protected areas (Ghermandi, 2016; Levin et al., 2017).

        Researchers have also used Foursquare, Instagram, Tencent QQ, Twitter and Weibo. Weibo, Twitter and Foursquare provide access to user activity through an API including location data, tags, image urls, user profiles and user interactions such as 'favourites' or 'likes' associated with the posts (Foursquare, 2019; Twitter, 2019; Weibo, 2019). Instagram has limited its public API access to hashtag searches. These platforms have been used for classifying urban land use based on user activity (Liu et al., 2017) and in developing indicators for CES provision (Guerrero et al., 2016; van Zanten et al., 2016). Similarly,

Foursquare, where users share information and opinions about locations (Glueck, 2018), has been used to spatially characterise cities based on the types of locations users visit (Zhou and Zhang, 2016). The posts on Twitter, known as 'tweets', have been used to track the effects of natural disasters (Chen et al., 2016; de Albuquerque et al., 2015; Middleton et al., 2014), measure user sentiments towards nature (Becken et al., 2017; Wilson et al., 2019) and determine the spatial distributions of outdoor recreation at small scales such as in urban park areas (Roberts et al., 2017; Zhou and Zhang, 2016).

(ii) *Outdoor activity-sharing platforms.* The Condoon, Geocaching, GPSies, MapMyFitness, Strava and Wikiloc activity-sharing platforms have also been utilised to measure human-nature interactions. Location data is collected on these platforms from mobile phones and other GPS devices. Strava is the largest of these platforms, with tens of millions of users (Riordan, 2016). The other platforms are smaller but still have a global dataset. Public activities on Strava are visualised in a global heatmap (Strava, 2018). Individual user activity is available through the Strava Metro product. Condoon offers a similar service through an API (Condoon, 2019). The GPSies, MapMyFitness and Wikiloc websites allow access to individual routes and imagery through interactive interfaces (GPSies, 2019; MapMyFitness, 2019; Wikiloc, 2019). Geocaching also offers an API service with data available on the location of caches, find counts, points-of-interest and user profiles (Geocaching, 2019). The data available has been used to directly measure recreational services (Dai et al., 2019), as well as preferences for natural areas (Cord et al., 2015; Rosário et al., 2019), cycling routes (Griffin and Jiao, 2015; Sultan et al., 2017; Sun et al., 2017) and protected areas (Jurado Rota et al., 2019; Norman et al., 2019; Norman and Pickering, 2017).

(iii) *Citizen science portals.* Citizen science portals also present evidence of human-nature interactions. The eBird and iNaturalist platforms host several million geo-located observational records, including imagery, available through the eBird website and iNaturalist API (eBird, 2019; iNaturalist, 2019). These are also made available through the Global Biodiversity Information Facility (GBIF) which hosts a global dataset of observations from citizen science platforms and scientific institutions (GBIF, 2019). eBird and iNaturalist were used by Jacobs and Zipf (2017) to examine civic measures of biodiversity.

(iv) *Mobile signal data.* Mobile signal data can also reveal spatial interactions with the environment. The data consists of call detail records (CDRs) from cell phone towers which are generated each time a device sends a text or makes a call. Researchers are able to triangulate the location of the user by measuring signal strengths and the coverage area of each cell phone tower (Pei et al., 2014; Toole et al., 2012). In these studies, the data was

privately made available by mobile phone network operators. Mobility patterns over time have been used to classify behaviour related to outdoor recreational zones (Pei et al., 2014; Toole et al., 2012; Tu et al., 2017) and determine the accessibility of urban green space (Wu et al., 2018; Xiao et al., 2019).

Table 2. Sources of crowdsourced data in analysing human-nature interactions.

Source	Source description	Data utilisation	Studies
Social media platforms			
Flickr	Photo-sharing social media platform	Visitation rates to natural areas based on user activity	Wood et al., 2013; Keeler et al., 2015; Levin et al., 2015, 2017; Ghermandi, 2016; Sessions et al., 2016; Sonter et al., 2016; Spalding et al., 2017; Tenkanen et al., 2017; Donahue et al., 2018; Mancini et al., 2019
		Indicators of CES provision using photos	Casalegno et al., 2013; Thiagarajah et al., 2015; Richards and Friess, 2015; Tenerelli et al., 2016, 2017; van Zanten et al., 2016; Martínez Pastur et al., 2016; Seresinhe et al., 2017; Yoshimura and Hiura, 2017; Figueroa-Alfaro and Tang, 2017; Walden-Schreiner et al., 2018; Langemeyer et al., 2018; Oteros-Rozas et al., 2018; Richards and Tunçer, 2018; Schirpke et al., 2018; Clemente et al., 2019; Sinclair et al., 2019; Kim et al., 2019
		Spatial density of users to infer cultural attachment to the landscape	Gliozzo et al., 2016
		Preferences for biodiversity using photos	Hausmann et al., 2018; Mancini et al., 2019
Foursquare	Social place recommendation mobile app	Urban activities	Zhou and Zhang, 2016
Instagram	Photo-sharing social media platform	Indicators of CES provision using photos	Guerrero et al., 2016; van Zanten et al., 2016
		Visitation rates to natural areas based on user activity	Tenkanen et al., 2017
		Preferences for biodiversity using photos	Hausmann et al., 2018
Tencent QQ	Micro-blogging site	User density for urban land use classification	Liu et al., 2017

Table 2. Sources of crowdsourced data in analysing human-nature interactions.

Twitter	Micro-blogging site	Natural disaster management	Middleton et al., 2014; de Albuquerque et al., 2015; Chen et al., 2016
		Spatial distributions of outdoor recreation	Zhou and Zhang, 2016; Roberts et al., 2017
		Sentiment analysis of people towards nature	Becken et al., 2017; Wilson et al., 2019
		Visitation rates to natural areas based on user activity	Tenkanen et al., 2017
		Urban park visitation	Roberts, 2017
Weibo	Micro-blogging site	Urban park visitation	Zhang and Zhou, 2018
Outdoor activity-sharing platforms			
Codoon	Route-sharing fitness app	Indicator for recreational CES in urban parks	Dai et al., 2019
Geocaching	Hide-and-seek treasure hunting site (caches)	Preferences for natural areas based on user cache choices	Cord et al., 2015; Rosário et al., 2019
GPSies	Route-sharing outdoor activity site	Park visitation and use	Norman and Pickering, 2017
		Cycling preferences in the urban environment	Sultan et al., 2017
MapMyFitness	Route-sharing fitness mobile app	Protected area visitation and use	Norman and Pickering, 2017; Norman et al., 2019
Strava	Route-sharing fitness mobile app	Cycling preferences in the urban environment	Griffin and Jiao, 2015; Sun et al., 2017; McArthur and Hong, 2019
Wikiloc	Route-sharing outdoor activity site	Protected area visitation and use	Norman and Pickering, 2017; Jurado Rota et al., 2019
Citizen science portals			
eBird	Citizen science portal	Citizen science measures of biodiversity	Jacobs and Zipf, 2017
iNaturalist	Citizen science portal	Citizen science measures of biodiversity	Jacobs and Zipf, 2017
Mobile signal data			
Telecommunications companies	Location data from cell phone towers	Urban land use classification	Toole et al., 2012; Pei et al., 2014; Tu et al., 2017
		Accessibility of urban green space	Wu et al., 2018; Xiao et al., 2019

2.3.   Defining CES as information-flows

Considering crowdsourced data as evidence for the quantification of CES, the CES definition in the GEM as *information functions* becomes especially relevant. In our review of the literature, we find that the crowdsourced data being utilised are collections of spatial records that reveal peoples' interactions with their physical environments. At its most basic, the mobility patterns from mobile signal data reflect patterns of behaviour related to the information available in a user's environment. At its most comprehensive, the posts, imagery, tags and titles available through social media are a detailed record of the information people have retained and promoted as something important to them. This information has subsequently been used to gauge the types of cultural interactions occurring. From a CES-perspective, the ecosystems which make up the natural environment are therefore *conveying* information to people, who retain, process and report this information, depending on the type of interaction.

Conceptualising CES as conveyed information is consistent with the CES definitions in the SEEA EEA and CICES as physical settings, locations or situations contributing to cultural benefits. However, CES become distinct from being opportunities or enabling environments. This type of wording is more evocative of the capacity or potential supply of ES; opportunities do not necessarily mean use (Schröter et al., 2014). Conceptualising CES as opportunities or enabling environments also encourages CES measurement using coarse indicators such as land cover classes. For example, a land cover based proxy for recreation was found to be an unreliable estimate as compared to primary data (Eigenbrod et al., 2010). In the absence of more detailed spatial data, this can be a valuable approach to CES measurement. Nonetheless, crowdsourced data provides a new level of spatial detail which allows us to move beyond measurement by land cover class.

In conceptualising CES as the information conveyed by an ecosystem, the service also becomes distinct from the benefit. The lack of distinction between services and benefits in the MA has been criticised because it makes it difficult to consistently measure ES (Boyd and Banzhaf, 2007; Satz et al., 2013). Making this distinction avoids double counting (TEEB, 2010b), and is particularly important from a national economic accounting perspective as it recognises the joint-production of final economic goods and services, representing the benefits to human well-being (UN et al., 2014). In the case of CES, the cultural benefit is generated using the contribution of the ecosystem in addition to an investment of human energy and or conventional goods and services. For example, the utility generated by a bike

ride in a national park is in part enabled by the natural surroundings, in combination with the bike and a person's physical efforts (Remme et al., 2014).

Thus, an alternative way of defining CES is as *information-flows generated by ecosystems that contribute to cultural experiences*. Hence, CES are conceptualised as the flow of information conveyed by the ecosystem to people. The cultural experiences are the cultural benefit or 'cultural good' enjoyed by the individual, thereby distinguishing ES and benefits. This definition reflects the thinking of Braat and de Groot (2012), who argue that CES are generated through the processing of ecosystem information by the human sensory organs and brain; an investment of human energy is required for a benefit to materialise. It also follows Schröter et al. (2014) and La Notte et al. (2017), who have also referred to CES as a flow of information transferred from ecosystems to people. In defining CES in such a way, we establish a definition which accounts for crowdsourced data as a major new source of information for measuring CES and build upon the thinking already present in the literature.

2.4. A typology for CES as information-flows

To clarify our definition of CES as information-flows and illustrate the use of crowdsourced data, we suggest a typology of eight service categories shaped by the information available through crowdsourced data. In addition, we draw upon the CES conceptualisations summarised in Table 3 to guide the development of the typology. We propose eight general service categories: activity, aesthetic, amenity, artistic, naturalist, heritage, knowledge, and religious and spiritual. These categories emphasise CES as contributions to benefits. Table 3 summarises the proposed typology, including example indicators. Spatial models of activity, aesthetic and naturalist services are presented in Section 2.5.

(i) *Activity services*. Route-sharing activity platforms such as MapMyFitness and Strava show us the physical interaction of people with their natural environment (Dai et al., 2019). Similarly, mobile network data can be employed to analyse the movements of people in recreational areas (Tu et al., 2017). This reveals a specific service-category that captures the contribution of ecosystems to physical activities in providing an attractive physical environment (Díaz et al., 2018; Haines-Young and Potschin, 2018; UN, 2017). This contribution is generated as an information flow to the individual as the brain and sensory organs interpret the immediate, physical configuration of the ecosystem while performing the physical activity. For example, the terrain on which a person is cycling or running constitutes the ecosystem contribution to the outdoor cycling or running

activity; the cultural benefit. Activity services are thus not related to the aesthetics of an ecosystem, which are generated separately as aesthetic services.

(ii) *Aesthetic services.* People use photo-sharing platforms such as Flickr and Instagram to show their appreciation for the aesthetic beauty of the landscape (van Zanten et al., 2016). In particular, Flickr has been used in a number of studies to measure aesthetic services (Figueroa-Alfaro and Tang, 2017; Tenerelli et al., 2017; Yoshimura and Hiura, 2017). Capturing positive sentiments towards the environment in the textual data on platforms such as Twitter presents additional opportunities to quantify the supply of aesthetic-related services (Becken et al., 2017; Wilson et al., 2019). Aesthetic services are generated when ecosystems communicate a sensory configuration of beauty (MA, 2005). This flow of information is registered and shared on social media sites such as Flickr, Instagram and Twitter. The information contributes to the cultural benefit of a scenic view for the individual, the benefit only manifesting itself through human cognitive action and choice.

(iii) *Amenity services.* No studies employing crowdsourced data to measure amenity services were identified through our literature review. Nevertheless, the existence of such a category is important in the context of online travel and property websites such as booking.com and funda.nl[1] in the Netherlands. The property values available through these websites include the contributing factor of nature to the desirability of a place or building (UN et al., 2014). The information flow in this case is the knowledge that a natural area such as a park or forest is visible, accessible and or unique to the location. This heightens its desirability and the utility a person derives it: the cultural benefit. Amenity services are all-encompassing in terms of the possible cultural uses of an ecosystem but are specific to creating a pleasant living environment for a person. The service contribution can be quantified in monetary terms using the hedonic pricing method which isolates the value of nature-related variables in the overall price of a property (TEEB, 2010b).

(iv) *Artistic services.* Ecosystems play a significant role in the realisation of art (TEEB, 2010b), including on photo-sharing platforms such as Flickr (Richards and Friess, 2015). Many users pursue photography in an artistic sense and share their camera specifications in the photo meta-data; a high-spec camera and any sort of framing, composition, lighting,

---

[1] https://www.funda.nl/en/

exposure or post-processing beyond a neutral registration of the natural environment could suggest an artistic representation of nature. Keywords such as hashtags related to events could also capture these creative interactions (Roberts, 2017). In these cases, creative information from the physical settings of the landscape is transmitted, interpreted and portrayed as art, the cultural benefit. These artistic services facilitate the representation of any number of cultural interactions with ecosystems in addition to ecosystems in a purely aesthetic sense.

(v) *Heritage services.* Social media sites such as Flickr and Twitter can highlight historical associations with the environment through the imagery and associated meta-data available (Richards and Friess, 2015; Thiagarajah et al., 2015; Wilson et al., 2019). Historical features in the landscape shape the cultural identity of people in the present while drawing others in to experience the cultural distinctiveness of an area (Haines-Young and Potschin, 2018; MA, 2005; TEEB, 2010b). These ecosystem characteristics are associated with cultural traditions, stories and skills (Díaz et al., 2018). For example, European heathlands, originally created as a function of prolonged, intensive sheep grazing, are now highly valued by people for their colourful appearance in summer, and their connection with a more pastoral society. In this way, ecosystem features communicate a sense of historical significance. This information is processed by the individual and contributes to their identity and sense of place in relation to the nature around them; the cultural benefit.

(vi) *Knowledge services.* The huge number of species records made available by scientific institutions such as universities and museums on GBIF are good evidence for contribution of ecosystems to the development of knowledge. Flickr photos also contain content related to scientific investigations of the natural environment (Richards and Friess, 2015). Acquiring and applying knowledge about our natural environment constitutes an important cultural aspect of human existence (Díaz et al., 2018; UN, 2017; van der Maarel and Dauvellier, 1978). Education is highly valued in society (MA, 2005). This ranges from traditional knowledge systems to modern science (Díaz et al., 2018; Haines-Young and Potschin, 2018). Ecosystems contribute information to the development of this knowledge. The cultural utility derived from its pursuit and application is the immediate benefit which can manifest itself in the additional knowledge generated or the resulting number of educated students.

(vii) *Naturalist services.* Citizen science platforms such as iNaturalist and eBird reveal an active cultural interest in the existence and conservation of living species (Jacobs and

Zipf, 2017). People hold strong bonds with nature and gain a sense of place and fulfilment knowing an ecosystem is functioning and in good health (Díaz et al., 2018; TEEB, 2010b). This can be through an interaction with a single animal, species or entire ecosystem (van der Maarel and Dauvellier, 1978). These interactions constitute an information flow in the sense that the ecosystem conveys a notion of ecological meaning. Hence, naturalist services are related to the human enjoyment of ecosystems rather than the development of knowledge. The physical existence of a species recorded on a citizen science platform is an indicator for this information flow because records are produced when individuals volunteer their leisure time. This contributes to the benefit of a species record, evidence of a functioning ecosystem and thus a sense of fulfilment for the individual, in combination with the effort expended in identifying and storing the record.

(viii) *Religious and spiritual services*. Social religious practices reveal themselves on social media platforms such as Flickr and Twitter (Roberts, 2017; Thiagarajah et al., 2015). Data from activity-sharing platforms such as Strava could also be analysed for routes along pilgrimage trails such as the Camino de Santiago in Spain. Ecosystems confer a strong sense of spiritual importance to humanity (Díaz et al., 2018; MA, 2005; TEEB, 2010b). Sacred sites can vary in scale, from pilgrimage routes and mountain ranges to small spaces of vegetation (Haines-Young and Potschin, 2018; MA, 2005). In each instance, an arrangement of ecosystem characteristics generates an information flow which is given a symbolic meaning by a person. Combined, this produces a spiritual experience for the individual, which represents the cultural benefit.

Table 3. CES, information-flows, data sources and benefits.

Type of service	Information-flow	Key sources	Benefits
Activity	Providing an attractive environment for recreation	Condoon, Foursquare, GPSies, MapMyFitness, Strava, Wikiloc, mobile signal data	Recreation, tourism
Aesthetic	Generating a sensory configuration of beauty	Flickr, Instagram, Tencent QQ, Twitter, Weibo	Scenic view, tourism
Amenity	Contributing to the desirability of a place or building	Property and travel websites	Pleasant living environment
Artistic	Role in the realisation of art	Flickr, Twitter	Artistic expression, inspiration
Heritage	Generating a sense of historical significance	Flickr, Instagram, Tencent QQ, Twitter, Weibo	Sense of place, cultural identity
Knowledge	Contributing to the development of knowledge	Flickr, Instagram, Tencent QQ, Twitter, Weibo, GBIF	Scientific knowledge, educated students
Naturalist	Conveying a notion of ecological meaning	iNaturalist, eBird, Flickr	Sense of place, connection to nature
Religious and spiritual	Conferring a sense of spiritual importance	Flickr, Instagram, Tencent QQ, Twitter, Weibo, Strava	Spiritual experience

2.5.   Spatial CES models

2.5.1.   *Methods*

To support the conceptual process, three CES models were developed to spatially quantify activity, aesthetic and naturalist services on the island of Texel. Each of these models drew upon a different source of crowdsourced data and are modelled for one year (2017). The ES were modelled and presented using R 3.6.0, GRASS 7.4. and ArcGIS 10.5. Spatial data in R was handled using the raster, sf and sp packages.

2.5.1.1.   *Study area*

Texel is an island of 160 km² located in the Northwest of the Netherlands. It is the first in a chain of barrier islands in the *Wadden Sea*, a shallow, intertidal area that stretches across the North of the Netherlands. The island is currently home to around 13,500 inhabitants (CBS, 2018). Its main urban centres are Den Burg in the centre of the island, Oosterend to the Northeast and De Koog in the West (Figure 2). In addition to these urban areas, the island is

home to a mix of ecosystems ranging from popular beach and coastal dune areas on its West coast, to agricultural land in its middle, and wetland areas which draw birdwatchers on opposite ends of the island. The dune areas in its West are protected as part of the Duinen van Texel National Park. The nature and wildlife available on the island make it a popular tourist destination and Texel hosts close to 1 million visitors every year (van Loenen, 2016).

Figure 2. Topographic map of Texel.

2.5.1.2. Activity services – hiking environment

To spatially quantify the ecosystem contribution to peoples' recreational activity on the island, we drew upon activity data sourced from Strava in combination with national statistics on hiking activities. We utilised the running activity data reported in the Strava

global heatmap, a visualisation of all public user activity over the last two years (Strava, 2018). This data was used to distribute hiking activities reported in a national recreation survey along the island road network and then used to establish a measure of the ecosystem contribution based on the immediate physical environment. This method therefore assumes that hikers follow the road network and that running activities reported on Strava are a good indication of hiking activity on the island.

To extract the activity data from the global heatmap, the mean 'heat' intensity was extracted from an 18 m circular area surrounding the mid-point of each road. Heat intensity was measured using the alpha (opacity) channel of map tiles in png format, accessible through a url constructed from the location of the mid-point. The heat intensity was then adjusted to compensate for a mechanism by which intensities are adjusted at each zoom level relative to the surrounding area (Robb, 2017). Thus, the intensity was adjusted to be relevant at a scale incorporating the whole of Texel. Finally, the intensities for each road segment were normalised relative to the total intensities of all road segments.

Hiking activity statistics were sourced from the 2015 'ContinuVrijeTijdsOnderzoek' (CVTO) survey of The Netherlands (NBTC-NIPO, 2015). This survey examines the recreational activities undertaken by Dutch citizens in their leisure time. It reports 440.5 million hiking activities in 2015 with an average hiking distance of 7 km. For this study, the number of hikes for Texel was approximated at 4.4 million based on Texel covering 0.1% of The Netherlands in area. Using this information, the number of hikers on each road segment was first calculated to create a hiking intensity per road segment:

$$I_i = \frac{N \cdot D}{L_i} \cdot \frac{S_i \cdot L_i}{\sum_{j=1}^{n}\left(S_j \cdot L_j\right)} \qquad\qquad EQ.\ 1$$

where I_i is the hiking intensity of the individual road segment per year, N the number of hiking activities for Texel in one year and D is the average hiking distance of each activity in metres (7 km in this case). L is the length of the road segment in metres. The first part of this equation thus calculates a maximum hiking potential for the road segment. This is then multiplied by a factor taking into account the length and normalised Strava intensity, S, of the road. This second part of the equation incorporates the interplay of Strava activity and length in determining the number of hikers on the road per year. Once the hiking intensity was calculated for each road segment, the hiking environment as an ES was quantified for the surrounding 50m area:

$$H_i = I_i \cdot \frac{L_i}{A_i}$$

<div align="right">EQ. 2</div>

where H_i is the hiking environment as an ES, measured in metres hiked/m²/yr, I_i is the hiking intensity, L_i is the length of the road in metres and A_i is the total area within 50m along the length of the road in m². Fifty metres was chosen because in our conceptualisation of activity services, it is the immediate physical surroundings of the ecosystems that are contributing to the cultural interaction with nature. We acknowledge that this distance depends upon the landscape and our conceptual and modelling approach can easily be adjusted to different distances.

2.5.1.3. *Aesthetic services – landscape presence*

To spatially quantify the ecosystem contribution to peoples' aesthetic enjoyment of the landscape, landscape presence was measured as an aesthetic service using the locations of photographs shared on Flickr. The Flickr API was used to download all geo-located photos on the island accurate to the street level using a moving 500 m search box. All photos were used after a visual check of the photos confirmed that most had an aesthetic element although we acknowledge that some photos will be unrelated. We return to this in the discussion.

The location of each photograph was used to simulate the visible area from each photo location, or 'viewshed', using a Digital Surface Model (DSM) for the Netherlands at 5 m resolution (AHN, 2014). The DSM takes into account the height of objects on land such as buildings and vegetation as well as the height of the terrain. A spatial distribution function was then applied to individual viewsheds to distribute the contribution of the ecosystems to the person's aesthetic enjoyment. This incorporates the idea that people enjoy the landscape differently at different distances (Schirpke et al., 2013; Tenerelli et al., 2017). In this initial, experimental case, an exponential decline function was applied, reflecting a greater enjoyment of immediate surroundings and no predefined maximum distance apart from the horizon.

In order to limit a user's photos dominating the results, the viewshed from one user's photographs on one day was only counted once to create a Photo-User-Day-Viewshed (PUDV). This PUDV was then divided by its total area, subject to the distribution function, to produce an ES supply of PUDV/ha/yr. The PUDV/ha/yr of all users through the year were then aggregated to produce the final spatial distribution of ES supply.

2.5.1.4. *Naturalist services – species observations*

Ecosystems contribute to human well-being by conferring a notion of ecological meaning. To capture this service flow on Texel, we drew upon the citizen science records available through the website waarneming.nl and used the species observations as an indicator for the ecosystem contribution to peoples' sense of connection with the biodiversity present on the island. waarneming.nl is the largest platform for volunteers to record and share their animal or plant sightings in the Netherlands. The data was downloaded through the Nationale Databank Flora en Fauna (NDFF) Ecogrid portal.

The observation records are available as mainly circular polygons whose size and centre depend on how accurately the observations have been geo-referenced. The size of the polygons range between 11 m² and 283 ha with a mean of 1.3 ha. We took the polygon centres and converted these into points. To model the contribution of the surrounding ecosystem, we generated a 100 m² grid and counted the point density per grid cell to generate a ES flow in records/ha/yr to represent the supply of naturalist services.

2.5.2. *Results*

2.5.2.1. *Activity services – hiking environment*

Figure 3 shows the distribution of hiking environment as an activity service using the Strava heatmap. Ecosystems surrounding the road network generated an attractive physical environment for spatially distributed distances between 1 m hiked/m²/yr and 3080 m hiked/m²/yr. The Strava activity concentrated ES flow in the dense network of footpaths in the western dune areas, on the northern end of the island and along the coastal roads and towns on the island. The agricultural areas in the middle of the island are clearly less popular and there is a noticeable decrease in ES supply as the roads go further inland. Other areas of interest include the concentrations of supply at the roundabouts and along the road leading up to the dunes from the main town of Den Burg in the centre of the island.
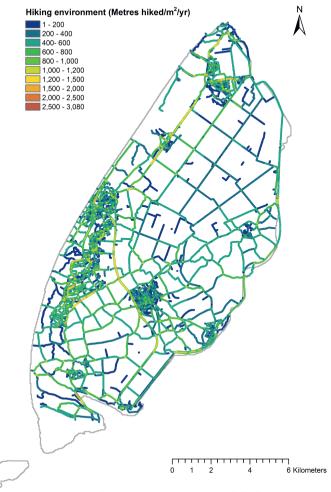
Figure 3. Hiking environment (Metres hiked/m²/yr).

2.5.2.2. *Aesthetic services – landscape presence*

Figure 4 shows the distribution of landscape presence as an aesthetic service in PUDV/ha/yr using the location of geo-tagged Flickr photos. The Flickr activity concentrated ES flow in the popular dune and beaches areas on the western side of the island. The landscape is also conveying a concentrated amount of aesthetic information at the northern end of the island and around wetland areas to the Northeast and in the South. In the town of Den Burg, at the centre of the island, the urban environment has captured and concentrated ES flow in its centre. Line-of-sight effects can also be observed further south where the landscape generates a large ES flow through the fragmented viewshed of a number of highly

concentrated photos. The agricultural landscape that makes up most of the island produces a low and largely uniform service flow with no concentrated hotspots.
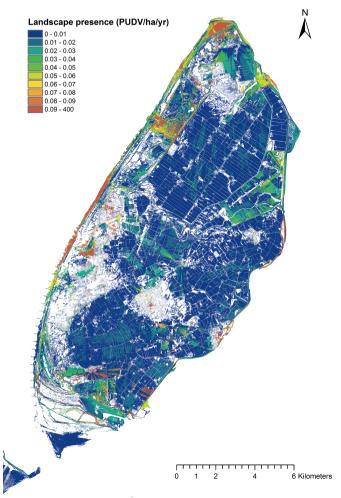
Figure 4. Landscape presence (PUDV/ha/yr).

2.5.2.3. *Naturalist services – species observations*

The distribution of naturalist services measured using species observations on Texel is shown in Figure 5. ES flow ranged between 0.01 and 44 records/ha/yr. The contributing areas are mainly distributed around the coast and road network of the island. Based on the species records on waarneming.nl, ecosystems are generating particularly concentrated ES flows at the northern tip of the island, the wetland areas in the Northeast and in the South. The dunes on the west side of the island also register some large contributions. ES flow is

much more sparsely scattered through the agricultural areas of the island where small contributions are restricted to the areas around the road network. The marine ecosystems surrounding the island are also generating naturalist services with a trail of observations leading up to the main island port in the South and a second trail encircling the island from South to West.
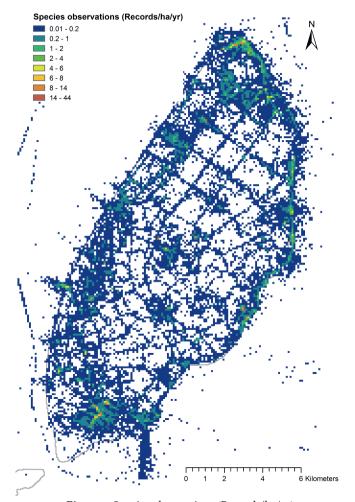
Figure 5. Species observations (Records/ha/yr).

2.6. Discussion

2.6.1. *Defining CES*

Employing crowdsourced data encourages a CES conceptualisation shaped by the data. In our investigations of these data sources, we discovered records of information conveyed by

ecosystems to people. The data available through Strava, Flickr and waarneming.nl enabled us to develop service indicators for some of these information-flows on Texel. In turn, these information-flows contribute to peoples' cultural experiences of nature such as recreation; the benefits to human well-being. This linear process aligns itself with the cascade model proposed in TEEB (2010b): the value of these benefits can be then determined through different valuation methods.

Others have argued that CES are inherent to all human-nature interactions and CES value should be conceptualised as non-material components of ecosystem-related benefits (Chan et al., 2012b; Fish et al., 2016), a conceptualisation reflected in the IPBES framework (Díaz et al., 2018). Partly, this thinking is driven by the argument that CES are intangible and pluralistic by nature which makes these services difficult to quantify (Chan et al., 2012b). The pluralistic nature of CES has also raised the issue of double counting the contributions of ecosystems to cultural benefits. For example, a sacred site may be used as a proxy indicator for services related to touristic activities as well as spiritual services (Hernández-Morcillo et al., 2013).

However, we would argue that the spatial models in this study show that CES as information-flows can be spatially quantified using crowdsourced data. We would also argue that CES are in fact benefit-specific because the information available through crowdsourced data, in the form of imagery, location and textual data, can be very specific about how the individual is appreciating their environment. This enables a detailed identification of service flows in assessments up to national and inter-national scales. Large-scale assessments are further supported by the information definition due to the strict distinction between services and benefits. For national accounting purposes, this recognises the joint-production of goods and services (Boyd and Banzhaf, 2007). Thus, some notable exclusions from the proposed typology are "recreation", "tourism", "inspiration", "cultural diversity", "sense of place", "social relations", or "symbolic meaning". These represent cultural experiences requiring human input and therefore constitute cultural benefits rather than information service flows.

2.6.2. Categorising CES

In order to summarise the broad array of data utilisations identified in the review, the typology consists of a general set of categories. Further examination of crowdsourced data sets in local contexts may uncover more specific service categories. In indigenous and local knowledge contexts, getting specific about CES and even moving beyond the ES paradigm

helps to identify ecosystem contributions that are relevant and important to the community (P. Pascual et al., 2017). Here the IPBES framework's context-specific assessment guidelines constitute an important tool in capturing these CES (Díaz et al., 2018). However, in the context of large-scale assessments, a level of generalisation is important to allow comparison between assessments and the aggregation of results. For example, in accomplishing the European Biodiversity Strategy (J. Maes et al., 2013). In these cases, we believe our typology provides a comprehensive-enough starting point to quantify CES using crowdsourced data based on our review of data utilisations, leading ES assessment frameworks and the distinction between services and benefits.

The service categories in our proposed typology were shaped by the information available through the identified sources. However, the data almost always represents a particular subset of the population. The demographics of the populations using different platforms and technologies is never entirely clear and is both variable between platforms and in time (boyd and Crawford, 2012; Liu et al., 2016). Flickr has been found to mostly consist of 40 to 60 year old males (Lenormand et al., 2018) while social media in general is understood to be biased towards younger generations (Liu et al., 2016). Mobile connectivity plays a major role (Li et al., 2016). Additional biases exist within platforms and user contributions are usually skewed towards small, highly active groups (Li et al., 2013). Consequently, there must be a careful consideration of the types of services and preferences available. Some CES may not be captured at all while some biases in user preferences can be addressed. For example, our Flickr-based model incorporated the PUD concept. Inferring demographics from user profile and socio-economic data can also reduce this bias (Li et al., 2013; Longley et al., 2015).

Categorising the data that is available through these sources presents another key challenge. For example, classifying scenic images as exclusive input into our Flickr-based model remains an unresolved issue. Similarly, uncertainty remains as to whether all the Strava data used in our activity services model is related to nature-focused physical activities. However, the advantage of using many sources of crowdsourced data is that tangible, quantifiable elements exist which can be more definitively categorised based on further investigation, debate and consensus (Oteros-Rozas et al., 2018). For example, the scenic compositions or objects present in Flickr images can determine the flow of aesthetic services. Machine learning methods then present promising approaches to automate this analysis over large amounts of data (Richards and Tunçer, 2018). Nonetheless, the models in this study still managed to capture known areas of corresponding cultural importance.

Popular hiking routes, scenic locations and biodiversity hotspots are captured by each of the respective models (Roos and van der Wel, 2013). This suggests some of the principle uses of these platforms are sufficient to identify three distinct service-types generated on the island.

2.6.3. Modelling CES

A key consequence of modelling CES using crowdsourced data is a shift towards user-driven CES models. This is in contrast to many existing models which spatially model CES using ecosystem features such as the number of sacred sites (Hernández-Morcillo et al., 2013). These measures are more in line with the capacity rather than use of ES supply as it does not capture the location where these features contribute to an individual's economic utility or wellbeing (Schröter et al., 2014). In this way, crowdsourced data-based models are more representative of the actual use of CES. The global reach of some crowdsourced data also enable researchers to include beneficiaries who would have been difficult to include using traditional survey techniques; an important aspect to CES research (Daniel et al., 2012). However, the prevailing user biases seriously affect the estimated spatial quantities. In order to gain a more representative spatial service flow of activity services in our study, hiking activities estimated using national survey data were distributed using Strava user preferences. This combination of empirical and crowdsourced data is one promising solution to address these user biases.

Nevertheless, the preferences captured in crowdsourced data-based models still contain bias. Self-selecting users also share self-selected content, resulting in a distorted representation of peoples' lives (Miller and Goodchild, 2015). Geographical concentrations also exist. For example, more accessible places draw greater numbers of observations on citizen science portals (Jacobs and Zipf, 2017). This was evident in our study with the species observations concentrated along the road network. However, in projecting a usually positive self-image in the content they share, users share what is of value to them, an important consideration for the purposes of measuring CES. Exploring what geographical concentrations mean is also important. For example, although observation concentrations on citizen science portals may reflect a biodiversity sampling bias, in a cultural sense these can be taken as good evidence for large CES supply.

Uncertainties in the location accuracy of crowdsourced data must also be taken into account. The location accuracy of the data used in our models was not considered. It is difficult to establish a definitive measure using social media data without manually checking the content of posts. In a global analysis, Zielstra and Hochmair (2013) found that

11 to 18 percent of Flickr photos had a positional error. Twitter posts have been found to be accurate to 20 m in urban areas (Longley et al., 2015). Even though accuracy measures were provided with the waarneming.nl data, the measures largely depend on the skill of the observer. In the case of mobile network data, the location accuracy of CDRs rely on the density and signal strength of cell phone towers (Liu et al., 2016). That being said, the location data that is available is a significant step forward in CES research where most studies do not spatially measure CES (Hernández-Morcillo et al., 2013). Spatially measuring CES using survey techniques also comes with its own uncertainties, relying on participant re-call (Adamowicz et al., 1997) and often measured within broad land cover categories (Eigenbrod et al., 2010).

Finally, the continued availability of crowdsourced data is a key source of uncertainty which affects the reproducibility of CES model results. In the case of social media, API access can change regularly. For example, Twitter and Instagram have both changed levels of access in recent years (Ghermandi and Sinclair, 2019). This threatens the feasibility of regular ES assessments such as the annual assessments required to maintain up-to-date ecosystem accounts (UN et al., 2014). Users may also edit, remove or alter access to their data themselves, with further consequences for reproducibility. However, data can still be stored independently for reproducible results. For example, the InVEST model provides a global database of Flickr photos to maintain a consistent recreation model (InVEST, 2017). Nevertheless, in these cases, important ethical considerations must be taken into account.

2.6.4. *Ethical considerations*

Employing crowdsourced data presents unique ethical challenges centred around privacy and consent. It is unclear in our study whether users fully appreciate the extent to which their data can be used and whether they would give permission for it to be used in further applications. Then again, it may be unreasonable to ask every user for their permission (boyd and Crawford, 2012). Social media platforms give users different options regarding the privacy of their data, including 'opt-in' choices for geo-tagging. The public nature of social media data signals a shift in the responsibilities of individuals and institutions (Elwood and Leszczynski, 2011). Legislative developments in the US, Canada and Japan have asserted the idea that civil actors are responsible for their privacy in using such services (Elwood and Leszczynski, 2011). Users are also becoming more conscious of how their personal data is being used through recently enacted laws such as the EU's GDPR (De Hert et al., 2018).

Nonetheless, researchers must consider whether technology providers have given users sufficient awareness and control over their data (boyd and Crawford, 2012).

In employing these new types of data, researchers must also consider their accountability to their field of research and their research subjects (boyd and Crawford, 2012). In the context of national statistics, statistical disclosure controls must be followed so that no individual can be identified from the results (Hundepool and de Wolf, 2012). Spatial quantification of CES benefits from a level of generalisation and abstraction which makes it very difficult to identify specific individuals. This was demonstrated by the results in this paper; the spatial metrics contain no personally identifiable information. Nevertheless, at the same time, is it important to ensure individuals' data is anonymised and secure when working with the data (King, 2011). Comprehensive data management practices should therefore be in place. Good data management practices include anonymising data fields so that information cannot be linked to an individual and restricting access to the data so that it is only accessible to a limited group of users (Wu et al., 2014).

2.7. Conclusion

Defining CES for the purposes of spatial quantification has been challenging due to the difficulties in spatially modelling CES. Now, the rapid increases in mobile connectivity and its use for leisure-oriented activities such as social media has generated a wealth of geo-referenced information to spatially model cultural interactions with nature. This study has analysed the information available through crowdsourced data sources to suggest a definition and typology which can help clarify CES quantification. To show how these can work in practice we presented the results of three spatial CES models employing crowdsourced data. The definition and typology are especially suited to measure CES in high-resolution, large-scale studies such as national or inter-national assessments. In these cases, employing crowdsourced data to model CES brings significant benefits in terms of the scale and detail in which studies can be carried out. However, in utilising crowdsourced data, the representativeness of the data, measurement uncertainties, and ethical considerations must be taken into account. Nonetheless, with these challenges considered, crowdsourced data enables new ways of spatially modelling CES and, in doing so, helps to clarify the CES concept for the purposes of spatial quantification. Ultimately, this can facilitate a better representation of these services in ES assessments.

Chapter 3.

Social media and deep learning capture the aesthetic quality of the landscape

Abstract. Peoples' recreation and well-being are closely related to their aesthetic enjoyment of the landscape. Ecosystem service (ES) assessments record the aesthetic contributions of landscapes to peoples' well-being in support of sustainable policy goals. However, the survey methods available to measure these contributions restrict modelling at large scales. As a result, most studies rely on environmental indicator models but these do not incorporate peoples' actual use of the landscape. Now, social media has emerged as a rich new source of information to understand human-nature interactions while advances in deep learning have enabled large-scale analysis of the imagery uploaded to these platforms. In this study, we test the accuracy of Flickr and deep learning-based models of landscape quality using a crowdsourced survey in Great Britain. We find that this novel modelling approach generates a strong and comparable level of accuracy versus an indicator model and, in combination, captures additional aesthetic information. At the same time, social media provides a direct measure of individuals' aesthetic enjoyment, a point of view inaccessible to indicator models, as well as a greater independence of the scale of measurement and insights into how peoples' appreciation of the landscape changes over time. Our results show how social media and deep learning can support significant advances in modelling the aesthetic contributions of ecosystems for ES assessments.

3.1. Introduction

Landscape aesthetics generate a large amount of cultural value for human well-being. The aesthetic quality of a landscape plays an important role in determining where people choose to recreate (Daniel et al., 2012). For example, recreational activities such as hiking are performed by people seeking aesthetic experiences related to the naturalness and perceived wilderness of a landscape (Gobster et al., 2007). As a consequence, the aesthetic contributions of ecosystems generated during peoples' outdoor recreation are an important contributing factor to peoples' mental and physical health (Abraham et al., 2010). The recent Covid-19 pandemic has especially highlighted the importance of outdoor recreation for peoples' well-being (Rice et al., 2020; Venter et al., 2020). Recreation is thus a key feature of environmental policy in Europe (Joachim Maes et al., 2013). To capture this value and integrate it into land-use planning, ecosystem service (ES) models of recreation that consider the aesthetics of the landscape are being developed for use in European ES assessments (Paracchini et al., 2014). ES assessments provide a science-policy interface through which the contributions of ecosystems to human well-being can be measured to achieve sustainable policy goals (Díaz et al., 2018; Hein et al., 2020a).

Large-scale surveys can provide statistical measures of ES contributions based on peoples' spatial interactions with the environment (Martínez-Harms and Balvanera, 2012; Raymond et al., 2014). In the U.K., a recreational model was developed for the National Ecosystem Assessment using survey data on peoples' outdoor recreation, the Monitor of Engagement with the Natural Environment (MENE). The model included land cover-based variables related to the aesthetic quality of the landscape (Bateman et al., 2013). However, due to their high cost and complexity, such large-scale surveys are rare. In this respect, the MENE survey in the U.K. is exceptional. Nevertheless, it only captures respondents' spatial interactions based on a single gazetteer look-up, thereby missing finer-grained interactions that can tell us more about how and where people are benefiting from the landscape.

Due to these constraints, quantitative studies of aesthetic landscape quality are mostly based on spatially-explicit environmental indicators (Hermes et al., 2018; Hernández-Morcillo et al., 2013). Common indicators include the presence of natural ecosystems, water, elevation, as well as spatial indices of landscape complexity such as the Patch Diversity Index (PDI) and the Shannon Diversity Index (SDI) (Hermes et al., 2018; Schirpke et al., 2013; Uuemaa et al., 2009). The application of these indicators are based on visual concepts and theories developed in the landscape aesthetics literature (Ode et al., 2008; Tveit et al., 2006).

However, crucially, these models do not incorporate peoples' individual interactions with the environment, an important methodological factor from an ES modelling perspective (de Groot et al., 2010; Schröter et al., 2015; Tenerelli et al., 2017). Any measurements over time are also limited by updates to the underlying datasets which can take several years, an inflexible timeframe when considering the annual accounting requirements of some ES assessments (Hein et al., 2020a).

Recently, social media has emerged as a rich new source of information on human–nature interactions. The image-sharing platform Flickr has proven to be a particularly useful source of information. The locations of images and associated metadata, including tags and descriptions, have now been widely employed across the ES (Richards and Tunçer, 2018; Sinclair et al., 2020; Tenerelli et al., 2016; van Zanten et al., 2016; Wood et al., 2013), land use (Antoniou et al., 2016; Mancini et al., 2019) and landscape research literature (Donahue et al., 2018; Hollenstein and Purves, 2010; Schirpke et al., 2013). Still, the data by themselves are difficult to interpret, mostly due to their volume and velocity. To respond to these challenges, researchers have turned to machine learning. In particular, deep learning, which uses artificial neural networks to generate predictions (LeCun et al., 2015). Supported by the increasing availability of training data and high-performance computer hardware, deep learning has made automatic image classification and object detection tasks possible over large datasets, including social media (Naik et al., 2017; Srivastava et al., 2020; Toivonen et al., 2019; Zhang et al., 2020). As a result, deep learning has been identified as an important new tool in the development of rapid, flexible and transferable cultural ES indicators (Egarter Vigl et al., 2021).

In the case of landscape aesthetics, an especially relevant training dataset exists: the Scenic-Or-Not (SoN) database. Through a web-based portal, the database has collected 1.5 million 'scenicness' ratings between 1 and 10 of 217,000 landscape images of Great Britain (ScenicOrNot, 2015). The images are sourced from Geograph, an online project to collect a geographically representative image of every square kilometre of the U.K. and Ireland. Studies have drawn on the SoN database to independently demonstrate both the potential of social media and machine learning in understanding peoples' aesthetic preferences. Flickr metadata has been used to generate spatial predictions of scenic beauty (Seresinhe et al., 2017a). Geograph tags have also been used to predict scenicness with random forests, a tree-based ensemble learning method for regression (Chesnokova et al., 2017). More recent studies have considered the image content directly using deep learning: image attributes related to the scenes and objects in SoN images have been used to generate scenicness

predictions (Seresinhe et al., 2017b; Workman et al., 2017). Subsequent research has focused on the detection of attribute groups co-influencing the perception of scenicness (Marcos et al., 2020), the discovery of new attributes using ancillary text corpora (Arendsen et al., 2020), and the relationship between scenicness and land cover as observed by remote sensing satellites (Levering et al., 2021).

These studies demonstrate the potential of modelling landscape aesthetics using social media and deep learning. At the same time, from an ES modelling perspective, social media provides the possibility of integrating peoples' revealed preferences through their spatial interactions with the environment, and to observe the aesthetic contributions of landscapes with high spatial and temporal granularity (Havinga et al., 2020). This is in contrast to indicator-based models, which only take into account a general set of stated preferences, are limited by their spatial resolution and rely on updates to the underlying datasets to track temporal changes. Still, user activity on social media may not reflect common aesthetic preferences and could fail to detect significant changes over time. This is because studies validating the use of social media for cultural ES indicators are lacking (Oteros-Rozas et al., 2018), a common problem in cultural ES studies (Englund et al., 2017). Examining the accuracy of social media and deep learning in modelling landscape aesthetics versus an indicator-based approach will thus generate much-needed evidence confirming the potential benefits of using these novel techniques.

In this study, we compare models of landscape quality using Flickr and deep learning with an environmental indicator model, and explore their synergistic use. We generate spatial predictions for Great Britain using random forests and draw on the SoN database and its concept of scenicness to train and test our models. Flickr-based variables are generated using the predictions of two deep learning models at the image-level. The first, a pre-trained Places365-ResNet-50 model (B. Zhou et al., 2017), predicts scene classes and image attributes using the SUN database (Patterson et al., 2014). A scene class can be defined as the overall semantic description of an image while an image attribute is a specific characteristic within it (e.g. a collection of objects or human activity). The second model, a SoN ResNet, generates scenicness predictions in individual images. Environmental indicator variables are linked to visual concepts in the literature and are calculated using ecosystem type maps of Europe and other open-source data. We also analyse the effect of limiting Flickr user activity and examine aesthetic enjoyment over time in national park areas. Our findings illustrate how these innovative methods can advance ES modelling to achieve sustainable policy goals.

3.2. Methods
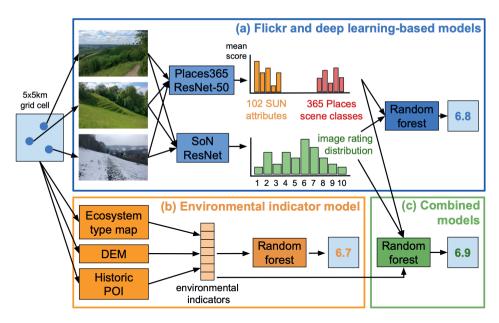
3.2.1. Study design

The research focused on comparing Flickr and deep learning-based models with an environmental indicator-based model, as well as different combinations of the two (Figure 6). Conceptually, we considered the aesthetic quality of the landscape equivalent to the concept of scenicness, and that scenicness constituted an integral factor determining the overall flow of aesthetic ES (Daniel, 2001). We made our comparisons using a 5×5 km grid covering the entire terrestrial area of Great Britain and at 500 m resolution in Greater London and the Lake District. As a ground truth, we calculated a mean scenicness rating per grid cell using the image scenicness ratings of intersecting SoN images. Each image has a collection of volunteer ratings between 1 (not scenic) and 10 (very scenic). We used the average of these ratings. For training, we used the 5×5 km grid. To reduce spatial autocorrelation, a larger 50×50 km grid was then overlaid onto this grid to create sample groups of which 70% was randomly allocated for training, 10% for validation and 20% for testing (Supplementary **Figure S2**). Random forests was used to model scenicness at the 5 km and 500 m grid level using both the environmental indicator and Flickr-based variables. All spatial analyses were done using the R 3.6.3 programming language including the raster 3.0–12, sf 1.0-1, caret 6.0–86 and tidyverse 1.3.1 packages. caret was used to automatically select the random forest hyperparameter settings *mtry*, *min node size*, and e*xtratrees*.

3.2.2. Datasets

In addition to the SoN database, a Flickr image dataset was compiled to generate the deep learning-based variables. To do this, image metadata for geo-located images taken in Great Britain between 2004 and 2020 were downloaded using Flickr's API and accessed using the Python programming language. A script was developed which iterated over a 1×1 km grid, requesting the metadata of the 4000 most recent, geo-located images per grid cell. Geo-location accuracy was set to "street level", the highest possible accuracy available through the API. The Places365-ResNet-50 model48 was then used to filter the dataset for outdoor images using its binary indoor/outdoor scene predictions. This resulted in a final dataset of 9.8 million outdoor images, resized to 250×250 pixel dimensions. The environmental indicator variables were also calculated using a number of geospatial datasets (Supplementary Table S1). These included the European Environment Agency (EEA) ecosystem type map, the EU DEM and OpenStreetMap. The EU GDPR on data protection and privacy were followed in the carrying out of the research.

Figure 6. The main study design comparing spatial predictions of scenicness at a 5×5 km grid cell resolution using random forests. These used different combinations of variables based on **(a)** the predictions of two deep learning models on Flickr images, **(b)** a set of environmental indicators, and **(c)** combinations of the two. Photos © Alun Ward (cc-by/2.0).

3.2.3.   *Flickr and deep learning-based variables*

To model scenicness at the grid level, spatial variables were generated using two deep learning models developed in Python 3.8.3 (Figure 6). The pre-trained Places365-ResNet-50 model48 was applied to Flickr images to produce a first set of variables: a mean of 365 scene classes and 102 SUN image attribute scores per grid cell (a complete list is available in Supplementary Table S2 and Table S3). Scene classes capture the overall semantic interpretation of an image, with scores representing probabilities between 0 and 1 based on the most likely scene out of 365 scene classes. Image attribute scores indicate the presence of objects and remarkable scene characteristics. These were normalised using a sigmoid function to produce a 0–1 probability per attribute.

The second model, the SoN ResNet, was used to predict scenicness in Flickr images and to generate a second set of variables: a normalised count of its image predictions across ten scenic rating bins between 1 and 10, representing a scenic rating distribution per grid cell. We constructed this model using a modified ResNet-50 convolutional neural network, available pre-trained on the ImageNet database through the PyTorch 1.6.0 library. The final two layers of the network, originally designed to output confidence scores for ImageNet's

1000 object classes, were removed and replaced with new layers designed to output an image scenicness score (Marcos et al., 2020). These consisted of an adaptive average pooling layer and two linear layers with a ReLU activation function on the output of the first linear layer. The network was trained and tested using SoN images according to the 70% training, 10% validation and 20% test areas. For training, this consisted of 152,470 images resized to 500×500 pixel dimensions. Images were also randomly flipped horizontally to increase the size of the training dataset. Batch size was set to 16. Model weights were optimised using stochastic gradient descent and a mean squared error loss function. Test statistics are shown in Supplementary Table S4.

3.2.4. *Environmental indicator variables*

Variables were calculated per grid cell based on visual preference concepts put forward in the landscape aesthetics literature. The EEA ecosystem type map was used to calculate the percentage of different ecosystems to capture the naturalness of the landscape; relief in m was measured using the EU DEM to capture the aesthetic appeal of higher elevation areas and elevation differences; the PDI and SDI were calculated using the EEA ecosystem type map to measure landscape complexity; and, finally, to capture the uniqueness of natural environments and cultural elements in the landscape, the relative difference in the percentage area of ecosystems within 10 km was calculated, as well as the number of historical points of interest (POI) using OSM (Figure 6). More details on the theoretical basis for these indicators and their calculation can be found in Supplementary Table S1.

3.2.5. *Environmental indicator reduction*

To improve model performance and interpretability, the initial environmental indicator set was reduced. First, ecosystem variables that could be calculated for less than 100km^2 or 0.04% of Great Britain were removed using a threshold analysis (Supplementary Figure S3). Then, a check for collinearity between the remaining variables was performed. The model accuracy effect of removing variables with a correlation $r \geq 0.7$ was measured through a leave-one-out process in which random forest models were iteratively generated without one of the indicator variables in the full indicator set. The collinear variable with the smallest effect on model accuracy was removed (Supplementary Table S5 and Figure S4). This resulted in a final indicator set of 41 variables.

3.2.6. Time-series analysis

An additional experiment was conducted to examine landscape aesthetics over time in the 15 national parks of Great Britain (Supplementary Figure S5). Flickr images within these areas were extracted for the time period June 2009 to May 2019. The image attribute scores were extracted using the Places365-ResNet-50 model and prevalence was calculated on an image-level basis by taking only attribute scores greater than 0.5, subtracting 0.5 and multiplying by 2. All other values were set to 0. The linear model was trained and tested using a random 80/20% sample of images. MODIS snow cover data used the MOD10CM product which reports monthly average snow cover in 0.05°. The centroids of the intersecting 5×5 km grid cells with national parks were used to extract percentage snow cover on a monthly basis. Additional spatial data sources are given in Supplementary Table S6.

3.3. Results

3.3.1. Scenicness predictions using Flickr images and deep learning

An example of a Flickr and deep learning-based prediction for a single 5×5 km grid cell is shown in Figure 7. Individual Flickr images (Figure 7a) are passed through the Places365-ResNet-50 model to generate a grid cell mean for 365 scene classes (Figure 7b) and 102 SUN image attributes scores (Figure 7c), while image scenicness scores generated by the SoN ResNet are used to produce a normalised rating distribution between 1 and 10 (Figure 7d). The scene class and image attribute scores show that, on average, the Places365-ResNet-50 model scored the images in the grid cell the highest for the "lagoon", "tundra" and "islet' scenes, and the lowest for "atrium", "shopping mall" and "living room". In terms of attributes, the images were scored the highest for "natural light", "open area" and "natural" while "enclosed area", "praying" and "indoor lighting" received the lowest scores. A full list of image attribute and scene classes is available in Supplementary Table S2 and Table S3. The normalised rating distribution shows that most images were rated 7 and above by the SoN ResNet. The predictions produced by the two deep learning models were then used as individual variables in a random forest model which predicted a final scenicness score of 6.9 for the grid cell (Figure 7e).
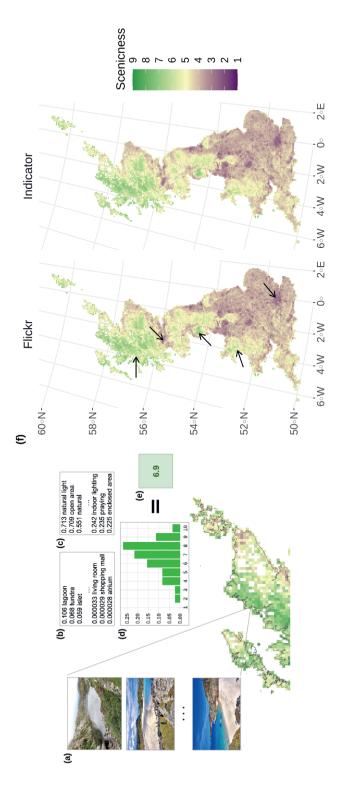
Figure 7. A Flickr and deep learning-based prediction of scenicness at 5 km resolution for a single cell covering Achmelvich Bay, Scotland, and for Great Britain, in comparison to the indicator model. The deep learning-based models used **(a)** Flickr images to generate **(b)** 365 scene class scores and **(c)** 102 SUN attribute scores, as well as **(d)**, a normalised scenic rating distribution. These were then used to build a random forest model to generate **(e)** a scenicness prediction. In **(f)**, predictions of the best-performing Flickr model for Great Britain are shown alongside those of the indicator model. From top to bottom, the arrows point to the Scottish Highlands, Glasgow, the Lake District, Snowdonia National Park and London. Photos © Sergio and © Graeme Churchard (cc-by/2.0).

3.3.2. Comparison of Flickr, environmental indicator and combined models

The accuracy of the random forest models using the Flickr and deep learning-based variables, environmental indicators, and different combinations of the two, within a 20% hold-out test area are show in Table 4. Accuracy is reported using r^2, root mean squared error (RMSE) and Kendall's τ, a ranking correlation coefficient between – 1 (inverse correlation) and 1 (absolute correlation). Using Kendall's τ to rank the models, the best-performing Flickr model used the Places365 scene classes and SUN attributes as variables. The model achieved a τ of 0.683 versus 0.730 achieved by the indicator model. Model performance was maximised when the environmental indicator variables and the scenic rating distribution were combined, producing a τ of 0.739.

Table 4. Scenicness model accuracy results on the gridded test set at 5 km resolution, derived from the SoN database.

Model	Places365 scene classes	SUN attributes	Scenic rating distribution	Environmental indicators	r^2	RMSE	Kendall's τ
Flickr							
1	–	–	✓	–	0.659	0.639	0.611
2	–	✓	–	–	0.754	0.542	0.671
3	–	✓	✓	–	0.757	0.540	0.672
4	✓	–	–	–	0.757	0.541	0.677
5	✓	–	✓	–	0.757	0.541	0.677
6	✓	✓	✓	–	0.766	0.529	0.680
7	✓	✓	–	–	0.770	0.525	0.683
Indicator							
8	–	–	–	✓	0.819	0.468	0.730
Combination							
9	✓	✓	–	✓	0.827	0.458	0.732
10	✓	✓	✓	✓	0.827	0.457	0.733
11	–	✓		✓	0.830	**0.453**	0.734
12	✓	–	–	✓	**0.832**	0.453	0.738
13	–	–	✓	✓	0.830	0.453	**0.739**

The spatial predictions generated by the best-performing Flickr model and indicator model for the whole of Great Britain at 5 km grid cell resolution are shown in Figure 7f. The two model types produced very similar spatial predictions. Areas of particularly high aesthetic value are captured well by both models, such as Snowdonia National Park in Wales, the Lake District in England and the Scottish Highlands. Similarly, urban areas of less scenic quality such as London in England and Glasgow in Scotland, are also clearly visible. In Figure 8, a more detailed comparison is shown of the model predictions at 500m resolution versus the observed values. In both the Greater London area (Figure 8a) and in the Lake District (Figure 8b), we see more nuanced predictions using the Flickr model, while the indicator model produces more extreme values and sharp boundaries. For example, in Greater London, Richmond Park and Heathrow Airport are predicted as very scenic areas in contrast to some of the neighbouring areas by the indicator model, while the predictions of the Flickr model are much more muted and in line with the observed values. In the Lake District, we also see more extreme values in the unscenic areas using the indicator model, while the Flickr model behaves again in a more conservative manner. Overall, the Flickr model predictions in both areas show more consistency with the observed values, although the least scenic areas in the Lake District are less visible.

Variable importance for the Flickr, environmental indicator and combination models at 5 km resolution are shown in Figure 9. The best-performing Flickr model, which used the Places365 scene classes and SUN attributes as variables, mainly drew on "climbing" and "rugged scene" in making its predictions. Natural scenes and attributes closely related to landscape aesthetics were also prominent such as "valley", "mountain" and "natural", as well as other recreation-related attributes such as "hiking". The indicator model relied heavily on the presence of arable land and market gardens (I1), relief, and the presence of buildings (J1 and J2) to generate a scenicness prediction. This was followed by the presence of natural ecosystems, including grasslands (E2), mires/bogs (D1), heathland (F3s, F4s and F3), and inland scree/bare surfaces (H3s). The complexity indices SDI and PDI did not constitute important variables. The best-performing combined model, incorporating the scenic rating distribution (model 13, Table 1), drew on a similar set of indicator variables and the more extreme scenic ratings, focusing on the distributions across rating bins 2, 3, 7 and 8.
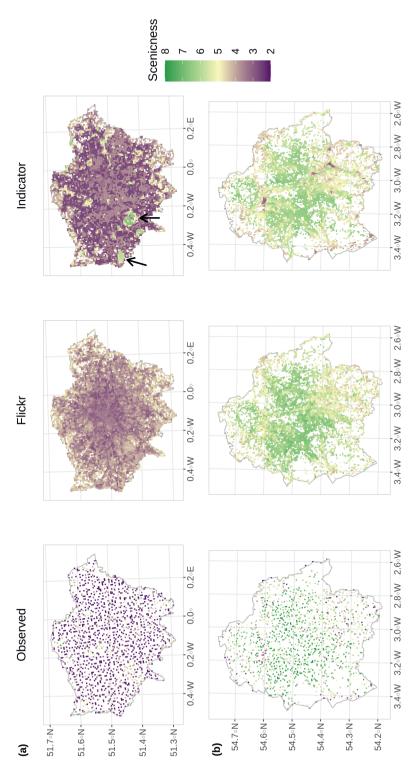
Figure 8. Observed scenicness versus the spatial predictions generated by the best-performing Flickr model and indicator model at 500 m resolution in (a) the Greater London area and (b) the Lake District national park. The arrows within the Greater London indicator model map point to Heathrow Airport (left) and Richmond Park (right). The observed versus predicted grid cell values are shown in Supplementary Figure S6.
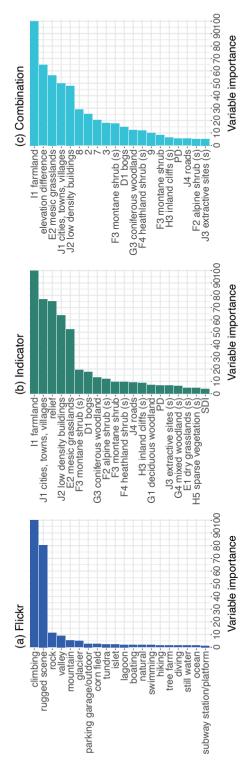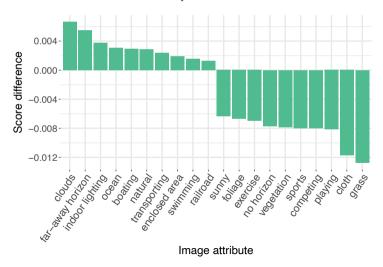
Figure 9. Most important variables for **(a)** the best-performing Flickr model, **(b)** environmental indicator model, and **(c)** best-performing combination model at 5 km resolution. "(s)" denotes an ecosystem in surrounding area variable. Supplementary **Table S7** contains a full list of ecosystem type codes and class descriptions.

3.3.3. Limiting Flickr user activity

For ES modelling purposes at national level, it is important to capture a representative measure of ecosystem contributions to human well-being. In the case of the Flickr models, accuracy results are reported after limiting individual Flickr users to one image per day per 5×5 km grid cell. We applied the limitation after finding large geographic disparities in images per user (Supplementary **Figure S7**). After applying the limitation, model accuracy improved versus a non-filtered dataset (Supplementary Table S8). Figure 10 shows the largest resulting change in image attribute confidence scores. A key change that can be observed is a decrease in the prevalence of images related to sporting. For example, "playing", "competing", "sports", and "exercise" all saw notable decreases. This suggests that a large number of images associated with sporting events, less relevant for measuring landscape aesthetics, were removed from the dataset by the filtering. This in turn appears to have increased the prevalence of landscape-focused imagery, indicated by the increase in confidence scores for the "clouds", "far-away horizon", "ocean" and "natural" attributes.

Figure 10. The largest differences in image attribute scores after limiting Flickr user contributions. To calculate the difference, a single image per user per day per grid cell was randomly selected ten times and the mean attribute scores were calculated per grid cell. The median difference versus the unfiltered dataset is shown here with summary statistics available in Supplementary Table S9.
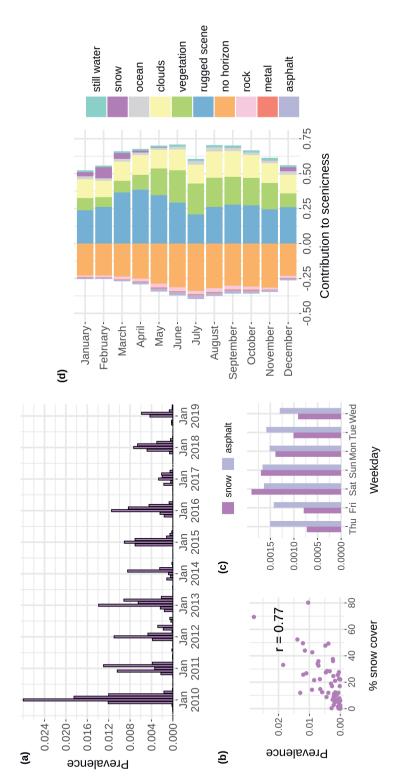
3.3.4. Measuring changes in aesthetic enjoyment over time

Deep learning-based variables generated using social media can also support measures of landscape aesthetics over time. This can support more frequent updates to national ES assessments, and tell us more about how the landscape is contributing to peoples' well-being. In an additional experiment aiming at studying the temporal dynamics of peoples'

aesthetic enjoyment through their interactions with the landscape, we analysed how scenicness evolves over time in national park areas. Figure 11 shows the contributions of a selected group of image attributes over a ten year period within the 15 national parks of Great Britain. These contain some of the most valuable natural areas in Britain, such as the Peak and Lake Districts in England, the Pembrokeshire coast in Wales, and the Cairngorms in Scotland.

The contribution of aesthetic-related image attributes change in these national parks according to the season. We focus on the "snow" attribute as a specific example of how these contributions change over time. Figure 11a shows how the prevalence of "snow", the average score accounting only for images with a score higher than 0.5, increases in the winter months. The winter of 2009/2010 reveals itself as a particularly snowy period. The prevalence of snow in user images correlates strongly with remote sensing-based measurements of snow cover using MODIS satellite data, shown in Figure 11b. In Figure 11c, we also see how the prevalence of "snow" increases around the weekend when people are more likely to visit snowy landscapes, whilst the prevalence of "asphalt" in images remains relatively constant throughout the week. This shows that the use of social media-based data provides a combination of information about the state of the environment and how people interact with it.

In a direct connection to aesthetic landscape quality, when the selected group of image attributes shown in Figure 11d, including "snow", are used to predict the image ratings generated by the SoN ResNet, we see again how the contributions change over time. For example, the contributions of "snow" appear between December and April, reaching a peak in the winter month of February, before disappearing again. In contrast, the contributions of "vegetation" grow to their highest between June and August, reflecting the positive influence of deciduous growth on landscape aesthetics in the summer. Although smaller in size, the contributions of "ocean" also grow in the summer, suggesting an increase in user posts of coastal images to Flickr in these warmer months. It is also notable that the contribution of "rugged scene" to scenicness increases in the rainy months of spring.

Figure 11. The influence of " snow" and other image attributes on aesthetic enjoyment over time. The **(a)** average monthly prevalence of " snow" attribute scores >0.5 are shown between 2009 and 2019. The average monthly scores show a strong correlation (Pearson's R=0.77) with **(b)** remotely-sensed snow cover data. The **(c)** average prevalence per weekday of " snow" versus " asphalt" is also shown. A constrained linear model (R^2=0.34) was trained using the scores >0.5 of a selected group of attributes including " snow" to **(d)** predict scenicness at the image-level. The changing monthly contributions of some of these attributes can be observed, with " snow" contributing in the winter months. Contributions represent individual image attribute scores multiplied by the model coefficients and averaged on a monthly basis.

3.4. Discussion

The potential of social media and deep learning to capture peoples' interactions with the landscape has yet to be fully confirmed. In an ES context, social media provides a rich new source of data to capture the cultural contributions of ecosystems to human well-being but its use is rarely validated46. In the ES community, deep learning applications also remain limited and those that do exist tend to limit their analysis to using the objects detected in images as proxies for cultural ES (Egarter Vigl et al., 2021; Lee et al., 2019; Richards and Tunçer, 2018). We have demonstrated that deep learning-based variables which consider the overall semantic meaning of an image can accurately capture the aesthetic quality of the British landscape. Crucially, these techniques also incorporate peoples' actual interactions with the environment, a key methodological requirement from an ES perspective.

Nevertheless, our study highlights the relevance of traditional environmental indicator models in capturing landscape quality in the absence of survey data. The visual concepts put forward in the landscape aesthetics literature serve well to capture the spatial variation in scenicness provided by the SoN database. The especially strong influence of unnatural, man-made environments on aesthetics is reflected in the high variable importance of arable land and buildings (Ulrich, 1979). At the same time, the importance of highly valued and unique natural environments, such as bog and heathland ecosystems, as well as the importance of relief, are also accurately identified by the random forest model (Cordingley et al., 2015; Newton et al., 2009; Tveit, 2009). Surprisingly, the SDI and PDI, normally key indicators for measuring landscape aesthetics (Frank et al., 2013) and relevant to Britain (Graham and Eigenbrod, 2019), did not constitute important variables in our results. The variety of ecosystem type indicators and their interaction in the non-linear model space may have offered enough opportunities to capture landscape complexity (Ryo and Rillig, 2017). Alternatively, visibility modelling of the landscape could produce a more accurate set of indicators (Foltête et al., 2020; Karasov et al., 2020; Tenerelli et al., 2017). Theoretically, these could capture more of the aesthetic quality of the landscape by providing a 3D perspective using the location of Flickr images. However, the challenge with visibility modelling at very large scales is the computational resources needed for the geo-spatial calculations (Labib et al., 2021). For example, in our case, the sightlines from 9.8 million images would need to be calculated using a 25×25 m Digital Elevation Model (DEM) for a 210,000 km² area. On the other hand, in the case of our Flickr model, the presence of image attributes including "far-away horizon" and scene classes such as "mountain" give the model a lot of indirect information on the 3D characteristics of an area.

The inclusion of individual spatial interactions offered by the Flickr and deep learning-based approach also makes it a more attractive method for ES modelling purposes. The comparable model accuracy versus the indicator model shows that this key methodological requirement from an ES perspective can be incorporated without significant losses in accuracy. The results also show that this individual perspective produces a finer-grained view which captures highly-valued and unique landscape elements such as rock or water features (Ode et al., 2008). For example, the highly aesthetic view of Achmelvich Bay in Scotland, shown in Figure 7. This is in contrast to the indicator model, which uses variables measured with remote sensing data at 25 m resolution and above. At the same time, important negative environmental contexts, such as Heathrow Airport in London (Figure 8), are also better captured by the Flickr model. Figure 8 also shows how the Flickr model stays relevant at different scales while simultaneously highlighting the scaling issues common to indicator models61. While the indicator model is heavily constrained by the scale of measurement, producing more extreme differences linked to land cover, the Flickr model is able to reproduce a more consistent view of the landscape using the images available to it (see also Supplementary Figure S6). At a national level, it appears that explicitly capturing this more nuanced view of the landscape through the scenic rating distribution, in combination with the strong overall predictive power of the indicator model, produces the highest level of model accuracy in our study.

In contrast to the static nature of the indicator approach, the granularity of the Flickr data also enables a detailed examination of aesthetics over time. The time-series analysis illustrated in Figure 11 shows how the aesthetic contributions of landscapes change over the course of a year in the national parks of Britain. The influence of seasonality on landscape quality, defined as 'ephemera' in the landscape aesthetics literature (Tveit et al., 2006), is notably captured. Such granularity can greatly benefit ES assessments requiring regular updates, such as those performed for the purposes of ecosystem accounting in the context of national annual accounts of economic production (Hein et al., 2020a). These results also show how the contributions of specific landscape characteristics to peoples' aesthetic enjoyment can be accurately captured using a social media and deep learning-based approach. The large prevalence of snow in images during the 2009/2010 winter is consistent with one of the last great snowfall events in Britain (Royal Meteorological Society, 2010). The consistency with remote sensing data further supports the reliability of the data. Understanding how ecosystems in the landscape contribute to individuals' aesthetic enjoyment of the landscape, and accurately tracking these contributions over time, can help

policy-makers manage and protect the most valuable natural areas for peoples' recreation and well-being.

Although the Flickr and deep learning approach has its advantages, some biases in the method should still be taken into account. By using the SoN database for training purposes, the models have largely learnt a British representation of aesthetic quality. For applications in other cultural and topographical contexts, additional fine-tuning will most likely be required. Challenges also lie in trying to gain an ES measure demographically-representative of the entire population. Flickr has been found to be the most popular with 40 to 60 year-old males (Lenormand et al., 2018) and user contributions, as in our study, are usually skewed by small, highly active user groups (Li et al., 2013). At the same time, a great number of differences in the content of images exist and not all images are relevant for measuring landscape aesthetics. However, in this respect, the user limitation in our study appears to have shifted the overall image content away from sporting scenes and more towards landscape images, improving model accuracy versus the SoN database. Notably, the agreement between the Flickr-based models, SoN and the environmental indicators shows that there is a strong consistency between the preferences captured by each dataset. This consistency is also promising for applications in other European contexts as the aesthetic concepts used to develop the environmental indicators have already been successfully applied in a number of European settings (Uuemaa et al., 2013).

3.5. Conclusion

In conclusion, landscape aesthetics are an important source of cultural value but large-scale measurement for ES assessments is difficult due to a lack of survey data. Now, social media offers the opportunity to measure the aesthetic contributions of ecosystems whilst integrating peoples' actual interactions with the environment, and tracking changes over time. In this study, we have demonstrated that models using Flickr images and deep learning enable a highly accurate measure of aesthetic landscape quality, with independence of the scale of measurement. This supports ES measures based on the revealed preferences of individuals rather than a set of broad theoretical concepts. Small gains in accuracy are also achieved when an explicit, deep learning-based measure of aesthetics in the form of an image rating distribution is combined with environmental indicator variables. Changes in the aesthetic contributions of landscapes over time can also be measured. Our results advance ES modelling to better capture the cultural contributions of nature to human well-being.

Chapter 4.

Deep learning and social media reveal specific contributions of biodiversity

Abstract. Biodiversity generates large contributions to human well-being. However, rarely are the cultural contributions of biodiversity to human well-being quantified at large scales in the form of Cultural Ecosystem Services (CES). We trained a deep learning model to capture peoples' interactions with selected flora and fauna on social media. We map the distribution of these interactions in Great Britain and compare user activity with citizen science data. We find that user activity is closely related to the accessibility of natural ecosystems and that urban green space plays a key role. Using a second, pre-trained deep learning model, we were also able to identify different preferences for individual species on social media versus citizen science. Finally, we compared peoples' cultural interactions with species richness and abundance for a group of 36 bird species, sometimes finding large differences between peoples' interactions and these ecological measures. Still, we found that peoples' interactions with a set of threatened migratory birds matched their presence in the country over time. Our findings show that deep learning and social media constitute powerful new techniques in capturing CES related to biodiversity and in understanding the cultural importance of biodiversity to achieve sustainable policy goals.

4.1. Introduction

The importance of biodiversity for human well-being is widely recognised (Bowler et al., 2010; Cardinale et al., 2012; Díaz et al., 2018). Alongside its intrinsic value, biodiversity generates a great amount of value for people through its contributions to a variety of instrumental and relational benefits (Chan et al., 2016). For example, contact with living species can improve an individual's mental health (Bratman et al., 2012; Hartig et al., 2003; Remme et al., 2021) while also contributing to better social relations (Herzog and Strevey, 2008; Kuo and Sullivan, 2001; Weinstein et al., 2015) and a stronger sense of collective identity (Chan et al., 2018; Hausmann et al., 2016). These contributions represent Cultural Ecosystem Services (CES) which can be broadly defined as ecosystems' contributions to the non-material benefits arising from human–ecosystem relationships (Chan et al., 2012a; United Nations et al., 2021) or, for more specific, quantitative purposes: information-flows contributing to cultural experiences (Havinga et al., 2020).

The complex socioecological relationships that determine the provision of CES by ecosystems require a wide range of methods to measure these services (Chan et al., 2012b; Daniel et al., 2012), all of which help encourage the inclusion of cultural values in environmental assessments and policy-making (Satz et al., 2013). For example, participatory mapping and deliberative approaches employing qualitative methods from the social sciences have been used to examine CES in local settings (Kenter et al., 2016; Klain and Chan, 2012). These approaches are able to represent the context-specific and situated knowledges in which ecosystems generate cultural value (Gould et al., 2020a). However, to inform decision-making at large scales, a level of generalisation is still needed (Gould et al., 2019a; Norton et al., 2012). The generalising perspective put forward by the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES) therefore suggests a universally applicable set of CES categories (Díaz et al., 2018), as does the System of Environmental-Economic Accounting Ecosystem Accounting (SEEA EA) framework which aims to better represent ecosystem value in national statistics (Edens et al., 2022; Hein et al., 2020a).

Generally, such large-scale applications require quantitative, spatially-explicit methods to measure CES (Gould et al., 2019a; Havinga et al., 2020). The spatial representation of CES supports assessments at multiple scales (Hernández-Morcillo et al., 2013), addresses issues of double-counting (Bagstad et al., 2013) and enables the identification of CES "hotspots'" to focus management efforts (Allan et al., 2015). However, these methods

are still faced with the challenge of capturing the large variety of preferences that underpin CES (Bieling and Plieninger, 2013) and in determining which ecosystem attributes are generating these services (Gould et al., 2019a). In particular, the connection between CES and biodiversity remains an underexplored area of research (Echeverri et al., 2020; Hevia et al., 2017; McGinlay et al., 2017), especially on a spatially-explicit basis (Gould et al., 2019a; Plieninger et al., 2013). Consequently, more investigation of CES provision and biodiversity is needed to better understand the complex interplay between CES and land management policies (Gould et al., 2020b), including those related to conservation (Echeverri et al., 2021; King et al., 2017).

In this context, spatial methods using social media data have gained an increasing amount of attention in CES applications (Ghermandi and Sinclair, 2019; Havinga et al., 2020). This is because social media data enables large-scale analyses of CES based on a wide range of self-reported, revealed preferences, with the level of detail necessary to identify specific ecosystem attributes as contributing factors (Havinga et al., 2021a; Richards and Friess, 2015; van Zanten et al., 2016). Still, research on peoples' spatial interactions with biodiversity on social media has so far been limited (August et al., 2020). More specific data for these purposes are available such as the data generated by eBird and iNaturalist, two citizen science platforms through which millions of amateur naturalists record their interactions with individual species (Havinga et al., 2020). Nevertheless, human-species interactions occur in numerous ways and citizen science initiatives do not capture the full range of peoples' interactions with biodiversity (Schröter et al., 2017). For example, a holiday trip can facilitate interactions with local biodiversity through wildlife photography (Hausmann et al., 2018). Closer to home, a walk in the park can lead to a number of casual interactions related to social and physical activities (Lopez et al., 2020).

Social media platforms therefore present themselves as promising sources of data in capturing a wider range of CES related to biodiversity. Flickr, an image-led platform, has already been broadly utilised in environmental research, offering a wide range of photography including images of individual species (Ghermandi and Sinclair, 2019). To process this data in large quantities, however, requires machine learning methods (Richards and Tunçer, 2018). Here, deep learning, which uses artificial neural networks to generate image predictions, has proven to be especially useful in examining CES and the biophysical elements generating these services (Egarter Vigl et al., 2021; Havinga et al., 2021a; Lee et al., 2022). In some recent examples using Flickr, deep learning models have accurately identified plant species (August et al., 2020), detected birdwatching activities (Koylu et al.,

2019) and classified the preferences of national park visitors (Väisänen et al., 2021). Meanwhile, deep learning is being directly integrated into citizen science platforms such as iNaturalist to support species classifications (Ceccaroni et al., 2019; McClure et al., 2020). On-going development work using the iNaturalist image database has also resulted in the release of tailored training datasets and pre-trained models for species detection (Van Horn et al., 2018).

These technological developments now enable large-scale CES analyses using social media. By utilising such large social datasets alongside citizen science data, large-scale CES assessments related to biodiversity can potentially include a greater diversity of preferences (Fox et al., 2021b; Scowen et al., 2021). At the same time, the detail with which particular aspects of biodiversity can be identified using deep learning, including individual species of flora and fauna, means that better connections can be made between biodiversity and CES (Echeverri et al., 2020; Gould et al., 2019a). For the purposes of large-scale CES assessments these points are particularly relevant (Havinga et al., 2020), especially if these are to contribute to national-level statistics (Hein et al., 2020a). On the other hand, the use of social media comes with a number of known biases including those related to sociodemographic factors and the accessibility of ecosystems (Levin et al., 2015; Toivonen et al., 2019). As a result, a closer examination of the CES that can be measured through the use of these novel techniques is important. In doing so, their contribution to environmental assessments can be better understood (Ghermandi and Sinclair, 2019).

The objective of our study is to assess the potential of deep learning and social media to measure CES related to biodiversity at large-scales. We focus on Great Britain as our case study area and use iNaturalist data to compare activity between social media and citizen science. In doing so, we seek to answer the following research questions: (1) what is the distribution of human-species interactions using Flickr data as a measure of CES related to biodiversity? (2) What species and species groups are users interacting with? (3) What is the relationship between users' activity and key socio-environmental and policy variables? (4) How do users' species interactions compare with biodiversity metrics? We hypothesised that most human-species interactions on Flickr occur in accessible areas and that urban green spaces are particularly important (Heikinheimo et al., 2020; Muñoz et al., 2020). We also hypothesised that Flickr users would have preferences for different species to users of citizen science data (Hausmann et al., 2018; Levin et al., 2017) and that these revealed preferences would not necessarily match ecological measures of biodiversity (Dallimer et

al., 2012). However, we expected that additional data could still be gathered on highly-valued species, such as those with special conservation status in Britain (Di Minin et al., 2015).

4.2. Methods

4.2.1. Study design

Our study focused on examining peoples' interactions with species using deep learning and Flickr images (Figure 12). We defined a human-species interaction as an image depicting an individual species as its main subject and broadly conceptualised these interactions as CES related to the cognitive enjoyment of biodiversity (Havinga et al., 2020). To capture peoples' interactions on social media, we first trained and applied a deep learning model using a novel training technique designed to capture a broad range of human-species interactions in Flickr images. To determine what species users were interacting with, we applied a second, pre-trained deep learning model to generate individual species classifications. We then explored the determinants of user activity using a set of socio-environmental and policy variables. For each of these steps, we compared our results to iNaturalist user activity to better understand social media as an alternative source of data. Finally, we compared users' interactions with bird population density data to examine the connection to species richness and abundance as well as preferences for threatened species.
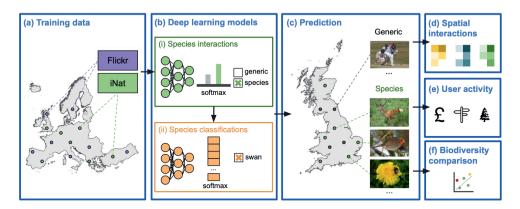
Figure 12. The overall study design. **(a)** Training data was collected using a random sample of Flickr and iNaturalist images within Europe. These were used to **(b)** (i) train a deep learning model to detect human-species interactions in Flickr images. Then, **(b)** (ii) the species depicted in these images were classified by a second, pre-trained deep learning model. Predictions were generated for **(c)** Great Britain. These were used to examine and compare **(d)** spatial interactions with species, **(e)** determinants of user activity and **(f)** biodiversity indicators using modelled population data for bird species.

4.2.2. Study area data

To apply our deep learning approach at national-scale in Great Britain, we used a Flickr image dataset created in previous research which provided 9.8 million geo-located images depicting outdoor scenes (Havinga et al., 2021a). These images were downloaded using metadata records retrieved through the Flickr Application Programming Interface (API) and filtered to outdoor images using the Places365 deep learning model (B. Zhou et al., 2017). At the same time, for comparison, we compiled a new dataset of research-grade iNaturalist observation metadata, including image urls, by using the 'rinat' package in R to access the iNaturalist API. In total, we downloaded 1.1 million iNaturalist records for Great Britain. The image corresponding to each record were accessed using the image urls during model prediction. Additional taxonomic information was downloaded using the 'taxize' package in R.

4.2.3. Species interaction model

4.2.3.1. Training data

To identify human-species interactions in images, we compiled a large dataset of images from iNaturalist and Flickr to train our deep learning-based species interaction model. For training, we used images uploaded to iNaturalist as a representation of peoples' interactions with individual species and Flickr images as a representation of all other, "generic" types of interactions to train our model. To download the images, we used the `flickrapi' library in Python to access the Flickr API and the 'rinat' package in R to access the iNaturalist API. We downloaded images using a randomly generated sample grid, representing a 10% random sample of a 25km resolution grid over the whole of Europe (Supplementary Figure S8). Within each grid cell, we downloaded an equal number of images from each source by randomly downsampling the greater image set in the case of imbalances. This produced a 50/50 training dataset of 1.3 million Flickr and iNaturalist images. Finally, the images were split into training (70%), validation (10%) and test (20%) sets.

4.2.3.2. Model architecture

Our model consisted of a ResNet-18 with an additional five layers replacing the two final layers (He et al., 2016). The model was developed using the 'PyTorch' library in Python. Using PyTorch's built-in model library, we downloaded the original architecture with the model weights pre-trained on the ImageNet database. We then adapted the model to produce a binary output, each converted to a 0-1 range using a softmax transformation. This

output represented either a human-species interaction, such as those observed on iNaturalist, or a generic interaction, consisting of any other kind of interaction. Generic interactions were only observable in the Flickr data and included, for example, images of buildings, sporting events, transport and landscapes.

4.2.3.3. *Model training*

Training was initialised with the model tasked to distinguish between images depicting human-species interactions and generic interactions. All iNaturalist images were labelled as human-species interactions and all Flickr images were labelled as generic interactions. We set our deep learning model to train on the image dataset for ten epochs with an initial learning rate of 1e05 for the weights of the final two layers and 1e04 for the rest of the network. The learning rate was halved every epoch. We used Adam as our optimisation algorithm and a cross-entropy learning loss (Kingma and Ba, 2014). Therefore the standard, cross-entropy loss for a single image during model training was calculated as:

$$\mathcal{L}(y, \hat{y}) = \sum_{i=1}^{C} y_i \cdot \log(\hat{y}_i) \qquad \text{EQ. 3}$$

with $\mathcal{L}$ denoting the loss calculated over y, the training labels, and $\hat{y}$, the model predictions, for C number of classes (two), with a softmax applied to the model class predictions before calculating the loss.

During normal training, the model is penalised if it identifies a Flickr image as a human-species interaction because all Flickr images are labelled as generic interactions. However, the Flickr image may still be of an individual species, in which case it is beneficial to introduce a level of leniency into the training scheme by adding noise to the image training label. This supports the inclusion of this type of Flickr image within the species image decision boundary of the final model (Figure 13). To do this, we applied a special minimum entropy regularisation technique in the training scheme to adjust the influence of the model's predictions versus their training labels in the case of generic-labelled images (Reed et al., 2015; Yves and Yoshua, 2006). Keeping the cross entropy learning loss unchanged for species-labelled images, we integrated a β regularisation coefficient in the learning loss for generic-labelled images as follows:

$$\mathcal{L}(y, \hat{y}) = \sum_{i=1}^{C} (\beta \cdot y_i + (1 - \beta) \cdot \hat{y}_i) \cdot \log(\hat{y}_i) \qquad \text{EQ. 4}$$

with $\mathcal{L}$ denoting the loss calculated over y, the training labels, and $\hat{y}$, the model predictions, with each training label y_i adjusted for the β coefficient. For example, if $\beta = 0.1$, this places a 10% emphasis on the original training labels, putting more trust in the predictions of the current model. On the other hand, if $\beta = 1$ this would represent the baseline model with only the training labels considered in the training. Model accuracy on the test set is reported in the results.
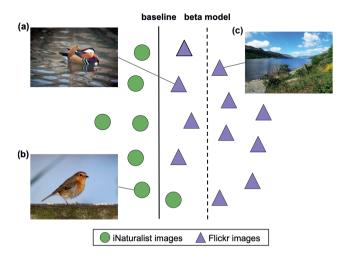
Figure 13. The effect of the β coefficient on the species interaction model's decision boundary. By placing a less strict emphasis on the training labels, applying the β coefficient allows more images within the Flickr dataset to be identified as human-species interactions. For example, image **(a)** joins image **(b)** as a human-species interaction as a result of the decision boundary being moved versus the baseline model, while image **(c)** is still predicted as a generic interaction.

4.2.3.4. Selecting the regularisation coefficient

To help identify the most optimal β regularisation coefficient, we calculated the entropy across the species classification scores predicted by the species classification model (introduced in Section 4.2.4) in Flickr and iNaturalist observation images in Great Britain. A much larger entropy across Flickr images predicted as human-species interactions as compared to generic image predictions and iNaturalist images would indicate a significant drop in model confidence and suggest the inclusion of irrelevant images as human-species interactions. We calculated entropy as:

$$H = \sum_{i=1}^{n=8142} P(\hat{y}_i) \cdot \log P(\hat{y}_i) \qquad \text{EQ. 5}$$

with H denoting the entropy across the 8,142 individual species classification scores $\hat{y}$. As an additional accuracy measure, we also conducted a visual check of the images predicted as human-species interactions in the test dataset at 0.1 softmax intervals for different regularised models. We report these results in Supplementary Table S11. Based on the model test accuracy statistics, the entropy across the species classification model's predictions and visual inspection of the predictions, the most optimal species interaction model was selected. This model was then used to predict the distribution of human-species interactions on Flickr in Great Britain.

4.2.4. Species classification model

To better understand the types of human-species interactions occurring on social media versus citizen science, we applied a second deep learning model to classify the individual species in Flickr images identified as human-species interactions and compared this with iNaturalist. Using the species classification model's predictions, we examined what the most popular species were at the genus level on Flickr versus iNaturalist. To make the fairest comparison and control for biases between datasets, we also ran the model on the images of the iNaturalist observations and used its predictions to compare the two datasets.

To classify species in images, we applied the pre-trained 2018 iNaturalist competition winner model, which is capable of detecting 8,142 species. The model consists of a fine-tuned Inception V3 deep learning model, pre-trained on ImageNet[2]. Because the model is trained to identify species sampled from a global geographic range, we were not primarily interested in using the individual species classifications as many would not be present in Great Britain. Rather, we were interested in their corresponding genus, family and class classifications, hypothesising that their accuracy would be sufficient to analyse the types of human-species interactions occurring.

Still, we felt it necessary to apply a second filtering step when conducting our analysis at the genus and family levels because model accuracy was found to be fairly low at these classification levels versus the taxonomic data associated with iNaturalist observations (Supplementary Table S12 and Table S13). This second image filter excluded all species images with a classification score entropy higher than 2.42. This cut-off point was identified based on the entropy distribution across the iNaturalist image predictions, 2.42 reflecting the mean entropy of image classification scores in the dataset (Supplementary Figure S9). At species class level this filter was not needed because accuracy at phylum level was already

---

[2] https://github.com/visipedia/inat_comp/tree/master/2018

found to be high at 89%. However, at genus and family level, accuracy needed to be improved to support the reliability of the results.

4.2.5. *Determinants of user activity*

To understand the factors influencing human-species interactions on Flickr, we modelled the relationship between these interactions and a number of socio-environmental and policy-related variables at 10km resolution. We then did the same for iNaturalist observations and compared the influence of the explanatory variables. In this case, our aim was to examine broad determining factors influencing user activity related to human-species interactions rather than every single interaction with individual species. We therefore restricted the number of images and observations per user per grid cell to one image or observation per user per day. This limited the effect of a small group of very active users. We used multiple linear regression, drawing on the 'caret' and 'AICcmodavg' packages in R.

Four sets of variables were considered (Table 5). First, the relationship between user activity and the accessibility of nature was modelled. We used population density as a proxy, with a higher population density indicating a greater amount of accessibility due to the shorter distances to peoples' homes and the associated infrastructure enabling access. For population density, we used the Office for National Statistics (ONS) and Scottish statistical office population density figures per lower administrative unit. These have an average area of 6km². For every 10km resolution grid cell, we took the mean population density of the intersecting administrative units.

Following this we generated a second and third set of models using policy-related and socioeconomic variables. For policy, we calculated the total area of urban green space and Special Areas of Conservation (SACs) per grid cell. Urban green space plays an important role in urban planning designs to provide people with access to nature while SACs are protected areas set up to conserve a variety of wild animals, plants and habitats. To represent socioeconomic factors, we included the mean total weekly income and mean age of the population in the intersecting administrative units of each 10km grid cell, sourced from the ONS and the Scottish statistical office.

Finally, we generated a fourth set of models based on environmental factors using the European Environmental Agency (EEA) ecosystem type map. For this, we calculated the total area of coastal, water, bog, grass, heath, wood, scree and farm ecosystem per grid cell to understand how this could affect the level of user activity. We calculated total area to

consider the likely interaction within each grid cell. As well as examining the accuracy of each set of models on their own, we also generated models using combinations of the variable groups to understand the total amount of explanatory power provided by the variables. To test the accuracy of the models, we overlaid a 50km resolution grid over the 10km grid and randomly split the larger grid cells into 5 cross-validation sets. We compared model fit using the Akaike Information Criteria (AIC) and R^2 statistics.

Table 5. Socio-economic and policy variables.

Group	Variable	Datasets	Sources
Accessibility	Population density (persons / km²)	ONS Mid-2019 LSOA Population density	(ONS, 2019)
		Statistics Scotland Datazone population Mid-2019	(Statistics Scotland, 2019)
Policy	Urban green space (km²)	OS Open Green Space	(Ordnance Survey, 2021)
	SAC (km²)	Special Areas of Conservation spatial boundaries	(JNCC, 2020)
Socio-economic	Mean weekly income (£ / week)	Mean weekly income & Income estimates for small areas, England and Wales	(ONS, 2014)
		Scotland Local Level Household Income Estimates	(Statistics Scotland, 2014)
	Mean age (years)	Population - all usual residents	(NOMIS, 2011)
Environmental	Ecosystem types (km²)	EEA ecosystem types of Europe	(EEA, 2019)

4.2.6. Connection to biodiversity

4.2.6.1. Bird species richness

To compare the human-species interactions on Flickr with ecological measures of biodiversity, we compared the perceived species richness of bird species on Flickr with a measure of species richness based on modelled species density data. To do this, we selected a group of bird species and drew on species abundance maps to spatially compare the variety of species in Flickr images with the variety in modelled bird densities at 10km² resolution (Massimino et al., 2015). To better understand the variation in species richness as compared to citizen science, we also compared to the species classification models' prediction in iNaturalist observation images and mapped population density as an additional point of reference.

The bird species abundance maps were generated in previous work using Generalised Additive Models (GAMs) \citep{Massimino2015}. These modelled species abundance per km² at 1km resolution using explanatory variables including the percentage of different land cover types such as forest, grassland, coastal and urban land cover, as well as a three-dimensional thin plate penalised spline with longitude, latitude and elevation. The models also accounted for the detectability of bird species. We calculated the total number of birds at 10km² and then, to compensate for the high variability in population density across species, we counted a species as present if the density per bird species was greater than its median density. As such, our indicator of species richness using modelled abundance data can be regarded as a high-likelihood measure of species presence on a grid cell basis.

We selected 36 bird species. This included a wide range of species from a number of different habitats including Kestrels, Swallows, Goldfinchs, Mallards, Curlews, Great Tits and Swifts. In some cases we grouped the modelled densities of individual bird species within the same genus to enable a better comparison with the species classification models' predictions at genus level. This was because the models' predictions were more reliable at this taxonomic classification level. As with the bird density maps, we counted the number of bird species in Flickr images per 10km² grid cell using the species classification models' predictions.

In most cases, we used the predictions of the model at the genus level for comparison with individual species. However, in some cases the visual variety within the genus was deemed to be too great to accurately capture the individual species in the bird density maps. In this case, we excluded some of the species models' predictions for individual species classifications within the genus. In other cases, it was more appropriate to group the models' predictions at the family taxonomic level. A full list of the species densities used, the corresponding species classification model classes and justifications can be viewed in Supplementary Table S14.

4.2.6.2. *Bird species abundance*

To examine the relationships between people and bird species in more detail, we also compared the total number of human-species interactions on Flickr with the 36 selected bird species and their total population. In doing so, we sought to gain an insight into the popularity of bird species versus their relative abundance. We did this by summing the modelled bird population densities per 10km² grid cell and comparing this to the total number of Flickr interactions per species. To better understand the individual relationships

between species interactions and total population, we fitted a linear model to capture the overall relationship between the two variables. At the same time, we also considered their conservation status in Britain to understand whether this had an effect on the preferences of Flickr users, adding this as a categorical variable to the linear model to test for significance.

4.2.6.3. Threatened migratory species

Finally, we also examined interactions over time on Flickr and iNaturalist with threatened migratory bird species. In doing so, we sought to understand peoples' preferences for a set of culturally significant and highly-valued species from a conservation perspective. At the same time, this also allowed us to validate the interactions against known migratory periods as well as verified iNaturalist observation data. Four migratory bird species were examined: the Nightingale (*Luscinia megarhynchos*), Swifts (*Apodidae*), Turnstones (*Arenaria*) and Wheatears (*Oenanthe*). We filtered the species classification model predictions using these individual and taxonomic groups with a species model class entropy score < 2.42.

The Nightingale is an iconic but threatened species in Britain. It has a great cultural resonance, being widely represented in music, art and literature. Its breeding season in Britain begins in mid-April and extends into early July. By mid-July, its autumn migration to Africa begins with the species becoming very scarce by September (Holt et al., 2012). Similarly, swifts, which also feature prominently in British culture, arrive in Britain from Africa in mid-May and begin their autumn migration between the end of July and early August (Hurrell, 1951). Both species feature on Britain's Birds of Conservation Concern Red List (Stanbury et al., 2021).

Turnstones, a coastal bird species, have two main migratory populations in Britain. The first arrive from Greenland and arctic Canada to winter in Britain in early August, many staying on till early March. At the same time, another large migratory population passes through in August on its way to Africa from the Scandinavian countries, returning again through Britain in the spring (Branson et al., 1978). These migratory patterns are similar to those of the ground-dwelling Wheatear with one migratory population arriving from Africa to breed in Britain in March/April while another continues on to Greenland. Both populations are seen returning to Africa in Britain between August and October (Bairlein, 2008). The Turnstone and the Wheatear are on the Amber List of Britain's Birds of Conservation Concern (Stanbury et al., 2021).

4.3. Results

4.3.1. *Species interaction model*

The accuracy of the species interaction models trained using different β coefficients is shown in Table 6. The overall accuracy of the models on the test dataset decreased with the value of the β coefficient. The overall accuracy of the baseline (β=1) model was high, at 98%. The β=0.1 model achieved a similarly high 97% accuracy, followed by the β=0.01 model with a 96% accuracy and the β=0.001 model, with an accuracy of 92%. Increasing the value of the β coefficient by another factor of 10 to β=0.0001 failed to produce a working model.

Table 6. Overall accuracy of the species interaction model on the test dataset using different β regularisation coefficients and the species classification entropy associated with each models' predictions for the Flickr image dataset in Great Britain. In comparison, a mean entropy of 2.42 was reported against the iNaturalist observation dataset.

Model	Test: Overall	Test: generic interactions	Test: species interactions	Entropy: species interactions	Entropy: generic interactions
β=1	98.0%	98.5%	97.5%	2.83	5.19
β=0.1	97.4%	99.4%	95.4%	2.89	5.27
β=0.01	95.5%	99.8%	91.2%	3.05	5.34
β=0.001	92.2%	99.9%	84.5%	3.56	5.40

The drop in accuracy in detecting generic interactions in Flickr images can be directly related to the human-species interactions that are also found within the Flickr dataset. This was also reflected in the ability of the β=0.001 model to predict images from iNaturalist as human-species interactions with almost perfect accuracy. This shows how the regularisation coefficient enables the model to detect a wider range of human-species interactions. However, there was a much larger drop in accuracy in detecting generic interactions relative to this accuracy improvement and versus the accuracy of the baseline model. We therefore found the β=0.01 model to be the most optimal in terms of its accuracy on the test dataset, maximising its ability to detect human-species interactions while maintaining a high level of overall accuracy.

For each β model's image predictions of human-species interactions, we also calculated the mean entropy across the species class scores predicted by the species classification model. We found entropy to increase from 2.83 for the baseline model to 3.56 for the β=0.001 model. This amounted to a 26% increase. For the β=0.1, a much smaller

increase of 2% to 2.89 was observed, with a small increase of 8% for the β=0.01 model. The entropy recorded against the models' generic image predictions stayed relatively similar, only increasing from 5.19 for the baseline to 5.40 for the β=0.001 model. In comparison, the entropy recorded for the species model predictions on the iNaturalist dataset for Great Britain was 2.42.

A full set of randomly sampled images of each β models' predictions at different confidence levels can be found in Supplementary Table S11. Overall, we observed a good ability by the β=0.01 model to identify species images, even at low confidence levels, with a very small amount of generic-type images present among the models' predictions. Based on these results, the test accuracy and species model entropy, we selected the β=0.01 model to predict human-species interactions using Flickr images in Great Britain.

4.3.2. Human-species interactions

Table 7 shows the total number of species interactions and interactions per user on Flickr for the main taxonomic groups. In all cases, the median number of images per user was quite low at 1 to 2 images. Birds were the most popular species with 352,177 images taken by 24,936 users. These saw the highest average amount of 14.1 images per user with one user taking 21,560 images. Plants were the second most popular species, with 261,948 images taken by 24,572 users, similar to birds. The maximum number of images taken by one user was much lower at 3,304 images. Insects were captured in 136,738 images by 12,553 users, about half of the level of activity for plants, with a similar average number of images per user. Mammals were captured by more users than insects, with 15,871 users, but there were less images at 89,095 interactions. Reptiles and Fungi saw a further drop in the number of interactions and users. In total, the species interactions model identified 950,601 images, representing 44,404 users. These took on average 21.4 species images each with one highly active user taking 28,457 images.
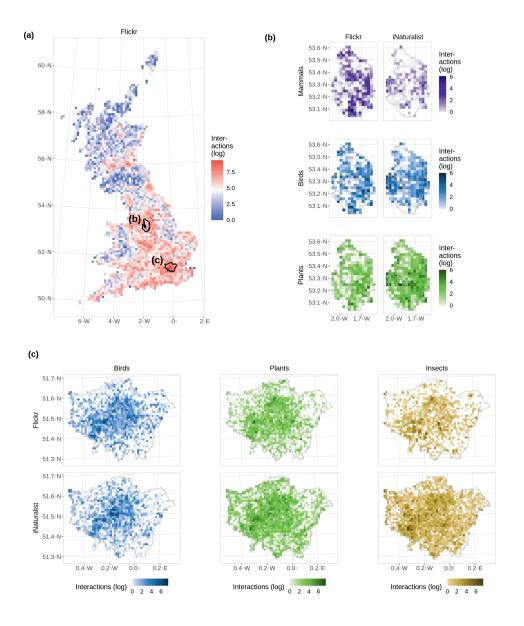
Figure 14 shows the spatial distribution of species images on Flickr in Great Britain, and is compared to iNaturalist observations at a more local-scale for different species groups in the Peak District and Greater London area. At national-scale, human-species interactions were concentrated around urban areas with large cities such as London, Birmingham, Manchester, Edinburgh and Glasglow showing some of the largest concentrations of interactions. On the other hand, higher elevation areas such as Snowdonia National Park in Wales, the North Pennines in England and the Scottish Highlands showed very little amounts of interaction.

Table 7. The total number of human-species interactions per user and taxonomic class on Flickr.

Species	Number of images	Number of users	Images per user (median)	Images per user (mean)	Images per user (max)
Birds	352,177	24,936	2	14.1	21,560
Plants	261,948	24,572	2	10.7	3,304
Insects	136,738	12,553	2	10.9	4,637
Mammals	89,095	15,871	1	5.61	4,320
Reptiles	31,596	9,106	1	3.47	964
Fungi	19,853	5,147	1	3.86	1,152
Other	59,194	23,071	1	2.57	532
Total	**950,601**	**44,404**	**2**	**21.4**	**28,457**

At a more local scale, differences in the types of human-species interactions occurring on Flickr versus iNaturalist could be observed. Flickr users appeared to have a stronger preference for mammals, as observed in the Peak District, with similar levels of interaction with birds species in both the Peak District and Greater London area, although in different areas. For plant species, Flickr users showed lower levels of interest as compared to iNaturalist, both in the Peak District and Greater London area. This difference was even more pronounced for insects, as observed in the Greater London area, with a much large number of interactions on iNaturalist versus Flickr.

The tendency of Flickr users to capture large, common species was also evident at the genus classification level (Figure 15). Flickr users took the most pictures of swans, ducks and robins. Herons were also popular, as where black geese, squirrels, deer, gulls, thrushes and white/grey geese. In comparison, iNaturalist users took the most pictures of butterflies with three genera appearing in the top ten most popular classes. Geraniums, lady bugs, honey bees and clover where also popular, again reflecting a much larger interest in plants and insects versus Flickr users. However, similar to Flickr, ducks, swans and thrushes were also captured a large number of times. Notably, the number of images per species was also more evenly distributed on iNaturalist than on Flickr.

Figure 14. Distribution of **(a)** all human-species interactions on Flickr in Great Britain at 10km resolution, **(b)** human-species interactions by taxonomic class on Flickr and iNaturalist in the Peak District at 2.5km resolution, as well as **(c)** human-species interactions by class and source in the Greater London area at 1km. A full species count comparison between Flickr and iNaturalist at the national level can be found in Supplementary Figure S10.
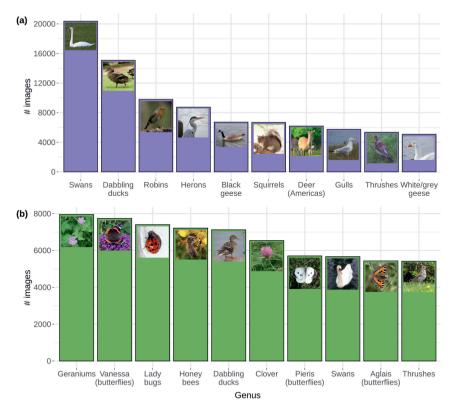
Figure 15. The most popular genera predicted by the species classification model in **(a)** Flickr species images and **(b)** iNaturalist observation images. Photos (top left to bottom right) © sagesolar}, Peter Trimming, Peter Trimming, Gareth Williams, Steve Parker, Peter Hurford, Daniel, Ron Knight , Julian Burgess, Daniel Cahen , William Stephens , Barry Walter, William Stephens, Stephen McWilliam, Daniel Cahen, Barry Walter, Jon Mortin Alec Mcclay, Don Loarie , (cc-by-2.0 and cc-by-4.0, cropped from originals). Species model accuracy statistics against the iNaturalist observation dataset can be found in Supplementary **Table S13**.

4.3.3. *Determinants of user activity*

Table 8 shows the linear model results using various combinations of explanatory variables to predict user activity relating to human-species interactions on Flickr versus iNaturalist in Britain. The AIC and R^2 statistics are used to measure and compare model fit. Combining all the explanatory variables produced the best model in predicting user activity on Flickr based on the AIC. This was the same for iNaturalist activity and, overall, the explanatory power of the various variable combinations was similar for both Flickr and iNaturalist. However, the variable combinations provided the most explanatory power for the distribution of Flickr interactions as compared to iNaturalist. For example, using the R^2 statistic to compare between platforms, all the variables combined produced an R^2 of 0.603 for Flickr versus 0.530 for iNaturalist.

Table 8. Linear regression model results per data source using different combinations of explanatory variables. The AIC is calculated using a final model fitted on the entire dataset while the R² is calculated using five-fold cross validation. AIC weights represent the probability of the model being the best model.

Model*	AIC	Delta	AIC weight	R²
Flickr				
Sac	39,205	2,624	0	0.012
Env	39,073	2,492	0	0.054
Socio	38,674	2,093	0	0.170
Urb	37,238	657	0	0.517
Pop+Env	37,169	588	0	0.517
Pop	37,168	587	0	0.525
Pop+Pol	36,758	177	0	0.587
Pop+Socio+Pol	36,587	5.38	0.064	**0.606**
Pop+Socio+Pol+Env	**36,581**	**0**	**0.936**	0.603
iNaturalist				
Sac	41,234	2,178	0	0.013
Env	41,136	2,080	0	0.042
Socio	40,747	1,691	0	0.153
Urb	39,526	69	0	0.469
Pop+Env	39,511	454	0	0.463
Pop	39,504	448	0	0.474
Pop+Pol	39,156	99.5	0	0.524
Pop+Socio+Pol	39,057	0.687	0.415	**0.532**
Pop+Socio+Pol+Env	**39,056**	**0**	**0.585**	0.530
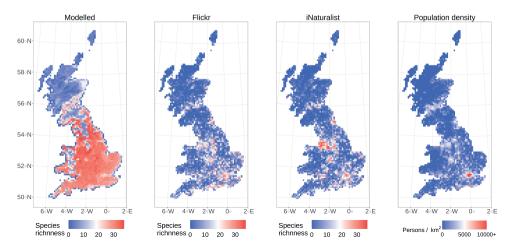
Notably, the variables population density and urban green space both independently explained around 50% of the variance in activity on both platforms. This highlights the accessibility of natural ecosystems as a major factor determining the amount of user interactions with species, if population density is taken as a proxy. Similarly, urban green space appear to play a major role in determining the distribution of user activity. On the other hand, socioeconomic variables did not provide a significant amount of explanatory power but did produce the strongest models in combination with other variables. This was in contrast to the environmental variables, which did not add any significant explanatory

power to the models. The presence of SACs were also not found to be a major determining factor, producing the weakest models for both Flickr and iNaturalist user activity.

4.3.4. Connection to biodiversity

4.3.4.1. Bird species richness

Figure 16 shows a comparison of species richness based on models of species abundance versus perceived species richness on Flickr and iNaturalist for a selected group of 36 bird species. Most of England and Wales saw a high level of species richness, with reductions in large urban areas such as London, Birmingham and Manchester. On the other hand, very low species richness was recorded in higher altitude areas such as Snowdonia National Park in Wales, the Yorkshire Dales and the Peak and Lake Districts. Similarly, the high altitude areas of Scotland including the Scottish Highlands also saw low bird species richness. However, richness increased further south in Scotland around key urban centres such as Edinburgh and Glasgow.

Figure 16. Species richness for a selection of 36 bird species calculated using models of species abundance, in comparison to the perceived species richness observed on Flickr and iNaturalist using the deep learning model predictions. Population density is shown as an additional point of reference. The maps show very different perceptions of species richness on Flickr and iNaturalist linked to high population areas versus a measure based on modelled abundance data.

In contrast, the perceived species richness on Flickr was mainly concentrated around highly-populated areas such as in London and large cities in the north including Birmingham, Sheffield and Leeds. Coastal cities also saw a large variety of species captured by Flickr users, including Portsmouth and Exeter in the south. One notable exception were the coastal and wetland areas on the northern coastline of Norfolk, England which saw a

concentration of perceived richness away from a major urban centre. Also notable was the moderate amount of species richness perceived in some higher elevation areas such as in the Peak and Lake Districts, even in the northern part of the Cairngorms national park, in contrast to the species richness based on models of species abundance.

Higher perceived species richness in urban areas also occurred on iNaturalist. These occurred in similar cities such as in London and Edinburgh as well as the large cities in the north including Birmingham and Sheffield. However, notably, a much larger number of species were observed in and around the cities of Liverpool and Manchester. Higher elevation areas including the Lake and Peak Districts as well as similar parts of the Cairngorms, like Flickr, saw moderate amounts of perceived species richness. The higher level of perceived richness on the north coast of Norfolk was also observed for iNaturalist.

4.3.4.2. Bird species abundance

Figure 17 shows the comparison between peoples' interactions on Flickr with 36 bird species and species population as well as their conservation status. A weak relationship was found between the two variables based on the linear model (R^2 = 0.17). A general divide can also be observed, as highlighted by the line of best fit, which shows two general groups of species. One group, below the line of best fit, see less interactions relative to their overall abundance while another group, above the line of best fit, see more interactions relative to their abundance. This pattern is most prominently featured towards the left-side of the figure with large, charismatic and visible birds such as the Kestrel, Buzzard, Great Spotted Woodpecker and Nuthatch experiencing a large number of interactions relative to their population. Similarly, coastal and wetland birds such as the Curlew, Moorhen and Mallard also see a much larger amount of interactions versus their population.

Bird species that experienced similar levels of interactions versus their population included the Goldcrest, Magpie, Goldfinch, Great and Blue Tit as well as Thurshes, Crows, the House Sparrow and Pigeons. On the other hand, other small birds such as the Long-tailed Tit, Coal Tit, Meadow Pipit and Warblers saw less interactions relative to their abundance. Similarly, the Skylark saw a lower relative amount of interaction versus its total population. Swifts and the Green Woodpecker experienced very little amounts of interaction relative to their small population sizes. Overall, conservation status did not determine any kind of relationship between interactions and species abundance as an additional categorical variable to the linear model (Amber, p-value=0.4 and Red, p-value=0.7, R^2=0.14).
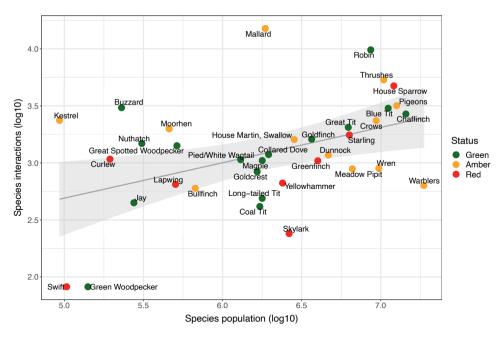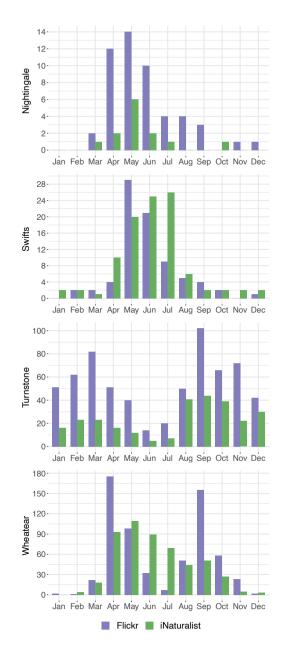
Figure 17. The total interactions on Flickr for a selection of 36 bird species compared to their total population and conservation status in Britain. The grey line shows the line of best fit between interactions and total population with 95\% confidence intervals (R^2=0.17). This shows a weak overall relationship and highlights a division between species with higher and lower popularity relative to their abundance. Conservation status was not found to be significant when it was added as an additional categorical variable to the linear model (Amber, p-value=0.4 and Red, p-value=0.7, R^2=0.14).

4.3.4.3. Threatened migratory species

The total monthly interactions on Flickr and iNaturalist with four threatened migratory species are shown in Figure 18. The Nightingale saw no or less than one interaction per month from October to February. In line with its spring migration, interactions started increasing from March up till May at which point interactions began falling again to September. There were a much larger number of interactions on Flickr versus iNaturalist. Swifts saw a similar pattern of monthly interactions with interactions increasing from a very low baseline in April up into the summer months of June and July, before dropping off in August. This matched its known migration to Britain in spring and autumn migration out of the country in late summer. In this case, there were similar amounts of interactions on Flickr versus iNaturalist with interactions on Flickr weighted towards the spring months and iNaturalist observations towards the summer months.

Figure 18. Total monthly interactions on Flickr and iNaturalist with migratory bird species of conservation concern.

A different pattern in monthly interactions was observed for the Turnstone. In contrast, interactions peaked twice in the year in line with its two known migrations in the year. June and July saw the lowest amount of interactions, with interactions increasing up to the late

summer and early winter months, before decreasing to a lower level, although higher than the lows in June and July. Interactions then peaked again around February and March. As with Nightingales, there were a much larger number of interactions on Flickr than on iNaturalist. Lastly, for the Wheater, two peaks in the number of interactions were also observed which were again much more pronounced on Flickr than on iNaturalist. The first peak occurred in April/May and the second in August/September. This was also in line with its known migrations in the spring and autumn. However, a slightly different pattern was observed in the interactions occurring on iNaturalist with much more interaction occurring on iNaturalist in June and July in comparison to Flickr.

4.4. Discussion

4.4.1. *User preferences*

The results of our study reveal key differences between the interactions occurring on social media and citizen science. This was in line with our hypothesis that Flickr and iNaturalist users would express different preferences for individual species. Flickr users mostly shared their interactions with large, charismatic species, common to urban areas, with birds as the most popular type of species. This was in contrast to iNaturalist users, who were most interested in smaller species, including plants and insects. This trend was also visible at a spatial level, with users' activity concentrated in different areas. For example, in the case of peoples' interactions with bird and plant species in the Peak District (Figure 14). Our results are similar to those of other studies that show large-bodied mammals and birds are more frequently captured on Flickr versus iNaturalist, as well as other social media sites and surveyed preferences (Hausmann et al., 2018; Lopez et al., 2020). This may be because Flickr users can more easily capture these type of animals from a distance with high-specification cameras (Singla and Weber, 2011). As a result, Flickr can be a good additional source of data alongside citizen science data due to the number and variety of interactions occurring in the same locations (August et al., 2020; Mancini et al., 2018). These findings support the need to include a wider diversity of preferences in CES assessments using large social datasets (Gould et al., 2020b; Scowen et al., 2021).

Nevertheless, although we found differences in user preferences between platforms, these may only reflect the varying preferences of a small number of people (Mancini et al., 2019; Tenkanen et al., 2017). We discovered strong user biases within our results such as the 28,457 human-species interactions occurring through one user, about 3% of the total number of interactions (Table 7). For large-scale assessments, including national assessments, it is

important that a representative sample is collected (Hein et al., 2020a; Raymond et al., 2014). These biases therefore present a key challenge in capturing a complete range of preferences using these new methods (Ghermandi and Sinclair, 2019). Still, these biases highlight the importance of using a combination of data sources as these may prove to be complementary in gaining a more representative measure of CES (Tenkanen et al., 2017; Wilkins et al., 2022). Our study also highlighted how combining multiple data sources with a spatial approach can help in identifying a greater number of potential CES hotspots despite user biases (van Zanten et al., 2016).

4.4.2. Spatial patterns

One common pattern to user behaviour between Flickr and iNaturalist were the large concentrations of interactions in urban areas. Through our linear model analysis, we found the accessibility of nature and urban green space to be key determinants of user activity on both platforms. The importance of urban green space for human well-being is well-documented (Gómez-Baggethun and Barton, 2013; Remme et al., 2021). However, similar to previous studies, we found human-nature interactions on Flickr to be especially associated with urban green space (Ilieva and McPhearson, 2018; Lopez et al., 2020; Song et al., 2020). This was also visible based on the most frequent species captured with all top ten genera common to local parks in Britain. The most frequent species captured on iNaturalist also point to the importance of private gardens in generating CES, with many of the smaller species including butterflies a feature of these small patches of vegetation in populated areas (Owen and Owen, 1975). On the other hand, SACs were not found to be related to user activity, despite their significant cultural importance (Environmental Audit Committee, 2021). Similar to Mancini et al. (2019), we found that these areas of high conservation value did not see a corresponding level of human-species interactions on social media.

4.4.3. Bird biodiversity and conservation

A further mismatch between peoples' perceptions of biodiversity and actual biodiversity was found in our comparison of user-bird interactions and modelled abundance data. While some studies have found a connection between higher levels of biodiversity and cultural appreciation (King et al., 2017; Lindemann-Matthies et al., 2010), our comparisons at national level did not. For example, the perceived species richness of the 36 selected species on Flickr and iNaturalist was highest in urban areas. A misalignment between peoples' perceived and actual biodiversity has been reported in similar studies at smaller scales (Belaire et al., 2015; Dallimer et al., 2012; Graves et al., 2017). Preferences for bird species also showed no clear

relationship with conservation status, nor were interactions necessarily related to species abundance. This further highlighted the effect of species visibility in terms of size, charisma and preferred habitat on the level of interaction. For example, the large number of interactions with Kestrels and Buzzards relative to their total population can be related to their iconic status, size and presence in the skies above open farmland. In contrast, other birds with less amounts of interaction such as the Meadow Pipit and the Skylark, besides its brief song flight, are mostly inconspicuous on the ground, or Warblers, which are fast-moving and prefer woodland (Sharrock, 1976).

Still, our time-series analysis captured interactions with a set of threatened migratory species during known migratory periods. This showed how the use of social media data can still enable an accurate analysis of how people express preferences for highly-valued species from a conservation perspective (Di Minin et al., 2015). Notably, interactions were also much higher on Flickr versus iNaturalist. Nevertheless, generally the weak connection between interactions and both species and areas of high conservation value shows how social media can only reveal specific cultural contributions of biodiversity. That is, CES captured through the methods employed in our study are most useful in determining the value of highly-accessible nature which may not be under the same level of conservation management as more remote, protected areas. For example, urban parks can play a critical role in local biodiversity conservation (Aronson et al., 2017). The CES captured using social media can therefore provide vital support for urban conservation policies (Andersson et al., 2015). In Britain, this includes the proposed Natural Recovery Network which aims to link protected sites with green and blue urban infrastructure (The Wildlife Trusts, 2018). In doing so, this would support the creation of multi-purpose habitats for both recreation and biodiversity (Hansen and Pauleit, 2014).

Our comparison, however, only considered species richness in terms of the 36 bird species we selected. Considering a larger group of species across different taxonomic classes may reveal stronger relationships. The use of a median threshold to count a bird species as present using the modelled data may also have affected our comparison as this value may not be appropriate for all species (Nenzén and Araújo, 2011). In addition, we relied on the accuracy of the species interaction and classification models to generate image predictions. A large user study could be conducted to definitively measure model accuracy. Alternatively, the use of user-generated metadata associated with Flickr images, such as tags and descriptions could also be used to confirm prediction accuracy (Havinga et al., 2021b). Applying more conservative filters to image predictions is also possible. For example, we

saw significant improvements in the accuracy of the species classification model after applying the maximum entropy filter of 2.42 (Supplementary Table S12) which resulted in the majority of the most frequently captured genera being identified with 70% accuracy or more (Supplementary Table S13). This strengthened the reliability of our results.

4.4.4. Large-scale CES assessment

Finally, the specificness with which CES can be measured using social media and deep learning presents both challenges and opportunities in conducting large-scale CES assessments. The key challenge facing decision-makers in ecosystem management is how to integrate culture in a way that both reveals its diversity and makes it amendable to systematic appraisal (Fish et al., 2016). The scale and level of detail provided by social media and deep learning enable the systematic appraisal of CES at large scales (Egarter Vigl et al., 2021). Such appraisals can support the quantification of CES beyond simple scoring methods (Boerema et al., 2017) and better link ecosystem condition and processes to CES (Gould et al., 2020b). For example, we were able to identify specific species and locations generating CES in our study, and capture changes related to threatened bird species through the seasons. This is especially relevant to ecosystem service assessment frameworks such as the SEEA EA which aim to connect CES measurements to national statistics while monitoring ecosystem service supply and ecosystem condition over time (Hein et al., 2020a, 2015). Making such information available, and in a format compatible with frameworks such as the SEEA EA, is one important way in which to make the ecosystem service concept more relevant to decision-making (Mandle et al., 2021).

However, in seeking to capture CES at large-scales, deep learning and social media-based methods take on a reductionist approach to CES assessment which may ignore important context-specific meanings (Gould et al., 2020a). We approached our study of CES in very broad terms, relating human-species interactions to the cognitive enjoyment of biodiversity (Havinga et al., 2020). Still, there are many different individual, collective and sometimes overlapping contexts in which CES are generated and these may have varying degrees of value (Chan et al., 2012b; Fish et al., 2016). Much of this value may not be measurable through the quantification of single human-species interactions because not all are recorded on social media (Calcagni et al., 2019) or because they only emerge through deliberative approaches (Kenter et al., 2016). Nevertheless, the data that is available through social media does make it possible to untangle some of this cultural variation. For example, the text data associated with Flickr images can contain quite specific motivations for

peoples' interactions (Havinga et al., 2021b). At the same time, social media also offers the opportunity to examine collective experiences through the presence of virtual communities (Langemeyer and Calcagni, 2022). It is therefore still important to use a variety of approaches to CES assessment with different epistemological underpinnings (Raymond et al., 2014; UK NEA, 2014).

4.5. Conclusion

Our findings show that deep learning and social media reveal specific contributions of biodiversity to cultural well-being. Peoples' species interactions on social media were found to be closely linked to the accessibility of nature and peoples' perceptions of biodiversity based on a selected group of bird species did not always match ecological measures. The use of social media and deep learning is therefore most useful in determining the cultural contributions of accessible nature, especially in urban settings. Here, the use of social media alongside citizen science data captures a greater variety of preferences due to the differences in user activity between platforms. These preferences can then be linked to specific biophysical attributes in terms of spatial location and species classes using deep learning, including preferences for species of conservation concern over time. These novel techniques can therefore make key contributions to large-scale CES assessments. In doing so, the cultural value of nature can be better represented in ecosystem service assessments to achieve sustainable policy goals.

Chapter 5.

Understanding the sentiment generated by cultural ecosystem services using social media and natural language processing

Abstract. Social media is increasingly being employed to develop Cultural Ecosystem Services (CES) indicators. The image-sharing platform Flickr has been one of the most popular sources of data. Most studies, however, tend to only use the number of images as a proxy for service supply quantity, but this does not fully represent the benefit generated by ecosystems in terms of peoples' positive experiences. To address this gap, we apply a number of natural language processing (NLP) models to measure the sentiment associated with Flickr-based CES estimates using the accompanying text posted by users. We find that the aesthetic quality of the landscape and the presence of particular species results in higher levels of sentiment. However, we also find that different biophysical settings influence this sentiment and that sentiment is sometimes more strongly related to social activities than many natural factors. Nevertheless, we find clear connections between CES and sentiment captured on social media and a national, geo-referenced survey of recreational well-being. Our findings illustrate that using only the number of images to establish CES indicators using social media may ignore the varying degrees of CES generated by nature. The additional detail provided by these novel techniques can also help policy makers identify optimal biophysical features for recreational land use management.

5.1. Introduction

The experience of nature generates a great amount of human well-being (Chang et al., 2020; Russell et al., 2013). Peoples' interactions with individual species and ecosystems at the landscape level contribute to a number of benefits including better mental and physical health (Sandifer et al., 2015). These contributions can be broadly defined as Cultural Ecosystem Services (CES) which capture the contributions of ecosystems to the non-material benefits arising from human-nature interactions (Chan et al., 2012a). For example, human-ecosystem interactions with individual flora and fauna can produce a level of cognitive enjoyment related to biodiversity (Keniger et al., 2013) while also generating feelings of aesthetic appreciation at the landscape level (Bratman et al., 2012).

The benefits derived from CES are closely tied to the positive experiences generated by human-nature interactions (Havinga et al., 2020). Such experiences are currently under threat as opportunities to experience nature and develop positive emotional attachments have decreased with increasing urbanisation and the rise of alternative multisensory experiences such as electronic media (Soga and Gaston, 2016). Termed the "extinction of experience" (Miller, 2005), this decrease in human-nature interactions, and the positive sentiment attached to these experiences, has motivated calls for careful land use planning and management to reconnect people with the natural environment (Abson et al., 2017).

However, land management policies, especially at large scales, are often restricted by the amount of quantitative, spatially-explicit information available (Edens et al., 2022; Gould et al., 2020b). As well as employing a number of qualitative methods such as deliberative approaches, CES assessments also seek to provide quantitative information on ecosystem service supply to achieve sustainable policy goals (Raymond et al., 2014). For these purposes, social media has emerged as a promising new source of data due to the scale and detail in which CES measures can be established (Gould et al., 2019a; Havinga et al., 2020). This has led to a number of studies exploring the potential of social media including the image-sharing platform Flickr, which has become one of the most widely utilised due to the accessibility and geographic scope of its data (Ghermandi and Sinclair, 2019; Richards and Tunçer, 2018).

So far, CES measures based on social media data have generally relied on generic indicators, such as the number of Flickr images per site or spatial unit, with an implied uniform value (Graham and Eigenbrod, 2019; van Zanten et al., 2016; Wood et al., 2013). However, one human-nature interaction recorded on social media may hold more weight

than another in terms of the emotional response it elicits in the person (Fox et al., 2021a). This is especially relevant when considering CES as contributing factors to non-material benefits because this relies on people having a positive experience in nature (Havinga et al., 2020). Different biophysical features or settings may contribute to the level of mental or physical enjoyment experienced by an individual and this should also be considered in developing CES measures (Gould et al., 2019a).

Here, the text associated with Flickr images in the form of titles, tags and descriptions can offer a large amount of relevant information to determine the degree to which CES generate positive experiences (Wartmann et al., 2019). Some recent studies have begun to utilise this information from Flickr to assess peoples' experiences of nature using sentiment analysis, a form of natural language processing (NLP) used to predict affective states in text (Becken et al., 2017; Brindley et al., 2019; Fox et al., 2021a). A range of NLP models are available to conduct sentiment analyses (Soleymani et al., 2017), including bag-of-words approaches such as hedonometer, a corpus of 10,000 words each with a crowdsourced sentiment rating between 1 and 9 (Alshaabi et al., 2021) and Sentiment140, a maximum entropy-based model trained using emoticons on Twitter (Go et al., 2009). This is in addition to more advanced methods such as RoBERTa, a deep learning-based model which uses artificial neural networks to extract abstract feature representations from text, which are then used to assess its sentiment (Liu et al., 2019).

Nevertheless, despite the availability of these models, the application of sentiment analysis to better understand CES measures based on social media has so far been limited (Fox et al., 2021a). Machine learning methods, including deep learning, have now enabled detailed CES predictions using the image content on Flickr (Egarter Vigl et al., 2021; Havinga et al., 2021a; Lee et al., 2022) or their relations to satellite imagery (Levering et al., 2021). The application of a range of NLP models can in turn enable an assessment of the sentiment associated with these predictions and, ultimately, the degree to which these are associated with a positive experience of nature. At the same time, the application of deep learning models to predict image scenes and attributes can reveal the different factors determining the sentiment associated with CES supply (Cao et al., 2022). Still, validating the use of social media for CES assessment using alternative sources such as surveys remains an important research priority (Englund et al., 2017; Oteros-Rozas et al., 2018).

The objective of our study is to examine the positive experiences associated with CES supply using sentiment analysis. To do this, we utilise Flickr and deep learning-based predictions of CES generated in previous research for Great Britain (Havinga et al., 2021a).

We deploy NLP models to associate those predictions with sentiments related to the text accompanying the images. We seek to answer the following research questions: (1) What is the sentiment associated with CES-related human-nature interactions on social media? (2) How do different biophysical and human-related settings influence the sentiment generated by these interactions? (3) Do measures of sentiment and CES match national survey measures of well-being? In doing so, we aim to understand sentiment analysis and social media more broadly as an effective tool in measuring CES and, in particular, the positive experiences derived from human-nature interactions (Langemeyer and Calcagni, 2022).

5.2. Methods

5.2.1. Study design

Our study sought to examine the positive experiences associated with human-nature interactions using social media data and NLP. We focused on two CES: landscape enjoyment and cultural appreciation of biodiversity. We used information relating to these two CES generated in previous research in the form of geo-located Flickr images with aesthetic quality and human-species interaction predictions (Havinga et al., 2021, Havinga et al., under review). These predictions were generated using deep learning-based models and trained using crowdsourced datasets. We conceptualised aesthetic quality as an integral factor in determining aesthetic ecosystem service flow and a human-species interaction as CES broadly related to the cognitive enjoyment of biodiversity. CES are, in turn, determined by whether people are having a positive experience and the size of contribution to this experience from nature, in terms of CES supply, can be determined by the setting and type of interaction occurring, alongside other contributing factors such as social context and the effort of the individual themselves (Havinga et al., 2020).

In addition, we also utilised image scene and attribute predictions to understand the biophysical and human-related factors influencing CES supply such as landscape features or human activities. A scene class can be defined as the overall semantic description of an image while an image attribute is a specific characteristic within it (e.g. a collection of objects or human activity). To understand the positive experiences linked to these human-nature interactions, we compared three NLP models tasked to estimate the sentiment expressed in user-generated image text and also looked at the adjectives employed by users. We examine the differences in predicted sentiment for aesthetic quality and used the best-performing model for the remaining analysis. To validate and compare our Flickr and NLP-based

measures of sentiment and CES, we compared our results to a national-wide survey of nature recreation in England, including self-reported well-being measures.

5.2.2. *Dataset: a collection of outdoor Flickr images in Great Britain*

To examine the sentiment associated with landscape enjoyment and cultural appreciation of biodiversity, we drew on a Flickr image dataset and CES predictions generated in previous research (Havinga et al., 2021, Havinga et al., under review). This consisted of 9.8 million outdoor images, identified using the Places365 deep learning model (B. Zhou et al., 2017). For this research, we also utilised the image scene class and attribute predictions generated by the Places365 model: we used 35 of the most relevant attribute classes and 30 scene classes (see Supplementary Table S2 and Table S3), taking only the most confident scene class predictions per image. To conduct the sentiment analysis in this study, we then also utilised the associated Flickr image metadata in the form of titles, tags and descriptions by accessing the Flickr Application Programming Interface (API) using the 'flickrapi' library in Python.

5.2.3. *Text data processing*

To conduct part of our analysis, an additional text processing step was needed to better structure the data. This was because the image titles, tags and descriptions generated by users contained a large amount of irrelevant text such as website links, stopwords and duplicated words. For example, without removal, duplicated words recognised by the hedonometer model would contribute multiple times to the overall sentiment of a single image. We therefore took a number of text filtering steps to produce a second, processed text dataset to apply this model and look at individual words employed by users through different types of interactions.

To filter the dataset, first, we removed all html, numeric characters, punctuation, English stopwords and words less than three characters in length using the 'tm' package in R. Second, we removed local toponyms by querying local place names using a 5km grid overlay and the OS Place Names API[3]. This was because local place names generate a considerable amount of semantic ambiguity. For example, "Lizard" can mean the name of the southernmost peninsula in Britain rather than someone's interaction with the type of animal. As a final step, we only used images with at least three words to limit the bias of single or small groups of words on overall sentiment. This ultimately meant working with a

---

[3] https://www.ordnancesurvey.co.uk/business-government/products/names-api

dataset of 4.7 million images to conduct our analysis, with the unfiltered dataset reduced to the size of the filtered dataset for an equal comparison.

5.2.4. *CES predictions*

The Flickr dataset contained both CES measures of landscape enjoyment and cultural appreciation of biodiversity. For landscape enjoyment, this consisted of an aesthetic quality rating between 1 and 10 per image. These predictions were generated using a Convolutional Neural Network (CNN) trained on a crowdsourced image dataset of the British landscape (Havinga et al., 2021a). Cultural appreciation of biodiversity was captured as a binary prediction representing a generic or human-species interaction. This prediction was also generated using a CNN model, trained to distinguish between species and generic interactions using a dataset of Flickr and iNaturalist images, a citizen science platform (Havinga et al., under review). We took only the most confident predictions and structured our analysis around five of the most frequent species classes captured by users: Plants, birds, insects, mammals and arachnids. We then looked at the sentiment associated with the most common species orders per class (0.75 quantile, with a minimum of 100 interactions).

5.2.5. *NLP models*

5.2.5.1. *Hedonometer*

To estimate the sentiment associated with peoples' aesthetic enjoyment and cultural appreciation of biodiversity, we applied three different NLP models. The first model, the Hedonometer dataset, was applied using a bag-of-words approach which meant estimating sentiment using the intersection of a dictionary of words with individual sentiment scores. This hedonometer dataset consists of a 10,000 word corpus each with a crowdsourced sentiment rating between 1 and 9 collected using the Amazon Mechanical Turk platform (Alshaabi et al., 2021). The dataset has been successfully applied to Twitter data in the context of national well-being measures in the USA (Mitchell et al., 2013), examining the sentiment of urban green space visitors (Schwartz et al., 2019) and peoples' attitudes towards climate change (Cody et al., 2015). The mean sentiment per image was calculated by taking a "bag" of words from the filtered Flickr text dataset and then taking an average of the crowdsourced sentiment assigned to the subset of words that appear in the Hedonometer dataset. We then normalised to a range of -1 to 1 so as to compare with the predictions of the two other models.

5.2.5.2. Sentiment140

The second model applied we applied was the Sentiment140 model which uses the machine learning classifier Maximum Entropy (MaxEnt) to generate predictions (Go et al., 2009). MaxEnt models are feature-based models which calculate a conditional probability across a set of classes using optimised feature weights generated after training. The model was trained on a dataset of Tweets with emoticons as training features and a model output of -1 for negative, 0 for neutral, and 1 for positive sentiment. It has been applied in the context of public health monitoring to infer Twitter users' health status over time (Kashyap and Nahapetian, 2014) and to test the relationship between sentiments expressed on Twitter and socio-demographic indicators (Ostermann, 2021). In our case, we applied the model to the descriptions of the unfiltered Flickr images to capture whole sentences, similar to the format of Twitter. We did this using the Sentiment140 API[4], before normalised the resulting scores to be between -1 and 1.

5.2.5.3. RoBERTa

Finally, the third model we applied to generate sentiment predictions was the RoBERTa model. RoBERTA is a deep learning-based model which uses artificial neural networks to generate feature representations of words and then uses these to produce sentiment estimates (Liu et al., 2019). It has produced state-of-the-art results based on a two-step training scheme, drawing on both large amounts of unlabelled training data and task-specific, labelled data. It has previously been used to estimate the effects of the Covid-19 pandemic on student sentiment using data from the social media site Reddit (Yan and Liu, 2021) and the sentiment associated with common points of interests such as parks in cities globally (Stelzmüller et al., 2021). We used a RoBERTa-base model trained on 124 million tweets from January 2018 to December 2021[5], and finetuned for sentiment analysis using a crowdsourced, annotated training dataset of tweets (Barbieri et al., 2020; Loureiro et al., 2022). The model produced a softmax score across a negative, neutral and positive class. We used the Python libraries 'Transformers' to download the model and apply it to our dataset, taking the positive score and subtracting the negative score before normalising the model output to a -1,1 range. As with the Sentiment140 model, we applied the model to only the descriptions of the unfiltered Flickr text dataset to preserve whole sentences similar to the format of Twitter.

---

[4] http://help.sentiment140.com/api
[5] https://huggingface.co/cardiffnlp/twitter-roberta-base-sentiment-latest

5.2.6. Adjective analysis

To gain additional insight into the sentiments expressed by users in the text associated with their images, we also looked at the most common and unique adjectives used across aesthetic quality ratings and for different species. Adjectives are the most emotive elements of language and can therefore provide one of the clearest indications of the affective state of people (Bush, 1973). To do this, we looked at how users employed positive and negative adjectives across aesthetic quality ratings. We looked at a selection of adjectives, choosing "beautiful", "enjoy", "like", "calm", "happy", "love" as well as "afraid", "awful", "sad", "angry", "hate" and "ugly". In addition, we also examined the most uniquely employed adjectives for the species orders spiders (*Araneae*), songbirds (*Passeriformes*), butterflies/moths (*Hymenoptera*) and the *Asparagales* plant order, which includes the daffodil flowering plant genus (*Narcissus*). This was done by calculating the term frequency-inverse document frequency (tf-idf) of adjectives used by Flickr users for each species order in comparison with each other. Employing tf-idf meant we could analyse the frequency of an adjective used to describe a particular species in proportion to the frequency of its use for other species. This was done using the 'udpipe' package in R to identify adjectives and the 'tidytext' package to calculate the tf-idf. To gain a more balanced view of the adjectives employed by all users, we took a 10% sample of images per user and only included adjectives if they occurred at least twice for each species order.

5.2.7. MENE survey

To validate our results, we compared our social media and NLP model results with nature trips and well-being measures reported in a national recreation survey of England. The Monitor for Engagement with the Natural Environment (MENE) is a demographically-representative survey of England conducted throughout the year in which respondents are asked about their trips to nature in the past week. Respondents are then asked more information about one of these trips, such as the location and motivation for their visit, with some then asked to report measures of well-being as a result of the trip. For our study, we used the survey results collected over a ten year period between 2009 and 2019 (Natural England, 2019).

In the survey, people are given a number of options to choose from to state the motivation for their trip. The options most relevant to our study were the statements "to enjoy the scenery" and "to enjoy the wildlife" to which people could answer either "Yes" or "No". As a first point of comparison, we compared the mean sentiment, aesthetic quality and

species interactions captured in Flickr images within a 1km radius of these visits using the trip coordinates. This subset consisted of 82,950 respondents. This enabled us to compare whether "Yes" responses were associated with higher sentiment and CES measures generated using Flickr data. We checked the significance of these differences using two sample tests chosen after checking for normal distributions using the Shapiro-Wilk test. This included the Welch Two Sample t-test as a parametric test and the Wilcoxon rank sum test as a non-parametric test.

A further subset of respondents (11,667 people) were asked to report feelings of well-being associated with their trip. These respondents were asked to what degree they agreed with the statements "I enjoyed it", "it made me feel calm and relaxed", "it made me feel refreshed and revitalised", "I took time to appreciate my surroundings", "I learnt something new about the natural world" and "I felt close to nature". We took the responses to these statements as a second point of comparison, also calculating the mean sentiment, aesthetic quality and species interactions in Flickr images within a 1km radius and then comparing the level of agreement with these Flickr-based measures.
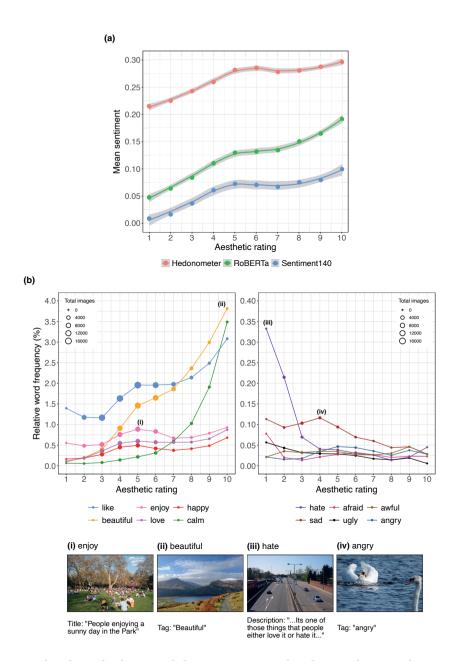
5.3. Results

5.3.1. *Sentiments associated with CES*

5.3.1.1. *Aesthetic quality*

Figure 19 shows the relationship between sentiment and aesthetic quality using the predictions of the three NLP models as well as the relative word frequencies of a set of positive and negative adjectives. All three models resulted in significant ($p<.001$) trends in the relationship between aesthetic quality and sentiment, with a clear upward overall trend. The application of all three models showed a similar pattern with sentiment the lowest for the lowest aesthetic quality ratings, a small levelling-off between the 5 and 7 ratings, before increasing again with the highest ratings. This increase was the most prominent for the RoBERTa sentiment predictions, followed by the Sentiment140 and hedonometer models, with the hedonometer predictions barely increasing from the average ratings. The sentiment140 saw the largest range of uncertainty, indicating a wider range of positive/neutral predictions for each rating. Ultimately, although the RoBERTa model showed the strongest relationship with higher aesthetic ratings, the Hedonometer model showed the best overall relationship (Supplementary Table S15), and the highest correlation with the MENE survey responses (Pearson's $R=0.142$) versus Sentiment140 (Pearson's $R=0.053$) and RoBERTa (Pearson's $R=0.09$) (Supplementary Table S16).

In terms of the adjectives employed by users across the aesthetic ratings, more positive adjectives and less negative adjectives were used per image relative to the total number of images per rating as aesthetic quality increased (Figure 19b). The positive adjectives "beautiful", "calm" and "like" showed the clearest relationship with aesthetic quality, showing substantial increases with higher ratings. For example, many landscape images were associated with the word "beautiful". The words "happy", "enjoy and "love" showed less of a clear relationship, with a slight increase across the average ratings associated with activities such as picnicking in the park. Conversely, the use of the word "hate" fell steeply from low to high aesthetic quality. The use of the word "hate" was associated with urban settings such as the road network being described in Figure 19b (i). Generally, the words "sad" and "ugly" also fell with increasing aesthetic quality while the words "afraid", "awful" and "angry" showed less of a clear relationship, sometimes being used to describe the behaviour of animals in images. Notably, the number of positive adjectives employed by users was far greater than negative adjectives.
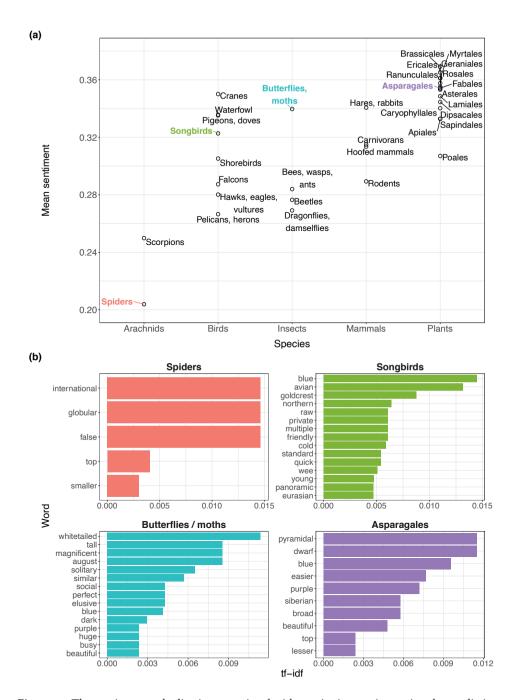
Figure 19. The relationship between Flickr user sentiment and aesthetic quality. In **(a)** the sentiment predictions of the three NLP models are shown versus aesthetic quality. Images were grouped into aesthetic quality rating bins (e.g. 1 represents images with a rating between 0 and 1) and the mean sentiment calculated per rating bin with a loess smoothing filter showing the 95% confidence intervals. All three models were found to produce a significant (*p*<.001) relationship between sentiment and aesthetic quality. In **(b)** the relative word frequencies are shown of six positive and six negative adjectives per rating, in addition to four image examples for **(i)** "enjoy", **(ii)** "beautiful", **(iii)** "hate" and **(iv)** "angry". Photos © Marco Verch, Scott Wylie, Lydia and Stephen Gidley (cc-by/2.0).

We found that, overall, the hedonometer model produced the strongest correlations with the MENE survey responses (Supplementary Table S15) as well as the number of species interactions (Supplementary Table S17). For example, the responses to "I felt close to nature" saw a 0.06 correlation with the number of species interactions. We therefore used its predictions to look at the relationship between different species interactions and sentiment, shown in Figure 20, although, overall, correlations for all sentiment predictions were low.

Plants produced the highest levels of sentiment with plant orders such as *Asparagales*, which includes daffodils, seeing some of the highest levels of sentiment. Other flowering orders such as *Ranunculales* which includes the buttercup family, also saw high levels of sentiment versus others, such as *Caryophyllales*, which includes cacti, and *Poales*, which includes grasses, with lower sentiment. After plants, birds and specifically butterflies and moths as insects saw the next greatest level of sentiment associated with user interactions. In terms of birds, this included cranes, waterfowl and songbirds, while pelicans and herons produced the lowest levels of sentiment. Mammals also saw relatively high levels of sentiment in comparison to the other species while arachnids, including spiders and scorpions, saw the lowest sentiment expressed towards them out of all species.

Considering the difference in the words used by Flickr users for a selection of these species, the tf-idf scores in Figure 20 shows the uniqueness of the adjectives employed by users in their interactions with spiders, songbirds, butterflies/moths and the *Asparagales* plant order. Spiders saw very little unique words with only five words gaining a non-zero tf-idf score, the strongest of which were "international" and "globular". In contrast, songbirds, butterflies/moths and the *Asparagales* order saw a much larger and more positive range of adjectives more uniquely employed by users versus the other species. For example, in the case of butterflies/moths, the adjectives "magnificent", "perfect" and "beautiful" gained relatively high tf-idf scores. "beautiful" was also often used to describe *Asparagales* versus the other species orders. In the case of songbirds, adjectives such as "young" and "friendly" were more often used in comparison to the other species.
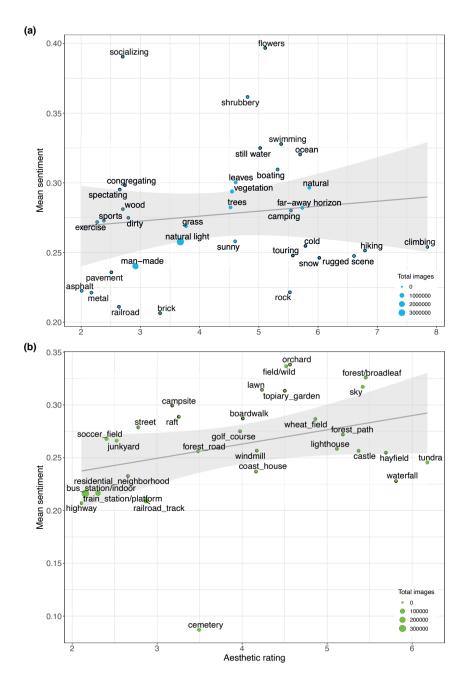
Figure 20. The sentiment and adjectives associated with species interactions using the predictions of the hedonometer NLP model. In **(a)** mean sentiment for the most common species order interactions are shown while **(b)** shows the adjectives with the highest tf-idf scores employed by Flickr users to describe their interactions with spiders, songbirds, butterflies/moths and the asparagales order. Some additional place and camera-related words such as "nationaltrust" and "macro" have been removed.

Figure 21 shows the sentiment and aesthetic quality related to different image attributes and scenes based on the prediction of the hedonometer model. Again, we used the hedonometer model for this as it showed the strongest correlation with the responses in the MENE survey. However, overall, the correlation was still small. For example, the statement "I enjoyed it" saw a Pearson's R of 0.05 (Supplementary Table S15). This was also reflected in the weak overall correlation between sentiment and aesthetic quality in Figure 21 per attribute (R^2=0.05) and scene class (R^2=0.08). The sentiment and aesthetic quality linked to different attributes varied greatly. The attributes "flowers" and "socializing" were linked to the highest levels of sentiment while "railroad" and "brick" experienced the lowest sentiment. Most of the urban or man-made attributes, including other attributes such as "pavement" and "asphalt", saw both low sentiment and low aesthetic quality. Also, notably, other social activity-related attributes such as "congregating" and "spectating" were linked to high levels of sentiment but low aesthetic quality. In contrast, "hiking" and "climbing" were associated with high aesthetic quality but fairly low sentiment. This was also true of nature-related attributes such as "ocean", "natural" and "snow", although water-related activities and features elicited fairly high levels of sentiment.

Although the overall relationship between sentiment and aesthetic quality again varied greatly for scene classes, a similar pattern of both low sentiment and aesthetic quality associated with man-made and urban-related settings was also detected (Figure 21). For example, the scenes "train station/platform", "highway" and "bus station/indoor". In particular, "cemetery" was associated with the lowest sentiment. However, it was still associated with a moderate level of aesthetic quality. "orchard" and "filed/wild" were linked to the highest levels of sentiment, suggesting a link with nature, while "golf course" and "campsite" also generated high levels of sentiment versus moderate aesthetic quality, an indication that social activities are also important to peoples' positive experiences. Scenes linked to natural settings, such as "tundra", "waterfall" and "hayfield" were linked to very high aesthetic quality but moderate sentiment.

Figure 21. Sentiment versus aesthetic quality for a selection of **(a)** image attributes and **(b)** scene classes generated by the Places365 model. The size of points for attributes indicate the number of images with a score > 0.6 and for scenes images with a softmax score > 0.5. The grey lines indicate the line of best fit with 95% confidence intervals (attributes R^2=0.05 and scenes R^2=0.08).

5.3.3. Comparison with surveyed well-being measures

Table 9 shows Flickr-based measures of CES and sentiment, using the mean prediction of the hedonometer model, compared with trips reported in the MENE survey. A clear relationship was observed between the locations visited by survey respondents and the CES measures estimated using Flickr images. Trip locations visited to enjoy the scenery saw a mean aesthetic quality of 4.29 in Flickr images within 1km versus 3.91 in images near trip locations not taken for this reason ($p<.0001$). The sentiment associated with Flickr images near trip locations undertaken for enjoying the scenery was also significantly higher ($p<.0001$). There was also a significant difference between trips taken to enjoy wildlife and the mean number of species interactions, with 19.3 species interactions for wildlife-related trips versus 10.9 for trips not taken for this reason ($p=.001$). Again, sentiment was found to be significantly higher in Flickr images in the same areas as wildlife-related trips reported in the MENE survey ($p<.0001$).

Table 9. Comparison of Flickr-based sentiment and CES measures within 1km of trips taken to enjoy the scenery or wildlife as reported in the MENE survey.
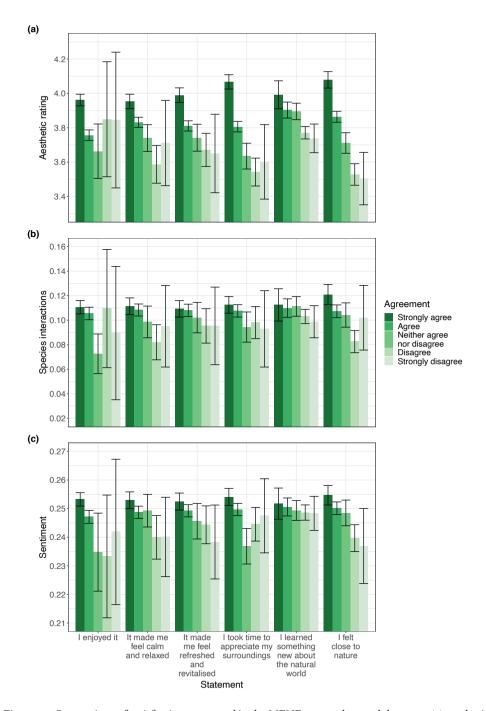
Trip Motivation	Response	Flickr-based CES measure	Mean CES	Mean sentiment
To enjoy scenery	Yes	Aesthetic quality	4.29 (± 0.03) ($p<.0001$)[†]	0.14 (± 0.003) ($p<.0001$)[‡]
	No		3.19 (± 0.02) ($p<.0001$)[†]	0.13 (± 0.002) ($p<.0001$)[‡]
To enjoy wildlife	Yes	Human-species interactions	19.3 (± 5.46) ($p=.001$)[‡]	0.145 (± 0.004) ($p<.0001$)[‡]
	No		10.9 (± 0.780) ($p=.001$)[‡]	0.135 (± 0.002) ($p<.0001$)[‡]

[†]based on Welch Two Sample t-test, [‡]based on Wilcoxon rank sum test

Similarities were also found between Flickr-based CES measures and sentiment and the self-reported well-being statements in the MENE (Figure 22). Significant differences were especially visible for the level of agreement with the statement "I took time to appreciate my surroundings" and aesthetic quality. The statements "it made me feel calm and relaxed" and "I felt close to nature" also showed significant differences between the levels of agreement and aesthetic quality. Further analysis looking at the correlations between aesthetic quality and the levels of agreement with each statement confirmed this

(Supplementary Table S18). The levels of agreement with the different statements and number of species interactions generally showed large standard errors which affected the significance of some of the differences. However, the statement "I felt close to nature" produced significant differences in the number of species interactions associated with "strongly agree" and almost all other levels of agreement. Correlation analysis again confirmed this relationship between the statement and peoples' level of agreement (Supplementary Table S19).

In terms of sentiment, significant differences were also observed. The most notable were associated with the statement "I enjoyed it" which saw larger sentiment associated with stronger levels of agreement. Less notable but still significant differences were also observed between levels of agreement for the statements "I took time to appreciate my surroundings' and "I felt close to nature". Levels of agreement with other statements were generally not associated with significant differences. In particularly, "strongly agree" was affected by large standard errors. This was because there were only a small number of people (<60) that gave this response in the survey. Further correlations between sentiment, CES measures and the MENE survey results can be found in Supplementary Table S15, Table S16 and Table S17).

Figure 22. Comparison of satisfaction expressed in the MENE survey data and the mean **(a)** aesthetic quality, **(b)** number of species interactions and **(c)** sentiment expressed in Flickr images within 1km distance of the geo-located visits.

5.4. Discussion

The use of social media to measure CES has seen rapid growth in recent years (Ghermandi and Sinclair, 2019). Nevertheless, so far, it's potential has not been fully realised, and key challenges remain regarding the representativeness of the data and its use in producing policy-relevant indicators (Havinga et al., 2020; Oteros-Rozas et al., 2018). In our study, we have demonstrated that, through the application of NLP methods and machine learning, connections can be made between social media-based CES measures and peoples' positive experiences of nature, a key consideration for CES indicator development in the context of public health (Sandifer et al., 2015). At the same time, our findings highlight a number of biophysical features and settings that influence peoples' positive experiences of nature.

Overall, there was a clear relationship between aesthetic quality and sentiment, with a clear uptrend towards higher aesthetic ratings. This finding is consistent with the health-promoting impacts of outdoor environments outlined in the landscape aesthetics literature (Abraham et al., 2010). For example, landscapes of high aesthetic quality, in terms of their perceived naturalness and diversity, evoke positive emotions in people, resulting in improvements to their general mood and mental health (Bieling et al., 2014; Seresinhe et al., 2019). Notably, there was a levelling-off in sentiment for the images within the average aesthetic rating bins. This may highlight the greater variability in peoples' responses to landscapes of ordinary quality and the more consistent responses elicited by either very ugly or attractive environments (Workman et al., 2017). This effect was observable in the relative word frequencies of adjectives employed by users in our study, such as "beautiful" and "calm" versus "ugly" and "sad", which showed strong relationships with high and low aesthetic quality.

In terms of species sentiment, some notable differences between species groups were also observed, with plants, especially flowering plants, generating the highest level of sentiment, following by insects and birds. These results are in line with those of survey-based studies in Great Britain (Aerts et al., 2018). For example, in public green spaces around England, higher levels of flower cover were associated with larger restorative effects (Hoyle et al., 2017). Similarly, in a survey of public attitudes towards biodiversity attributes, butterflies were found to be one of the most valued insect species (Austen et al., 2021), confirming our results. In another study of urban households, songbirds were especially appreciated by people out of all garden birds (Cox and Gaston, 2015). It has been argued that more positive overall reactions to plants versus birds or insects may be due to their static

and thus more visible presence (Dallimer et al., 2012; Fuller et al., 2007). Some insects can also appear as a threat to people, evoking less positive emotions (Austen et al., 2021). This is also true of arachnids such as spiders which saw the lowest levels of sentiment expressed towards them in our study (Zvaríková et al., 2021).

Previous studies employing survey methods have also shown the importance of particular biophysical features and settings on the positive experiences people gain from their interactions with nature. For example, social cohesion has been found to be one of the strongest mediators between green space and health (de Vries et al., 2013; Wolf and Wohlfart, 2014). This was also reflected in the results of our study, with the image attribute and scene classes "socializing" and "campsite" linked to some of the highest levels of sentiment, and the word "enjoy" being associated with picnicking in an urban park. Similarly, the high sentiment associated with the attributes "flowers" and "shrubbery", as well as the more colourful plant species orders, reflect the significant positive effects of colour diversity and green planting (Carrus et al., 2015; Hoyle et al., 2018). Conversely, the sentiment linked to "tundra", "hiking" and "climbing" versus aesthetic quality suggests very appealing but less comfortable environments may elicit more reflective responses rather than explicitly positive ones (Baklien et al., 2016; Stevenson and Farrell, 2018).

The comparison with the MENE survey results showed good consistencies between CES measures, sentiment and respondents' trip motivations and reported well-being. This provides good evidence that Flickr-based measures of CES are consistent with a large sample of self-reported visits across a large geographic and seasonal range, evidence that is generally missing in the CES literature (Oteros-Rozas et al., 2018). The positive experiences recalled by respondents in the survey such as "I enjoyed it" were also consistent with the sentiment expressed by Flick users, suggesting a common level at which these CES contribute to non-material benefits such as better mental health. Social media sentiment has been linked to national indicators of well-being (Kokil et al., 2020) while higher levels of vegetation cover and bird abundances have been found to be positively associated with a lower prevalence of depression, anxiety, and stress (Cox et al., 2017; Methorst et al., 2021). Social media-based measures of CES can therefore integrate these casual pathways to better study the effect of nature on people below the ecosystem scale (Botzat et al., 2016).

However, not all statements of agreement in the MENE survey matched sentiment levels on Flickr. This may again be due to the fact that statements such as "I took time to appreciate my surroundings" are linked to more thoughtful experiences, rather than expressly positive ones. The number of people disagreeing or strongly disagreeing was also

very low, reflecting a general human positivity bias in relation to peoples' voluntary trips to experience nature (White et al., 2013). Nevertheless, the significant differences between the more stronger levels of agreement and the Flickr-based sentiment measures is encouraging evidence that these novel data and techniques capture representative information on peoples' interactions with nature. This confirms the results of some more recent studies which have started looking at validating social media-based indicators of CES with survey data (Johnson et al., 2019; Moreno-Llorca et al., 2020).

The more reflective nature of some peoples' positive experiences during their outdoor recreation also highlights some of the limitations of the approach taken in our study. Not all positive experiences related to nature may be expressed on social media while the full range of positive experiences that are expressed in users' text may not be fully captured through the application of NLP models. For example, we found the image scene class "cemetery" to be associated with the lowest level of sentiment. However, cemeteries are associated with significant restorative effects (Quinton and Duinker, 2018), produced through feelings of peacefulness and contemplation (Nordh et al., 2017). Such positive but more ambiguous emotions are difficult to detect through sentiment analysis and require additional contextual information to generate accurate predictions (Poria et al., 2020). At the same time, Flickr users may be less eager to share more contemplative experiences such as these due to the heavy positivity bias found on social media platforms (Waterloo et al., 2017).

The manner in which people use Flickr may also have resulted in the hedonometer model achieving the highest correlation with the MENE survey, even versus the more advanced RoBERTa model. This is because RoBERTa has been trained to predict sentiments using Twitter data, a platform on which users express much stronger opinions versus Flickr (Samani et al., 2018). Therefore, the way in which Flickr users refer to the natural environment around them, such as a particular flower species, may be more neutral than the model is trained to detect. In contrast, the positive benefit gained from the interaction is better picked up by the hedonometer model just based on the inclusion of these words and their crowdsourced sentiment rating. The accurate performance of the hedonometer model has previously been demonstrated versus other national well-being survey data with the added advantage of a high level of interpretability (Loff et al., 2015; Mitchell et al., 2013). In contrast, understanding the factors influencing the predictions of machine-learning based NLP models is a challenge and these types of models have often been criticised for being "black boxes" (Barredo Arrieta et al., 2020). For example, it is not

always clear how RoBERTa is using the words in a sentence, such as verbs or adjectives, to generate a prediction (Clark et al., 2019).

Nevertheless, our findings illustrate the relevancy of these novel data and techniques in the development of CES indicators. From a CES perspective, it is important to move beyond the use of simple proxies such as the number of images to better incorporate peoples' positive experiences (Richards and Tunçer, 2018; Zhang et al., 2020). In a broader context, public health measures also typically miss specific but important details of nature exposure such as the quality of the nature (Hartig et al., 2014). In our study, we were able to relate different levels of aesthetic quality to different levels of sentiment using social media and deep learning. This can support CES measures that incorporate both aspects, and those that move beyond simple image counts (Fox et al., 2021a). However, the configuration of these different elements into a single indicator per CES requires further research. For example, simple weights using the sentiment and aesthetic quality scores could be used. This would follow similar weighting approaches taken in survey-based CES assessments using expert opinion and stakeholder views (Alvarez-Codoceo et al., 2021; Nahuelhual et al., 2014). These measures could then be validated by comparing with survey-based data on the most appreciated ecosystem types or other biophysical attributes (Gould et al., 2019a).

5.5. Conclusion

There is an increasing urgency to address rapidly falling levels of human-nature interaction and policy-makers need relevant indicators to maximise the public health benefits generated by peoples' positive experiences of nature. CES indicators representing the contributions of nature to peoples' mental and physical health should therefore also account for this experiential aspect in their measures. In our study, we have demonstrated that social media and machine learning can account for the varying degrees of peoples' positive experiences associated with two CES: landscape enjoyment and the cultural appreciation of biodiversity. We find that sentiment increases with aesthetic quality and that different human-species interactions generate varying levels of sentiment. These CES and sentiment measures were found to match relevant well-being measures in a national survey of nature recreation. At the same time, we find that biophysical attributes and settings also influence peoples' positive experiences such as those related to social activities. Our findings illustrate the relevancy of applying these novel techniques for CES indicator development.

Chapter 6.   Synthesis

The main aim of this thesis is to explore the potential of crowdsourced data and machine learning in measuring CES. In the previous four chapters, a variety of datasets and machine learning methods have been utilised in order to help further clarify the CES concept, develop spatial CES models and demonstrate the relevancy of these models in addressing key challenges in a CES context. This work was carried out in the form of four scientific papers which addressed the following four research questions:

RQ1.   How can CES be defined and spatially modelled in the context of crowdsourced data?

RQ2.   How can social media and deep learning capture the aesthetic quality of the landscape in support of aesthetic ecosystem service models?

RQ3.   What do social media and deep learning-based indicators of biodiversity-related CES capture in comparison to citizen science and ecological measures?

RQ4.   How can social media and NLP capture the positive experiences associated with different CES measures?

In this synthesis chapter, I summarise the main findings of my research in relation to the overall aim and individual research questions, I critically discuss the methods employed to answer these questions as well as the relevancy of the results in a broad ecosystem service and policy context. Reflections on future research directions in the development of CES indicators using crowdsourced data and machine learning are then summarised with some final concluding remarks.

6.1.   Main findings

6.1.1.   Defining and spatially modelling CES in the context of crowdsourced data

Crowdsourced data provides a useful lens through which to conceptualise and spatially quantify CES. Working within the context of different crowdsourced data sources and established CES conceptualisations in Chapter 2, I found that defining CES as *information-flows generated by ecosystems that contribute to cultural experiences* best enables the spatial quantification of CES. This definition considers a range of established conceptualisations, including the SEEA EA and IPBES frameworks. As a result, in the course of writing this thesis, this conceptual work was used in the final consultation stages of the SEEA EEA before it grew out of its experimental phase and was adopted as an international statistical standard by the UN Statistical Commission (Barton et al., 2019). In the adopted standard,

CES are defined as "the perceived or realized qualities of ecosystems whose existence and functioning enables a range of cultural benefits to be derived" (United Nations et al., 2021, p. 146). The standard makes three further clarifications: CES are "(i) the ecosystem contribution in terms of providing places and opportunities for activity by people", "(ii) linked to flows from ecosystems to people that may be considered 'experiential'" and "(iii) able to contribute to multiple benefits" (United Nations et al., 2021, p. 146), with the second clarification specifically drawing on the conceptual exercise undertaken in Chapter 2.

The definition developed in the SEEA EA makes an explicit link between biophysical features and peoples' cultural preferences with ecosystem qualities generating CES as they relate to people. This additional operational aspect to measuring CES as information flows is further demonstrated through the aesthetic and biodiversity-related measures developed in Chapters 3 and 4. Using deep learning, specific biophysical features can be predicted as information conveyed to people across space and time in geo-located images on Flickr. In these cases, the information-flow conceptualisation is also broad enough to include full semantic representations of CES generated using machine learning for aesthetic enjoyment and appreciation of biodiversity. These were produced by training a deep learning model to predict a measure of aesthetic quality and another to identify human-species interactions in images. In this way, peoples' cultural preferences from a first-person perspective can be directly linked to complete impressions of the surrounding nature as well as specific biophysical features.

The definition presented in Chapter 2 also emphasises the human effort and/or goods and services involved in producing the resulting benefit enjoyed by people. I found this conceptual feature of the definition to be further reinforced through the findings of Chapter 5. In it, the varying importance of the information conveyed to people by ecosystems is captured through the varying levels of sentiment associated with different human-nature interactions, many of which relied on social contexts rather than natural ones. Nevertheless, the social aspect to many different sources of crowdsourced data produces a rich variety of datasets than can be used in a variety of ways. The Strava-based activity model in Chapter 2, for example, highlights the possibility of combining crowdsourced data with national survey data to produce CES indicators representative of the whole population. At the same time, access to citizen science platforms such as iNaturalist further enrich spatial CES assessments as these provide very different distributions versus social media, as I found in Chapter 4.

6.1.2. Measuring landscape aesthetics using social media and deep learning

Social media and deep learning provide large-scale measures of landscape aesthetics in support of aesthetic ecosystem service models. In Chapter 3, I found the application of deep learning to outdoor Flickr images in Great Britain to provide accurate measures of landscape aesthetic quality versus an environmental indicator model. In doing so, these measures enable the inclusion of individuals' first-person, revealed preferences, without a significant drop in accuracy in comparison to traditional indicator models, a key methodological advancement from an ecosystem service perspective. As well as using deep learning-based image attribute and scene classifications, a deep learning model was also successfully trained to generate an aesthetic quality rating per image, providing a full semantic measure of peoples' landscape enjoyment. This supported the highest level of model accuracy when combined with the environmental indicator variables.

The application of these novel methods also provides a number of other advantages. One primary advantage is a fine-grained view of highly-valued and unique landscape elements. The point-based, geo-located image data from social media, coupled with the information captured using deep learning, meant that the aesthetic appeal of specific rock or water features and their complex interaction could be integrated into the model. This included, for example, the 3D impression of an ocean bay view from a person's perspective on an a nearby set of cliffs. Important negative environmental contexts are also better represented, such as Heathrow Airport in London. This means that social media and deep learning-based models stay relevant at different scales in contrast to indicator models which are constrained by the input data and their spatial resolution. In Chapter 2 I also found that capturing the 3D experience of people as they enjoy the aesthetic appeal of the landscape is possible with a 3D viewshed model using only the location of Flickr images. Nevertheless, this assumed a uniform value for all Flickr images and did not allow any further quantitative insights into which ecosystem features were generating the service.

The fine-gained view of the landscape provided by deep learning and social media also captures specific contributions over time. For example, the contribution of snow to landscape aesthetic quality increased in the winter but especially on the weekends during peoples' leisure time. On the other hand, the contributions of the ocean increased in summer. These changes show how social media and deep learning can provide a combination of information about the state of the environment and how people interact with it over time, reflecting their changing seasonal preferences from a first-person

perspective. This constitutes a significant modelling advantage in the context of regular ecosystem service assessments. Finally, the limitation places on the number of images per user to gain a more balanced set of preferences in both Chapters 2 and 3 was found to be useful in achieving a better measure of landscape aesthetics. In the modelling exercise in Chapter 3, this limitation decreased the number of sporting-related images and increased the number of landscape images, resulting in a higher accuracy versus the ground truth.

6.1.3.   *Using deep learning and social media to model biodiversity-related CES*

In Chapter 4, I found that deep learning and social media reveal specific cultural contributions of biodiversity in comparison to citizen science and ecological measures of bird biodiversity. Using a large training dataset of images from citizen science and social media, a deep learning model was trained to identify a broad range of human-species interactions in images versus generic interactions. This incorporated a special training hyperparameter to enable the model to recognise a larger variety of species interactions also occurring on social media versus citizen science due to some of the differences between the platforms. This hyperparameter, in the form of a regularisation coefficient, meant a greater number of human-species interactions were detected in the test dataset while maintaining a high level of overall accuracy.

The application of the deep learning model enabled large-scale predictions of human-species interactions in Great Britain using Flickr images. The distribution of interactions showed some notable differences in comparison with interactions on iNaturalist, a citizen science platform. This was particularly evident in terms of the types of species users were interacting with after a applying a second, pre-trained deep learning model to predict species classes. Flickr users most frequently interacted with birds and mammals whilst iNaturalist users interacted more with plants and insects, reflecting a difference in peoples' preferences between data sources in relation to specific biophysical features in their environment. Despite these differences, interactions on both platforms were heavily influenced by the accessibility of nature with large population centres and urban green space key determining factors of users' activity in contrast to more natural areas. This presents a key limiting factor in that the presence and or absence of species together with their cultural importance cannot be fully captured using only these methods.

This observation was further emphasised by the notable differences found between human-species interactions and ecological measures of bird biodiversity. Peoples' perceived bird species richness in terms of 36 bird species was again found to be highest in more

accessible places such as in major urban centres. This was in contract to a measure of species richness based on modelled distribution data which saw concentrations in low elevation areas outside of urban centres. More visible, charismatic bird species were also found to be more popular versus their modelled abundance. For example, Kestrels and Buzzards saw a large number of images versus relatively small populations. On the other hand, Warblers, with larger populations, saw a smaller number of interactions. Nevertheless, interactions with specific, highly-valued birds species in terms of their conservation status were accurately captured, highlighting the utility of social media and deep learning in developing specific CES indicators.
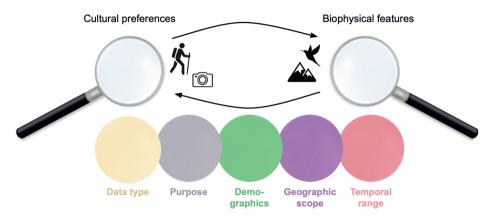
6.1.4. *Using social media and machine learning to connect peoples' positive experiences to CES measures*

In Chapter 5, after applying a number of different NLP models to produce measures of sentiment using the text associated with Flickr images, I found that machine learning and social media can provide a better understanding of the positive experiences associated with CES. However, a simple bag-of-words model still outperformed machine learning-based methods using national survey data as a ground truth. Higher sentiment was linked to higher levels of aesthetic quality and the presence of particular species. The lowest and highest aesthetic quality ratings saw significant sharp downward and upward trends in sentiment, the more advanced deep learning model predicting the strongest effect of high aesthetic quality on sentiment. Higher sentiment was also associated with specific species, such as flowering plants, songbirds and butterflies versus other species such as spiders. The species and aesthetic quality ratings with the highest sentiment were also found to be associated with more positive, affective words such as "beautiful", "calm" and "happy".

As well as capturing the sentiment associated with different CES-related measures, I found that the text provided by users on Flickr also reveal the influence of different biophysical settings on peoples' positive experiences. Natural elements, in particular flowers, were associated with higher sentiment, reflecting the positive influence of nature. This was in contrast to image attributes and scenes associated with the urban environment, such as "highway", "asphalt" and "metal". Although natural elements generated higher sentiment, social activities were found to have the greatest effect, with scene and attributes such as "golf course" and "socialising" producing very high levels of sentiment. However, these social activities were not associated with high levels of landscape aesthetic quality, highlighting the varying contributions of nature to peoples' positive experiences.

The CES measures and associated sentiment captured using the NLP models and social media were also consistent with a national, geo-referenced survey of recreational well-being in England. Trips taken to enjoy the scenery and wildlife were found to have significantly higher measures of aesthetic quality and species interactions in nearby Flickr images. Surveyed trips for which people strongly agreed with the statements "I enjoyed it" and "it made me feel calm and relaxed" were also associated with higher Flickr sentiment. Higher aesthetic quality was also related to stronger agreement with the statement "I took time to appreciate my surroundings" while larger numbers of human-species interactions were associated with "I felt close to nature". Peoples' trip motivations were also consistent with these CES measures. This confirmed the relevancy of using these novel techniques as an alternative to survey data in developing CES indicators.

6.2. Cultural preferences through the lens of new technologies

Figure 23. The main characteristics, or "lenses", inherent to crowdsourced data and machine learning-based approaches that determine the cultural preferences and biophysical features reflected in CES measures. CES are quantified based on the relationship between peoples' cultural preferences and the biophysical features in their environment. The extent to which these are revealed depends on the type, purpose, demographics, geographical scope and temporal range of both the crowdsourced data and the datasets used to train the machine learning models.

6.2.1. Key factors determining CES measures

Ultimately, CES measures are representations of peoples' cultural preferences for particular biophysical features such as individual species or landscape elements (Gould et al., 2020b). Machine learning and crowdsourced data provide novel techniques to generate such measures for large areas. In this thesis, crowdsourced datasets were used to both train machine learning models and generate spatial measures based on peoples' interactions on platforms such as social media. This represents a step-change from traditional survey

methods which are rare at large scales due to the cost and complexity involved in carrying out such surveys (Richards and Tunçer, 2018). Nevertheless, CES must accurately reflect the cultural preferences of the relevant population (Raymond et al., 2014) and at large scales this is particularly challenging due to the varying individual and collective contexts through which CES are generated (Satz et al., 2013).

The degree to which CES are captured using crowdsourced data and machine learning depends on several key factors. These factors are common to both crowdsourced data and the training datasets used to train machine learning models. The factors include the data type, purpose of the dataset, demographics, geographical scope and temporal range (Figure 23). These key characteristics act as filters, or what I would call "lenses", in determining the extent to which the cultural preferences and biophysical features generating CES are captured using crowdsourced data and machine learning. As the use of these novel technologies become more widespread, these factors form a set of important points of consideration in the assessment of CES. In the following sections, I explore these in more detail.

6.2.2. Data type

The type of data used to generate predictions using machine learning can determine the nature of the final CES measures used in ecosystem service assessments. For example, in Chapter 5, sentiment models were applied to the textual data associated with Flickr images to reveal the positive experiences generated by human-nature interactions, an important feature of CES measures. Sentiment analysis using image-based data is also possible but relies on the image training datasets used to train a machine learning model rather than the words expressed by the users themselves, adding a layer of uncertainty (Ortis et al., 2020). This means that without the accompanying text describing the nature of the specific interaction, only a more restricted representation of CES supply is possible. Similarly, in the case of mobile signal data, an even more restricted measure of CES supply is available as only movement data can be inferred through these digital records (Venter et al., 2021).

In terms of the training datasets used to train machine learning models and generate CES measures, the type of data also matters. In Chapter 5, sentiment models were applied which were trained using tweets from Twitter. Tweets are restricted to 280 characters in a micro-blogging format while on Flickr, descriptions can be much longer (Tenkanen et al., 2017). This adds an element of uncertainty to the models' predictions as the change of format could lead to spurious predictions without fine-tuning (Edwards et al., 2022). In other words,

the preferences expressed by Flickr users may not be captured in their entirety. Recently, video formats have also been used to establish CES measures in the form of clips uploaded to YouTube (Huertas Herrera et al., 2021; Park et al., 2017). These constitute extremely rich media formats that open the possibility of integrating sound into an assessment, an additional experiential dimension along which the contribution of biophysical features to CES can be measured (Buie and Blythe, 2013; Chesnokova and Purves, 2018).

6.2.3. Purpose

The purpose behind the existence of a source of crowdsourced data or model training dataset also affects the extent to which the relevant preferences and features are captured in CES measures. In terms of social media, Flickr is primarily a photo-sharing platform with an emphasis placed on aesthetics, including landscape photography (Schifanella et al., 2021). On the other hand, platforms such as Instagram also generate a lot of content centred around social activities (de Juan et al., 2021). Activity on Twitter's platform is primary focused around topical discourse (Manikonda et al., 2021). These framings have an effect on the type of preferences expressed through different sources of crowdsourced data because users work towards the social norms established within the online space (Calcagni et al., 2019; Venturelli et al., 2017). Similarly, the technology through which spatial records are generated will also affect how users express their preferences for particular biophysical features (Malik and Pfeffer, 2016). For example, iNaturalist data are primarily generated using its mobile app. This makes distant sightings of bird or mammal species more challenging due to the limited camera specifications of many smartphones (Di Cecco et al., 2021).

Training datasets used for the application of machine learning also have defined purposes which determine the ability of the models to detect preferences and features in the data. For example, the species classification model applied in Chapter 4 was trained using an iNaturalist image dataset of 8,142 species. However, the Flickr dataset on which the model was applied does not only include images of living species and is not restricted to a limited number of species (Edwards et al., 2021). This places a boundary up to which peoples' preferences for particular species can be measured and creates a source of uncertainty in relation to the model's existing predictions. Other pre-trained computer vision models, such as the Places365 model used in Chapter 3, will also have a predefined set of classes to generate predictions, the purpose of which may not be relevant to the generation of all CES measures (Ghermandi et al., 2022). For example, the indoor-related classes of the Places365

model. Ideally, new, purpose-built models can be trained. A large number of potential training datasets continue to be produced for different purposes and these can support a greater variety of preferences in CES measures (Bubalo et al., 2019; Scowen et al., 2021).

6.2.4. Demographics

Social demographics influence both the availability of spatial data on peoples' cultural preferences and the representativeness of training datasets used to detect these preferences. Each source of crowdsourced data comes with its biases towards specific demographic groups (Olteanu et al., 2019; Yuan et al., 2018). Flickr users have been found to mainly originate from an older, white and well-educated demographic (Lenormand et al., 2018; Li et al., 2013). In some areas, images are heavily biased to those of visiting tourists (Echeverri et al., 2022; Li et al., 2018). The rapid rise of technology has resulted in the global adoption of smartphones although internet use in developing countries lags behind richer countries (Roser et al., 2015). This means underserved and poorer communities may not be properly represented (Arts et al., 2015). Even with mobile signal data, data can be biased towards more mobile, urban populations and sourcing the data through different providers may lead to different preferences based on different customer bases (Wesolowski et al., 2013).

Factors related to social demographics will, therefore, also determine the importance of various biophysical features revealed through crowdsourced data. For example, older, more educated groups of users tend to express preferences for a wider range of species, including species of conservation concern, versus only the most charismatic or visible species (Niemiller et al., 2021). On the other hand, many tourist preferences captured through social media focus on flagship species such as the Big Five in Africa (Hausmann et al., 2018; Roberge, 2014). In many cases, the preferences of local people are at odds with those of conservationists. For example, farmers do not always appreciate the presence of predators such as wolves as they pose a real or perceived threat to their livestock (Krafte Holland et al., 2018; Nilsen et al., 2007). Demographics can also affect the types of interactions with the landscape, with younger populations more inclined to participate in active sports such as climbing and canoeing, both of which do not allow as many photos to be taken but may be visible in activity-sharing apps such as Strava (Griffin and Jiao, 2015; Wood et al., 2013).

The social demographics integrated into machine learning training datasets will also influence the preferences revealed by CES measures. For example, the deep learning model trained using the British SoN database in Chapter 3 may not accurately represent the

preferences of people in another country. This is because the perceived quality of the landscape can change with varying socio-cultural norms, such as the value placed on agricultural landscapes (Gobster et al., 2007). Similarly, many studies have found that older generations place greater aesthetic value on natural landscapes than younger people (Fischer et al., 2018), and that gender can also play a role (Palliwoda et al., 2017). If the demographic sample involved in the crowdsourcing to generate training datasets does not match the population in the study area, biophysical features may be over or under-valued. For the model to sufficiently capture peoples' preferences in other socio-cultural settings, fine-tuning of model parameters is likely required using additional training data, some of which may need to be generated through new crowdsourcing activities (Bubalo et al., 2019; Li and Hoiem, 2016).

6.2.5. *Geographic scope*

The geographic scope of the available data will also determine the extent to which cultural preferences and biophysical features are sufficiently captured in CES measures. Social media data is generally concentrated in different geographic regions. For example, Flickr is most popular in Western Europe and the United States (Wood et al., 2013) whilst Weibo and VK are largely constrained to China and Russia-speaking countries (Gao et al., 2012; Semenov et al., 2018). On the other hand, the availability of mobile signal data is more universal due to the global adoption of mobile devices. However, this data may not be available in remote locations which could, for example, be very important to people due to their "off-grid" nature (Giddy and Webb, 2018). Restrictions on peoples' mobility for conservation reasons, such as those found in national park areas, will also effect the geographical distribution of the data (Tenkanen et al., 2017). In other cases, the geography itself will determine the data available, with marine ecosystems underrepresented in CES assessments for accessibility reasons (Retka et al., 2019).

Machine learning models may also struggle to accurately capture peoples' preferences for biophysical features due to the geographical ranges of the training datasets. For example, the geography of the British landscape learnt by the deep learning model trained in Chapter 3 does not include representations of landscapes in other parts of Europe. This includes countries such as Spain and the Canary Islands, which feature desert and volcanic landscapes absent in Britain (Balzan et al., 2018). The geographic range of the individual features a model is trained to detect will also have an effect. This was evident in the results of Chapter 4 where the *Odocoileus* genus of deer native to the Americas was

misclassified as one of the most popular species by the species classification model. This was because the model lacked a species class for the European, and visually similar, *Cervus* genus of deer. Similarly, language models trained on data from specific geographic regions will not be as effective if applied in another geographical areas because of differences in language and cultural expression such as humour or sarcasm (Medrouk and Pappa, 2017; Mocanu et al., 2013).

6.2.6. *Temporal range*

Finally, the temporal range of the data used to measure CES with crowdsourced data and machine learning also has a significant effect on the extent to which the preferences and biophysical features in the study area are captured. In Chapter 3, the seasonal effects of natural elements to landscape aesthetics such as deciduous vegetation and snow was visible with their changing contributions to landscape quality over time. The increase in the relevance of snow in users' images over the weekend showed how this biophysical attribute contributed more in peoples' leisure time. These effects would not have been visible if data had been used from a narrow space in time. Examining crowdsourced data over time can also reveal peoples' preferences for natural areas such as urban parks just based on mobility patterns (Soliman et al., 2017; Venter et al., 2020), in addition to the associated benefit associated with these trips in terms of the change in peoples' sentiment (Schwartz et al., 2019). In this way, integrating crowdsourced data over time can provide useful baseline measures for the quantification of CES (Wood et al., 2020).

The timeframe of the data used to train machine learning models also matters. For example, the deep learning model trained in Chapter 4 to identify human-species interactions was trained using images over an entire year to capture seasonal interactions with species, such as migratory species (Borowiec et al., 2022). Seasons and weather can also greatly affect the composition of landscape images and their appeal to people if their preferences are being crowdsourced to build a training dataset (Joglekar et al., 2020). Understanding peoples' preferences based on temporal patterns in user activity also relies on having the training data available within a large-enough timeframe to detect these patterns (Heikinheimo et al., 2020). Sometimes platform access has been suddenly cut off such as in the case of the photo-sharing site Panaramio (Ghermandi and Sinclair, 2019). Cultural preferences also change over the long-term under the influence of education, advertising and cultural assumptions (Norton et al., 1998). As the application of machine

learning to measure CES matures over time, it is important that the training datasets used remain relevant to the assessment being carried out.

6.3. Epistemological contexts and opportunities

In addition to the key characteristics or "lenses" determining CES measures developed using crowdsourced data and machine learning, a wider, epistemological context must also be considered. A key feature of the debate surrounding the CES concept and its relevancy to policy-making centres around the need to incorporate a variety of approaches based on a range of worldviews, knowledge systems, and input from stakeholder groups (IPBES, 2022; Kadykalo et al., 2019). This follows common critiques of CES, as well as the ecosystem service concept more broadly, that these are too firmly rooted in a western-scientific view of the world (Kirchhoff, 2019; Tengö et al., 2017). It is argued that this is not only true in indigenous contexts but also in western settings such as in Great Britain because peoples' accounts of nature's cultural value do not necessarily revolve around individual, consequential activities and objective elements in the landscape (Cooper et al., 2016; Satterfield et al., 2013). Alternative methods from the social sciences have therefore been proposed such as deliberative approaches which seek to incorporate situated knowledges, cultural narratives and shared cultural values through collective reasoning (Kenter et al., 2016).

From this more qualitative research perspective, the applications of crowdsourced data and machine learning explored in this thesis fits more within the universal and reductionist approaches to CES measurement suited to western-scientific modes of inquiry (Echeverri et al., 2018; Gould et al., 2020a). That is, the CES measures generated using these novel techniques are aimed at providing standardised, quantitative metrics based on single interactions between individuals and specific biophysical elements (Hirons et al., 2016). This approach is based within a standard stock-to-flow framing of people-nature relationships (Chan et al., 2012b) while seeking to illuminate existing objective phenomena rather than co-creating these through the research process (Satterfield et al., 2013). Such an approach is motivated by the need to integrate cultural information into large-scale assessments of ecosystem value (Gould et al., 2019a). At these scales, a level of generalisation is necessary, especially in the context of economic accounting standards, and therefore qualitative information is not immediately compatible with these systems of measurement, constituting an on-going challenge (Raymond et al., 2014).

Nevertheless, crowdsourced data and machine learning also provide an opportunity to combine measurement approaches from different epistemological standpoints. Both quantitative and qualitative approaches have previously been combined. For example, CES preferences gathered using interviews and deliberative processes were mapped to the English landscape using quantitative variables (Norton et al., 2012). Such combinations enable a pragmatic solution whereby knowledge of reality is informed both by physical evidence and shared social constructions (Derungs and Purves, 2016; Raymond et al., 2014). In terms of crowdsourced data such as social media, these already provide a quantitative framing to a number of deliberative-like practices such as sharing, commenting and liking content (Calcagni et al., 2019). Similarly, crowdsourcing to create training datasets for machine learning models can employ deliberative processes to ascribe shared cultural meanings to the content of digital media (Chang et al., 2017). For example, groups can discuss and agree upon image annotations to come to collective decisions about the cultural importance of certain biophysical features. Consequently, these data would fit comfortably within current proposals to use digital tools for deliberative processes including the use of participatory mapping and online polls (Kenter et al., 2015).

Despite this compatibility, the scope of crowdsourced data and machine learning to capture peoples' cultural preferences on a spatial basis has its ultimate limitations. Some knowledge systems will always resist digitalisation due to their metaphysical nature or the legitimate resistance of certain populations to the use of digital technologies (Ginsburg, 2008). This includes, for example, cultural beliefs such as the moral values represented by ancestral beings in indigenous cultures (Gould et al., 2019b). Similarly, intrinsic values of nature are based on the idea of nature holding value independent of people (Chan et al., 2016). These limitations are not, however, only restricted to the application of digital technologies, as these cultural values also cannot be mapped based on single interactions using other methodological approaches (Nahuelhual et al., 2016), presenting a challenge for all ecosystem service assessments aimed at integrating these into mainstream policy-making (Pascual et al., 2021). Nevertheless, as digital technologies become more widespread and their use in cultural contexts evolves, a greater number of opportunities will emerge to include more of these diverse cultural values of nature in CES assessments (Garneau, 2018; Rice et al., 2016).

6.4. Relevancy in an ecosystem service and policy context

6.4.1. *Global sustainability agenda*

The rapid degradation of the Earth's ecosystems has resulted in a number of headline, international policy responses, including the 2030 Agenda for Sustainable Development, the UN Decade on Ecosystem Restoration and the drafting of the Post-2020 Global Biodiversity Framework. These all require monitoring frameworks, underpinned by science, with explicit outcomes at the country-level (Nature – Editorial, 2020). As a result, recent commitments to achieve these global policy objectives have emphasised the use of the SEEA EA and IPBES assessment frameworks. Following the meeting of the ministers of the G7 in May 2022, their communiqué included a commitment to implement the SEEA EA and a call on the IPBES to enable long-term transformative change towards the international sustainability agenda (G7, 2022). In this section, I explore the relevancy of the findings of this thesis to these leading international monitoring frameworks.

6.4.2. *SEEA EA*

The SEEA EA provides a comprehensive statistical framework for organizing data about habitats and landscapes in relation to economic and other human activities. Using the conceptual guidelines set out in the SEEA EA framework, national statistical institutes and researchers have developed CES models for integration with national statistics. Currently, most models have focused on producing models of outdoor recreation and nature-based tourism as broad CES categories (Hein et al., 2020a; Remme et al., 2014). For example, in the Netherlands, outdoor recreation was measured by allocating surveyed trips per province and environment to the density of hiking paths at a 500m resolution, with the distance from population centres also considered (Statistics Netherlands and WUR, 2021). These models are considered state-of-the-art, representing the most accurate indicators with the current availability of data (Hein et al., 2020b). Nevertheless, the SEEA EA guidelines encourage compilers to include as many ecosystem service types as possible to ensure accounts are as comprehensive as possible, citing a range of other potential services including education, scientific and research services as well as spiritual, artistic and symbolic services (United Nations et al., 2021). Thus, generally, a level of spatial granularity and service specificity is still missing from current efforts to compile CES indicators in line with the SEEA EA.

Here, crowdsourced data and machine learning offer an opportunity to achieve a greater amount of spatial variation and a larger range of service categories in SEEA EA-related assessments. Instead of uniform areas or environments, the spatial records of

crowdsourced data can highlight specific hotspots of service supply, with the associated media in the form of images or text allowing for more specific service categorisation. Machine learning can then, in turn, automate this process at large scales (Richards and Tunçer, 2018). Nevertheless, the use of these novel technologies also brings up a new set of challenges. The demographic and geographic representativeness of the data is a key issue when considering SEEA EA measures should be compatible with national economic statistics (United Nations et al., 2021). Encouragingly, the model for landscape aesthetic quality developed for Great Britain in Chapter 2 achieved a high level of accuracy. However, its accuracy in other geographic and demographic settings is yet to be tested.

Moving from measures of aesthetic quality to measures of aesthetic CES supply is another challenge. In this regard, more work is needed to develop relevant indicators of CES based on the information generated by crowdsourced data and machine learning. In on-going experimental work, it has been proposed to multiply, on a grid cell basis, the image-based aesthetic quality predictions produced in Chapter 2 by the quantity of images to produce a measure of aesthetic utility (Havinga and Hein, 2021). This would be analogous to the economic utility derived from the quality and quantity of different fuels at the fuel pump (Hirshleifer et al., 2005). Nevertheless, more empirical work is needed to determine the numeric relationship between aesthetic quality and a persons' enjoyment as well as the overall conceptual alignment with the SEEA EA. Alternatively, the cultural preferences captured through these novel techniques can also be used to better distribute national survey data. For example, in the case of the recreational model in the Netherlands, the total metres hiked could be linked to the distribution of Flickr activity as well as its relation to more specific biophysical features such as elevation or the presence of water.

Many other opportunities also exist to integrate the information generated by crowdsourced data and machine learning into SEEA EA-related assessments because this information is comprised of revealed preferences. These are particularly compatible with the conceptual basis of the SEEA EA which ultimately uses exchange values (Hein et al., 2020a). These reflect observed, or sometimes equivalent, market price transactions for goods and services (United Nations et al., 2021). In contrast, many survey methods are not directly compatible with the SEEA EA because these gather peoples' stated preferences. For example, their stated choices or willingness to pay in relation to ecosystems and particular biophysical features such as species types (United Nations et al., 2021). Crowdsourced data can therefore also be used to establish economic values using monetary valuation methods such as the travel cost method. This has been used to estimate the total value of trips made

by Flickr users to travel to national parks using the distance travelled from users' home locations (Sinclair et al., 2020). However, the method must be adapted and combined with other valuation approaches so as to be compatible with the SEEA EA (Caparrós et al., 2017).

As the SEEA EA establishes itself as an international statistical framework for use in environmental monitoring, several new research priorities have been identified (Edens et al., 2022). One of these includes the spatial modelling of ecosystem services and its further development, especially with respect to the use of ecosystem services and its relation to ecosystem capacity, the ability of an ecosystem to generate an ecosystem service (United Nations et al., 2021). From a CES perspective, crowdsourced data and machine learning provide one of the best new opportunities to develop spatial ecosystem service models, as demonstrated in this thesis. These novel techniques can therefore play an important role in the work needed to meet this particular research priority. Drawing on the granularity of the data, ecosystem service use versus capacity can also be assessed. For example, in understanding the carrying capacity of national park areas, where social media use may have negative environmental consequences due to concentrations of activity (Barros et al., 2019). Finally, the continued generation of crowdsourced data from different technologies and platforms will also support the spatial assessment of CES over time, which is essential in producing annual accounts of ecosystem service supply (United Nations et al., 2021).

6.4.3. IPBES

The IPBES assessment framework is much larger in its scope and objectives versus the SEEA EA in that it seeks to include a variety of knowledge systems to measure both monetary and non-monetary values, as well as the implications of different policy decisions (IPBES, 2019). It proposes both a generalising and context-specific perspective to measure these broad range of values, centred around the concept of Nature's Contribution to People (NCPs) (Díaz et al., 2018), equivalent in many ways to the concept of ecosystem services (Kadykalo et al., 2019). The generalising perspective is aimed at providing a universal set of categories to record the contributions of nature to peoples' well-being while the context-specific perspective seeks to do so in a way that is relevant to local knowledge (Hill et al., 2021). As part of both perspectives, relational values have also been introduced which are preferences, principals and virtues associated with peoples' relationships with nature and between themselves (Díaz et al., 2015). This includes, for example, individual environmental stewardship or increased social cohesion from being in nature (Chan et al., 2018).

Crowdsourced data and machine learning can be relevant to both measurement perspectives. From a generalising perspective, methods that are able to produce measures of NCP at large-scales are particularly relevant because these NCP are aimed at producing universal indicators. The spatial CES measures produced in this thesis are therefore especially amenable to this measurement approach. In particular, the measures in this thesis related to peoples' aesthetic enjoyment and appreciation of biodiversity are very much in line with the generalising NCP categories "physical and psychological experiences" and "learning and inspiration" (Díaz et al., 2018). A third culture-specific category, "supporting identities" is also proposed which relates more to the relational aspect of nature's contributions to people. Although not explored in this thesis, the advantage of crowdsourced data is that it provides a lot of information on these more relational interactions with nature (Langemeyer and Calcagni, 2022). In other research, for example, Flickr images and the associated text have been used to understand cultural properties such as digital identities (Davies, 2007) and peoples' sense of place (Jenkins et al., 2016; Wartmann et al., 2018). These rich new data sources can therefore also support measures of this more relational NCP at the generalising-level.

Relational NCP measures are even more relevant within the context-specific perspective (Hill et al., 2021). This is because this perspective makes room for reciprocal relationships between people and nature, common especially in the context of indigenous knowledge (Díaz et al., 2018). Because such relational contributions of ecosystems often defy reductionist empirical approaches, qualitative approaches are generally recommended (Tadaki et al., 2017). As previously discussed in Section 6.3, this does not, however stop social media from being relevant in these cases. For example, researchers have produced "spatial folksonomies' using the vocabularies employed by people in the Swiss alps through different sources of crowdsourced data (Derungs and Purves, 2016). Moreover, a quantitative approach to relational NCP has also been proposed based on methods such as regression analysis (Schulz and Martin-Ortega, 2018). This also leaves room for quantitative spatial measures of relational NCP measures based on crowdsourced data. However, measures will ultimately rely on data availability and the use of digital technologies by the relevant population (Calcagni et al., 2019).

Finally, the focus on interwoven analyses and plural perspectives in the application of the IPBES framework is also very conducive to the quantitative/qualitative nature of crowdsourced data (Hill et al., 2021). Contributions of nature in the context of local knowledge and expressed through digital technologies can be assessed through qualitative

methods. The quantitative basis of crowdsourced data can then be used to link these records to a more generalising layer of analysis relevant across large scales. For example, in East Africa, social media and mobile technologies have been found to facilitate and preserve the use of indigenous knowledge, including ideas of environmental conservation (Owiny et al., 2014). As a result, these unique relationships with nature expressed through stories and narratives are automatically linked with spatial records that can be classified according to the generalising perspective of the IPBES framework. In this way, crowdsourced data and machine learning can also support the pluralistic approach of the IPBES (U. Pascual et al., 2017).

6.5. Research outlook

6.5.1. *Moving to full measures of CES*

The research presented in this thesis seeks to explore the potential of crowdsourced data and machine learning in measuring CES. In doing so, I have demonstrated a number of advantages to the application of these novel techniques in CES assessment. Now, more conceptual and empirical work is needed to develop these indicators into full CES measures. In the context of the SEEA EA, this means quantitative measures, divisible to different scales and representative of national demographics (United Nations et al., 2021). For example, this would require developing the measure of aesthetic quality produced in Chapter 3 to a measure of aesthetic utility. This research is starting to be explored in other work with the conceptual idea of multiplying the number of images by their quality on a grid cell basis (Havinga and Hein, 2021).

In another example, this could involve weighting the human-species interactions produced in Chapter 4 by the sentiment expressed in the associated text to better reflect the size of the CES contribution per image. Other weights could also be applied, such as greater weights for interactions in less accessible places, implying a person has expended more effort to gain such an interaction. Not only sentiment could be used to weight human-species interactions as indicators of CES; species rarity could also imply an interaction of greater cultural importance. Recently, some studies have begun to explore this research challenge with promising results, using the text and content of the images to produce more advanced indicators (Fox et al., 2021a; Winder et al., 2022).

6.5.2. Testing and developing models in a broad range of cultural contexts

My research provides one of the first large-scale measurement exercises of CES-related indicators using crowdsourced data and machine learning. In the case of landscape aesthetics, the use of these novel techniques was validated versus a geographically-representative survey of the British landscape and a set of environmental indicators relevant to a variety of European landscapes. Nevertheless, more research is needed to understand the relevancy of the models in other geographical and cultural settings, including the development of new training datasets and model finetuning. This would involve carrying out questionnaires with demographically-representative samples to validate the predictions of the models versus particular biophysical features and environmental contexts. In this sense, CES research in this field is linked to one of the primary challenges of machine learning: the existence of appropriate training datasets for predictive tasks (Jordan and Mitchell, 2015). Machine learning models are ultimately constrained by their training datasets and further research should explore how well certain models generalise across different cultural contexts.

Moreover, for these techniques to be further developed in the context of CES, other related challenges in the field of machine learning must also be considered. This includes fairness which means ensuring models do not develop inherent biases that prioritise particular preferences or people over others (Mehrabi et al., 2021). Understanding why models make certain predictions, or the field of explainable AI, is therefore also worth exploring in the case of CES (Vinuesa and Sirmacek, 2021). Deep learning especially is often criticised for being a "black box", obscuring the processes behind model predictions (Barredo Arrieta et al., 2020). Planning decisions that directly affect peoples' cultural connection to the land can be the most controversial (Chan et al., 2012b). It is therefore of great importance that CES assessments applying machine learning techniques begin to incorporate a level of interpretability in their service predictions to satisfy the need for dialogue and transparency in a wider policy context (Langemeyer et al., 2016).

6.5.3. Working with the potential sources of bias in crowdsourced data

This thesis also provides novel contributions in the context of aesthetic and biodiversity-related CES measures for large-scale assessments. In particular, the development of a deep learning model to detect a broad range of cultural preferences for biodiversity on social media led to new insights into the differences between sources of crowdsourced data. In this case, Flickr versus the citizen science platform, iNaturalist.

However, further research is needed to understand the different sources of biases inherent to the data and how a combination of different data sources can address some of these biases to make measures more relevant to large-scale ecosystem service assessments. These biases (or "lenses" as I've referred to them in this chapter) are key limitations if CES assessments are to be compatible with national economic accounts or represent the cultural preferences of entire populations within other large-scale management areas.

Key to addressing this issue would be demographics in the case of the SEEA EA but also other factors are at play such as the purpose of different platforms. Combinations of data could address some of these biases. Existing research has started to explore this using estimated home locations of users using activity data (Li et al., 2013; Lopez et al., 2020). Nevertheless, these techniques also come with their limitations, introducing model uncertainty. Alternatively, mobile phone data, especially in countries with very high uptake has the potential to generate highly-representative indicators based on movement patterns. For example, which types of ecosystems and corresponding attributes are most visited during leisure hours including weekends. In this case, understanding which movement patterns are associated with nature recreation is a key research challenge. Ultimately, ground-truthing exercises using survey data will answer many of these questions.

6.5.4. Developing relational CES measures

Finally, the research presented in this thesis also demonstrated how crowdsourced data and machine learning can help establish connections between CES and peoples' positive experiences of nature. Using NLP models applied to the text associated with Flickr images, different levels of individual sentiment were linked to different levels of aesthetic quality and human-species interactions. Similar work using the text associated with social media images could also establish relational CES measures such as the generalising NCP category "supporting identities" proposed by IPBES. As discussed previously in this chapter, Flickr images and the associated text have already been used to understand peoples' sense of place which is similar in its conceptual underpinning (Jenkins et al., 2016). As the application of the IPBES conceptual framework matures, developing and testing these types of indicators using crowdsourced data while maintaining the connection to the concept of relational values constitutes an important research frontier (Hill et al., 2021).

Further research should also explore the collective benefits gained from interactions with nature in the context of relational values. Previous research has already highlighted the presence of virtual communities on social media and how these shape relational values

towards the environment (Calcagni et al., 2019). However, demonstrating the co-construction of these values using crowdsourced data, developing measures and integrating these into CES assessments remains an under-researched area. The quantitative foundation of digital data provides promising opportunities to capture these highly deliberative social processes in a way that could also be amenable to quantitative approaches. Nevertheless, more research is again needed to understand what these measures could mean in practice, especially in the context of the SEEA EA and IPBES conceptual frameworks.

6.6. Crowdsourced data, machine learning and society

As crowdsourced data and machine learning become ubiquitous in our society, their application and its consequences are still being realised, especially as these novel technologies continue to rapidly develop. "Big data" and "AI" have become familiar buzzwords, finding themselves into the vocabulary of engineers, medical practitioners, business people and policy-makers as well as scientists. Their application to CES assessment, especially the use of deep learning, is only just emerging and therefore many of the challenges are still yet to be explored (Ghermandi et al., 2022; Winder et al., 2022). Similarly, the use of key sources of crowdsourced data such as social media data have been demonstrated but rarely validated or explored from a conceptual standpoint. In this thesis, I have sought to provide some answers to these challenges.

The application of crowdsourced data and machine learning in the context of CES assessments, however, is an especially complex one as it tries to bring both understanding of natural and cultural processes together in a wider policy context. Any spatial metrics produced using these novel techniques must accurately reflect the biophysical reality and the cultural preferences of a population. Addressing pressing environmental issues such as land degradation, biodiversity and climate change all require difficult decisions to be made with the aim of balancing the interests of society. CES assessments produced using crowdsourced data and machine learning must not lose sight of this wider societal context. With technological advancement also comes complexity and CES measures employing crowdsourced data should remain credible through transparent and deliberative processes with the people the measures are meant to represent. How far digital worlds can really go to represent our physical reality is still an open question (Lahsen, 2020). I hope with the ideas set out in this thesis, this can continue to be explored in relation to the ecosystem service concept and the field of CES research.

References

Abraham, A., Sommerhalder, K., Abel, T., 2010. Landscape and well-being: a scoping study on the health-promoting impact of outdoor environments. Int. J. Public Health 55, 59–69. https://doi.org/10.1007/s00038-009-0069-z

Abson, D.J., Fischer, J., Leventon, J., Newig, J., Schomerus, T., Vilsmaier, U., von Wehrden, H., Abernethy, P., Ives, C.D., Jager, N.W., Lang, D.J., 2017. Leverage points for sustainability transformation. Ambio 46, 30–39. https://doi.org/10.1007/s13280-016-0800-y

Adamowicz, W., Swait, J., Boxall, P., Louviere, J., Williams, M., 1997. Perceptions versus objective measures of environmental quality in combined revealed and stated preference models of environmental valuation. J. Environ. Econ. Manage. 32, 65–84. https://doi.org/10.1006/jeem.1996.0957

Aerts, R., Honnay, O., Van Nieuwenhuyse, A., 2018. Biodiversity and human health: mechanisms and evidence of the positive health effects of diversity in nature and green spaces. Br. Med. Bull. 127, 5–22. https://doi.org/10.1093/bmb/ldy021

AHN, 2014. AHN3. Amersfoort.

Allan, J.D., Smith, S.D.P., McIntyre, P.B., Joseph, C.A., Dickinson, C.E., Marino, A.L., Biel, R.G., Olson, J.C., Doran, P.J., Rutherford, E.S., Adkins, J.E., Adeyemo, A.O., 2015. Using cultural ecosystem services to inform restoration priorities in the Laurentian Great Lakes. Front. Ecol. Environ. 13, 418–424. https://doi.org/10.1890/140328

Alshaabi, T., Arnold, M. V, Minot, J.R., Adams, J.L., Dewhurst, D.R., Reagan, A.J., Muhamad, R., Danforth, C.M., Dodds, P.S., 2021. How the world's collective attention is being paid to a pandemic: COVID-19 related n-gram time series for 24 languages on Twitter. PLoS One 16, e0244476.

Alvarez-Codoceo, S., Cerda, C., Perez-Quezada, J.F., 2021. Mapping the provision of cultural ecosystem services in large cities: The case of The Andean piedmont in Santiago, Chile. Urban For. Urban Green. 66, 127390. https://doi.org/10.1016/j.ufug.2021.127390

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

Antoniou, V., Fonte, C.C., See, L., Estima, J., Arsanjani, J.J., Lupia, F., Minghini, M., Foody,

G., Fritz, S., 2016. Investigating the Feasibility of Geo-Tagged Photographs as Sources of Land Cover Input Data. ISPRS Int. J. Geo-Information. https://doi.org/10.3390/ijgi5050064

Appleton, J., 1975. The Experience of Landscape. John Wiley and Sons, New York.

Arendsen, P., Marcos, D., Tuia, D., 2020. Concept Discovery for The Interpretation of Landscape Scenicness. Mach. Learn. Knowl. Extr. . https://doi.org/10.3390/make2040022

Aronson, M.F.J., Lepczyk, C.A., Evans, K.L., Goddard, M.A., Lerman, S.B., MacIvor, J.S., Nilon, C.H., Vargo, T., 2017. Biodiversity in the city: key challenges for urban green space management. Front. Ecol. Environ. 15, 189–196. https://doi.org/10.1002/fee.1480

Arora, P., 2012. The leisure divide: can the 'Third World' come out to play? Inf. Dev. 28, 93–101. https://doi.org/10.1177/0266666911433607

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

August, T.A., Pescott, O.L., Joly, A., Bonnet, P., 2020. AI Naturalists Might Hold the Key to Unlocking Biodiversity Data in Social Media Imagery. Patterns 1, 100116. https://doi.org/10.1016/j.patter.2020.100116

Austen, G.E., Dallimer, M., Irvine, K.N., Maund, P.R., Fish, R.D., Davies, Z.G., 2021. Exploring shared public perspectives on biodiversity attributes. People Nat. 3, 901–913. https://doi.org/10.1002/pan3.10237

Bagstad, K.J., Johnson, G.W., Voigt, B., Villa, F., 2013. Spatial dynamics of ecosystem service flows: A comprehensive approach to quantifying actual services. Ecosyst. Serv. 4, 117–125. https://doi.org/10.1016/j.ecoser.2012.07.012

Bairlein, F., 2008. The mysteries of bird migration – still much to be learnt. Br. Birds 101, 68–81.

Baklien, B., Ytterhus, B., Bongaardt, R., 2016. When everyday life becomes a storm on the horizon: families' experiences of good mental health while hiking in nature. Anthropol. Med. 23, 42–53. https://doi.org/10.1080/13648470.2015.1056056

Balaji, T.K., Annavarapu, C.S.R., Bablani, A., 2021. Machine learning algorithms for social media analysis: A survey. Comput. Sci. Rev. 40, 100395. https://doi.org/10.1016/j.cosrev.2021.100395

Balzan, M. V, Potschin-Young, M., Haines-Young, R., 2018. Island ecosystem services: insights from a literature review on case-study island ecosystem services and future prospects. Int. J. Biodivers. Sci. Ecosyst. Serv. Manag. 14, 71–90. https://doi.org/10.1080/21513732.2018.1439103

Barbier, E.B., 2011. Progress and Challenges in Valuing Coastal and Marine Ecosystem Services. Rev. Environ. Econ. Policy 6, 1–19. https://doi.org/10.1093/reep/rer017

Barbieri, F., Camacho-Collados, J., Neves, L., Espinosa-Anke, L., 2020. TweetEval: Unified Benchmark and Comparative Evaluation for Tweet Classification. https://doi.org/10.48550/ARXIV.2010.12421

Barredo Arrieta, A., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., Garcia, S., Gil-Lopez, S., Molina, D., Benjamins, R., Chatila, R., Herrera, F., 2020. Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. Inf. Fusion 58, 82–115. https://doi.org/https://doi.org/10.1016/j.inffus.2019.12.012

Barros, C., Moya-Gómez, B., García-Palomares, J.C., 2019. Identifying Temporal Patterns of Visitors to National Parks through Geotagged Photographs. Sustain. . https://doi.org/10.3390/su11246983

Barton, D.N., Obst, C., Day, B., Caparrós, A., Dadvand, P., Fenichel, E., Havinga, I., Hein, L., McPhearson, T., Randrup T., Z.G., 2019. Discussion paper 10: Recreation services from ecosystems. Paper submitted to the Expert Meeting on Advancing the Measurement of Ecosystem Services for Ecosystem Accounting. New York.

Barve, V., 2014. Discovering and developing primary biodiversity data from social networking sites : A novel approach. Ecol. Inform. 24, 194–199. https://doi.org/10.1016/j.ecoinf.2014.08.008

Bateman, I.J., Harwood, A.R., Mace, G.M., Watson, R.T., Abson, D.J., Andrews, B., Binner, A., Crowe, A., Day, B.H., Dugdale, S., Fezzi, C., Foden, J., Hadley, D., Haines-Young, R., Hulme, M., Kontoleon, A., Lovett, A.A., Munday, P., Pascual, U., Paterson, J., Perino, G., Sen, A., Siriwardena, G., van Soest, D., Termansen, M., 2013. Bringing Ecosystem Services into Economic Decision-Making: Land Use in the United Kingdom. Science (80-.). 341, 45 LP – 50. https://doi.org/10.1126/science.1234379

Becken, S., Stantic, B., Chen, J., Alaei, A.R., Connolly, R.M., 2017. Monitoring the environment and human sentiment on the Great Barrier Reef: Assessing the potential

of collective sensing. J. Environ. Manage. 203, 87–97. https://doi.org/10.1016/j.jenvman.2017.07.007

Belaire, J.A., Westphal, L.M., Whelan, C.J., Minor, E.S., 2015. Urban residents' perceptions of birds in the neighborhood: Biodiversity, cultural ecosystem services, and disservices. Condor 117, 192–202. https://doi.org/10.1650/CONDOR-14-128.1

Bieling, C., Plieninger, T., 2013. Recording Manifestations of Cultural Ecosystem Services in the Landscape. Landsc. Res. 38, 649–667. https://doi.org/10.1080/01426397.2012.691469

Bieling, C., Plieninger, T., Pirker, H., Vogl, C.R., 2014. Linkages between landscapes and human well-being: An empirical exploration with short interviews. Ecol. Econ. 105, 19–30. https://doi.org/10.1016/j.ecolecon.2014.05.013

Boerema, A., Rebelo, A.J., Bodi, M.B., Esler, K.J., Meire, P., 2017. Are ecosystem services adequately quantified? J. Appl. Ecol. 54, 358–370. https://doi.org/10.1111/1365-2664.12696

Borowiec, M.L., Dikow, R.B., Frandsen, P.B., McKeeken, A., Valentini, G., White, A.E., 2022. Deep learning as a tool for ecology and evolution. Methods Ecol. Evol. 13, 1640–1660. https://doi.org/10.1111/2041-210X.13901

Botzat, A., Fischer, L.K., Kowarik, I., 2016. Unexploited opportunities in understanding liveable and biodiverse cities. A review on urban biodiversity perception and valuation. Glob. Environ. Chang. 39, 220–233. https://doi.org/10.1016/j.gloenvcha.2016.04.008

Bowler, D.E., Buyung-Ali, L.M., Knight, T.M., Pullin, A.S., 2010. A systematic review of evidence for the added benefits to health of exposure to natural environments. BMC Public Health 10, 456. https://doi.org/10.1186/1471-2458-10-456

boyd, danah, Crawford, K., 2012. Critical questions for Big Data. Information, Commun. Soc. 15, 662–679. https://doi.org/10.1080/1369118X.2012.678878

Boyd, J., Banzhaf, S., 2007. What are ecosystem services? The need for standardized environmental accounting units. Ecol. Econ. 63, 616–626. https://doi.org/10.1016/j.ecolecon.2007.01.002

Boyd, J.W., Bagstad, K.J., Ingram, J.C., Shapiro, C.D., Adkins, J.E., Casey, C.F., Duke, C.S., Glynn, P.D., Goldman, E., Grasso, M., Hass, J.L., Johnson, J.A., Lange, G.-M., Matuszak, J., Miller, A., Oleson, K.L.L., Posner, S.M., Rhodes, C., Soulard, F., Vardon, M., Villa, F., Voigt, B., Wentland, S., 2018. The Natural Capital Accounting Opportunity: Let's Really Do the Numbers. Bioscience 68, 940–943. https://doi.org/10.1093/biosci/biy135

Braat, L.C., de Groot, R., 2012. The ecosystem services agenda:bridging the worlds of natural science and economics, conservation and development, and public and private policy. Ecosyst. Serv. 1, 4–15. https://doi.org/10.1016/j.ecoser.2012.07.011

Branson, N.J.B.A., Ponting, E.D., Minton, C.D.T., 1978. Turnstone Migrations in Britain and Europe. Bird Study 25, 181–187. https://doi.org/10.1080/00063657809476593

Bratman, G.N., Hamilton, J.P., Daily, G.C., 2012. The impacts of nature experience on human cognitive function and mental health. Ann. N. Y. Acad. Sci. 1249, 118–136. https://doi.org/10.1111/j.1749-6632.2011.06400.x

Brindley, P., Cameron, R.W., Ersoy, E., Jorgensen, A., Maheswaran, R., 2019. Is more always better? Exploring field survey and social media indicators of quality of urban greenspace, in relation to health. Urban For. Urban Green. 39, 45–54. https://doi.org/10.1016/j.ufug.2019.01.015

Bubalo, M., van Zanten, B.T., Verburg, P.H., 2019. Crowdsourcing geo-information on landscape perceptions and preferences: A review. Landsc. Urban Plan. 184, 101–111. https://doi.org/10.1016/j.landurbplan.2019.01.001

Buie, E., Blythe, M., 2013. Meditations on YouTube, in: Proceedings of the 6th International Conference on Designing Pleasurable Products and Interfaces, DPPI '13. Association for Computing Machinery, New York, NY, USA, pp. 41–50. https://doi.org/10.1145/2513506.2513511

Bush, L.E., 1973. Individual differences multidimensional scaling of adjectives denoting feelings. J. Pers. Soc. Psychol. 25. https://doi.org/10.1037/h0034274

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

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. Indic. 137, 108756. https://doi.org/10.1016/j.ecolind.2022.108756

Caparrós, A., Oviedo, J.L., Álvarez, A., Campos, P., 2017. Simulated exchange values and ecosystem accounting: Theory and application to free access recreation. Ecol. Econ. 139, 140–149. https://doi.org/10.1016/j.ecolecon.2017.04.011

Cardinale, B.J., Duffy, J.E., Gonzalez, A., Hooper, D.U., Perrings, C., Venail, P., Narwani, A.,

Mace, G.M., Tilman, D., Wardle, D.A., Kinzig, A.P., Daily, G.C., Loreau, M., Grace, J.B., Larigauderie, A., Srivastava, D.S., Naeem, S., 2012. Biodiversity loss and its impact on humanity. Nature 486, 59–67. https://doi.org/10.1038/nature11148

Carpenter, S.R., Mooney, H.A., Agard, J., Capistrano, D., DeFries, R.S., Diaz, S., Dietz, T., Duraiappah, A.K., Oteng-Yeboah, A., Pereira, H.M., Perrings, C., Reid, W. V., Sarukhan, J., Scholes, R.J., Whyte, A., 2009. Science for managing ecosystem services: Beyond the Millennium Ecosystem Assessment. Proc. Natl. Acad. Sci. 106, 1305–1312. https://doi.org/10.1073/pnas.0808772106

Carrus, G., Scopelliti, M., Lafortezza, R., Colangelo, G., Ferrini, F., Salbitano, F., Agrimi, M., Portoghesi, L., Semenzato, P., Sanesi, G., 2015. Go greener, feel better? The positive effects of biodiversity on the well-being of individuals visiting urban and peri-urban green areas. Landsc. Urban Plan. 134, 221–228. https://doi.org/10.1016/j.landurbplan.2014.10.022

Casalegno, S., Inger, R., DeSilvey, C., Gaston, K.J., 2013. Spatial Covariance between Aesthetic Value & Other Ecosystem Services. PLoS One 8. https://doi.org/10.1371/journal.pone.0068437

CBS, 2018. Population dynamics; birth, death and migration per region [WWW Document]. Statline.

Ceccaroni, L., Bibby, J., Roger, E., Flemons, P., Michael, K., Fagan, L., Oliver, J.L., 2019. Opportunities and Risks for Citizen Science in the Age of Artificial Intelligence. Citiz. Sci. Theory Pract. 4. https://doi.org/10.5334/cstp.241

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. Opinion: Why protect nature? Rethinking values and the environment. Proc. Natl. Acad. Sci. 113, 1462 LP – 1465. https://doi.org/10.1073/pnas.1525002113

Chan, K.M.A., Goldstein, J., Satterfield, T., Hannahs, N., Kikiloi, K., Naidoo, R., Vadeboncoeur, N., Woodside, U., 2011. Cultural services and non-use values, in: Natural Capital. Oxford University Press, Oxford. https://doi.org/10.1093/acprof:oso/9780199588992.003.0012

Chan, K.M.A., Gould, R.K., Pascual, U., 2018. Editorial overview: Relational values: what are they, and what's the fuss about? Curr. Opin. Environ. Sustain. 35, A1–A7.

https://doi.org/10.1016/j.cosust.2018.11.003

Chan, K.M.A., Guerry, A.D., Balvanera, P., Klain, S., Satterfield, T., Basurto, X., Bostrom, A., Chuenpagdee, R., Gould, R., Halpern, B.S., Levine, J., Hannahs, N., Norton, B., Ruckelshaus, M., Russell, R., Tam, J., Woodside, U., 2012a. Where are Cultural and Social in Ecosystem Services? A Framework for Constructive Engagement. Bioscience 62, 744–756. https://doi.org/10.1525/bio.2012.62.8.7

Chan, K.M.A., Satterfield, T., Goldstein, J., 2012b. Rethinking ecosystem services to better address and navigate cultural values. Ecol. Econ. 74, 8–18. https://doi.org/10.1016/j.ecolecon.2011.11.011

Chang, C., Cheng, G.J.Y., Nghiem, T.P. Le, Song, X.P., Oh, R.R.Y., Richards, D.R., Carrasco, L.R., 2020. Social media, nature, and life satisfaction: global evidence of the biophilia hypothesis. Sci. Rep. 10, 4125. https://doi.org/10.1038/s41598-020-60902-w

Chang, J.C., Amershi, S., Kamar, E., 2017. Revolt: Collaborative Crowdsourcing for Labeling Machine Learning Datasets, in: Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems, CHI '17. Association for Computing Machinery, New York, NY, USA, pp. 2334–2346. https://doi.org/10.1145/3025453.3026044

Chen, X., Elmes, G., Ye, X., Chang, J., 2016. Implementing a real-time Twitter-based system for resource dispatch in disaster management. GeoJournal 81, 863–873. https://doi.org/10.1007/s10708-016-9745-8

Chesnokova, O., Nowak, M., Purves, R.S., 2017. A Crowdsourced Model of Landscape Preference. 13th Int. Conf. Spat. Inf. Theory (COSIT 2017) 86. https://doi.org/10.4230/LIPIcs.COSIT.2017.19

Chesnokova, O., Purves, R.S., 2018. From image descriptions to perceived sounds and sources in landscape: Analyzing aural experience through text. Appl. Geogr. 93, 103–111. https://doi.org/10.1016/j.apgeog.2018.02.014

Clark, K., Khandelwal, U., Levy, O., Manning, C.D., 2019. What Does BERT Look at? An Analysis of BERT's Attention, in: Proceedings of the 2019 ACL Workshop BlackboxNLP: Analyzing and Interpreting Neural Networks for NLP. Association for Computational Linguistics, Florence, Italy, pp. 276–286. https://doi.org/10.18653/v1/W19-4828

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. Indic. 96, 59–68. https://doi.org/10.1016/j.ecolind.2018.08.043

Cody, E.M., Reagan, A.J., Mitchell, L., Dodds, P.S., Danforth, C.M., 2015. Climate Change Sentiment on Twitter: An Unsolicited Public Opinion Poll. PLoS One 10, e0136092.

Condoon, 2019. Web API Technical Service Standard [WWW Document]. URL https://www.codoon.com/h5/codoon-welcome/stander.html (accessed 4.17.19).

Connors, J.P., Lei, S., Kelly, M., 2012. Citizen Science in the Age of Neogeography: Utilizing Volunteered Geographic Information for Environmental Monitoring. Ann. Assoc. Am. Geogr. 102, 1267–1289. https://doi.org/10.1080/00045608.2011.627058

Cooper, N., Brady, E., Steen, H., Bryce, R., 2016. Aesthetic and spiritual values of ecosystems: Recognising the ontological and axiological plurality of cultural ecosystem 'services.' Ecosyst. Serv. 21, 218–229. https://doi.org/10.1016/j.ecoser.2016.07.014

Cord, A.F., Roeßiger, F., Schwarz, N., 2015. Geocaching data as an indicator for recreational ecosystem services in urban areas: Exploring spatial gradients, preferences and motivations. Landsc. Urban Plan. 144, 151–162. https://doi.org/10.1016/j.landurbplan.2015.08.015

Cordingley, J.E., Newton, A.C., Rose, R.J., Clarke, R.T., Bullock, J.M., 2015. Habitat Fragmentation Intensifies Trade-Offs between Biodiversity and Ecosystem Services in a Heathland Ecosystem in Southern England. PLoS One 10, e0130004.

Cordts, M., Omran, M., Ramos, S., Rehfeld, T., Enzweiler, M., Benenson, R., Franke, U., Roth, S., Schiele, B., 2016. The Cityscapes Dataset for Semantic Urban Scene Understanding, in: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR).

Cox, D.T.C., Gaston, K.J., 2015. Likeability of Garden Birds: Importance of Species Knowledge & Richness in Connecting People to Nature. PLoS One 10, e0141505.

Cox, D.T.C., Shanahan, D.F., Hudson, H.L., Plummer, K.E., Siriwardena, G.M., Fuller, R.A., Anderson, K., Hancock, S., Gaston, K.J., 2017. Doses of Neighborhood Nature: The Benefits for Mental Health of Living with Nature. Bioscience 67, 147–155. https://doi.org/10.1093/biosci/biw173

Crampton, J.W., Graham, M., Poorthuis, A., Shelton, T., Stephens, M., Wilson, M.W., Zook, M., 2013. Beyond the geotag: situating 'big data' and leveraging the potential of the

geoweb. Cartogr. Geogr. Inf. Sci. 40, 130–139. https://doi.org/10.1080/15230406.2013.777137

Dai, P., Zhang, S., Hou, H., Yang, Y., Liu, R., 2019. Valuing sports services in urban parks: A new model based on social network data. Ecosyst. Serv. 36, 100891. https://doi.org/10.1016/j.ecoser.2019.01.003

Dallimer, M., Irvine, K.N., Skinner, A.M.J., Davies, Z.G., Rouquette, J.R., Maltby, L.L., Warren, P.H., Armsworth, P.R., Gaston, K.J., 2012. Biodiversity and the Feel-Good Factor: Understanding Associations between Self-Reported Human Well-being and Species Richness. Bioscience 62, 47–55. https://doi.org/10.1525/bio.2012.62.1.9

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

Daniel, T.C., Muhar, A., Arnberger, A., Aznar, O., Boyd, J.W., Chan, K.M.A., Costanza, R., Elmqvist, T., Flint, C.G., Gobster, P.H., Gret-Regamey, A., Lave, R., Muhar, S., Penker, M., Ribe, R.G., Schauppenlehner, T., Sikor, T., Soloviy, I., Spierenburg, M., Taczanowska, K., Tam, J., von der Dunk, A., 2012. Contributions of cultural services to the ecosystem services agenda. Proc. Natl. Acad. Sci. 109, 8812–8819. https://doi.org/10.1073/pnas.1114773109

Davies, J., 2007. Display, Identity and the Everyday: Self-presentation through online image sharing. Discourse Stud. Cult. Polit. Educ. 28, 549–564. https://doi.org/10.1080/01596300701625305

de Albuquerque, J.P., Herfort, B., Brenning, A., Zipf, A., 2015. A geographic approach for combining social media and authoritative data towards identifying useful information for disaster management. Int. J. Geogr. Inf. Sci. 29, 667–689. https://doi.org/10.1080/13658816.2014.996567

de Groot, R.S., Alkemade, R., Braat, L., Hein, L., Willemen, L., 2010. Challenges in integrating the concept of ecosystem services and values in landscape planning, management and decision making. Ecol. Complex. 7, 260–272. https://doi.org/10.1016/j.ecocom.2009.10.006

De Hert, P., Papakonstantinou, V., Malgieri, G., Beslay, L., Sanchez, I., 2018. The right to data portability in the GDPR: Towards user-centric interoperability of digital services. Comput. Law Secur. Rev. 34, 193–203. https://doi.org/10.1016/j.clsr.2017.10.003

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

de Vries, S., van Dillen, S.M.E., Groenewegen, P.P., Spreeuwenberg, P., 2013. Streetscape greenery and health: Stress, social cohesion and physical activity as mediators. Soc. Sci. Med. 94, 26–33. https://doi.org/10.1016/j.socscimed.2013.06.030

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

Di Cecco, G.J., Barve, V., Belitz, M.W., Stucky, B.J., Guralnick, R.P., Hurlbert, A.H., 2021. Observing the Observers: How Participants Contribute Data to iNaturalist and Implications for Biodiversity Science. Bioscience 71, 1179–1188. https://doi.org/10.1093/biosci/biab093

Di Minin, E., Tenkanen, H., Toivonen, T., 2015. Prospects and challenges for social media data in conservation science. Front. Environ. Sci. 3, 63. https://doi.org/10.3389/fenvs.2015.00063

Díaz, S., Demissew, S., Carabias, J., Joly, C., Lonsdale, M., Ash, N., Larigauderie, A., Adhikari, J.R., Arico, S., Báldi, A., Bartuska, A., Baste, I.A., Bilgin, A., Brondizio, E., Chan, K.M.A., Figueroa, V.E., Duraiappah, A., Fischer, M., Hill, R., Koetz, T., Leadley, P., Lyver, P., Mace, G.M., Martin-Lopez, B., Okumura, M., Pacheco, D., Pascual, U., Pérez, E.S., Reyers, B., Roth, E., Saito, O., Scholes, R.J., Sharma, N., Tallis, H., Thaman, R., Watson, R., Yahara, T., Hamid, Z.A., Akosim, C., Al-Hafedh, Y., Allahverdiyev, R., Amankwah, E., Asah, S.T., Asfaw, Z., Bartus, G., Brooks, L.A., Caillaux, J., Dalle, G., Darnaedi, D., Driver, A., Erpul, G., Escobar-Eyzaguirre, P., Failler, P., Fouda, A.M.M., Fu, B., Gundimeda, H., Hashimoto, S., Homer, F., Lavorel, S., Lichtenstein, G., Mala, W.A., Mandivenyi, W., Matczak, P., Mbizvo, C., Mehrdadi, M., Metzger, J.P., Mikissa, J.B., Moller, H., Mooney, H.A., Mumby, P., Nagendra, H., Nesshover, C., Oteng-Yeboah, A.A., Pataki, G., Roué, M., Rubis, J., Schultz, M., Smith, P., Sumaila, R., Takeuchi, K., Thomas, S., Verma, M., Yeo-Chang, Y., Zlatanova, D., 2015. The IPBES Conceptual Framework — connecting nature and people. Curr. Opin. Environ. Sustain. 14, 1–16. https://doi.org/10.1016/j.cosust.2014.11.002

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 (80-.). 359, 270–272. https://doi.org/10.1126/science.aap8826

Donahue, M.L., Keeler, B.L., Wood, S.A., Fisher, D.M., Hamstead, Z.A., McPhearson, T., 2018. Using social media to understand drivers of urban park visitation in the Twin Cities, MN. Landsc. Urban Plan. 175, 1–10. https://doi.org/10.1016/j.landurbplan.2018.02.006

eBird, 2019. eBird Data Access [WWW Document]. URL https://ebird.org/data/download (accessed 4.17.19).

Echeverri, A., Karp, D.S., Frishkoff, L.O., Krishnan, J., Naidoo, R., Zhao, J., Zook, J., Chan, K.M.A., 2021. Avian cultural services peak in tropical wet forests. Conserv. Lett. 14, e12763. https://doi.org/10.1111/conl.12763

Echeverri, A., Karp, D.S., Naidoo, R., Tobias, J.A., Zhao, J., Chan, K.M.A., 2020. Can avian functional traits predict cultural ecosystem services? People Nat. 2, 138–151. https://doi.org/10.1002/pan3.10058

Echeverri, A., Karp, D.S., Naidoo, R., Zhao, J., Chan, K.M.A., 2018. Approaching human-animal relationships from multiple angles: A synthetic perspective. Biol. Conserv. 224, 50–62. https://doi.org/10.1016/j.biocon.2018.05.015

Echeverri, A., Smith, J.R., MacArthur-Waltz, D., Lauck, K.S., Anderson, C.B., Vargas, R.M., Quesada, I.A., Wood, S.A., Chaplin-Kramer, R., Daily, G.C., 2022. Biodiversity and infrastructure interact to drive tourism to and within Costa Rica. Proc. Natl. Acad. Sci. 119, e2107662119. https://doi.org/10.1073/pnas.2107662119

Edens, B., Maes, J., Hein, L., Obst, C., Siikamaki, J., Schenau, S., Javorsek, M., Chow, J., Chan, J.Y., Steurer, A., Alfieri, A., 2022. Establishing the SEEA Ecosystem Accounting as a global standard. Ecosyst. Serv. 54, 101413. https://doi.org/10.1016/j.ecoser.2022.101413

Edwards, T., Jones, C.B., Corcoran, P., 2022. Identifying wildlife observations on twitter. Ecol. Inform. 67, 101500. https://doi.org/10.1016/j.ecoinf.2021.101500

Edwards, T., Jones, C.B., Perkins, S.E., Corcoran, P., 2021. Passive citizen science: The role of social media in wildlife observations. PLoS One 16, e0255416.

EEA, 2019. Ecosystem types of Europe [WWW Document]. URL https://www.eea.europa.eu/data-and-maps/data/ecosystem-types-of-europe-1

EEA, 2017. Copernicus Land Monitoring Service - EU-DEM [WWW Document]. URL

https://www.eea.europa.eu/data-and-maps/data/copernicus-land-monitoring-service-eu-dem

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. n/a. https://doi.org/10.1002/pan3.10199

Eigenbrod, F., Armsworth, P.R., Anderson, B.J., Heinemeyer, A., Gillings, S., Roy, D.B., Thomas, C.D., Gaston, K.J., 2010. The impact of proxy-based methods on mapping the distribution of ecosystem services. J. Appl. Ecol. 47, 377–385. https://doi.org/10.1111/j.1365-2664.2010.01777.x

Elwood, S., Goodchild, M.F., Sui, D.Z., 2012. Researching Volunteered Geographic Information: Spatial Data, Geographic Research, and New Social Practice. Ann. Assoc. Am. Geogr. 102, 571–590. https://doi.org/10.1080/00045608.2011.595657

Elwood, S., Leszczynski, A., 2011. Privacy, reconsidered: New representations, data practices, and the geoweb. Geoforum 42, 6–15. https://doi.org/10.1016/j.geoforum.2010.08.003

Englund, O., Berndes, G., Cederberg, C., 2017. How to analyse ecosystem services in landscapes—A systematic review. Ecol. Indic. 73, 492–504. https://doi.org/10.1016/j.ecolind.2016.10.009

Environmental Audit Committee, 2021. Biodiversity in the UK: bloom or bust? London.

Farrell, C.A., Aronson, J., Daily, G.C., Hein, L., Obst, C., Woodworth, P., Stout, J.C., 2021. Natural capital approaches: shifting the UN Decade on Ecosystem Restoration from aspiration to reality. Restor. Ecol. e13613. https://doi.org/10.1111/rec.13613

Figueroa-Alfaro, R.W., Tang, Z., 2017. Evaluating the aesthetic value of cultural ecosystem services by mapping geo-tagged photographs from social media data on Panoramio and Flickr. J. Environ. Plan. Manag. 60, 266–281. https://doi.org/10.1080/09640568.2016.1151772

Fischer, L.K., Honold, J., Botzat, A., Brinkmeyer, D., Cvejić, R., Delshammar, T., Elands, B., Haase, D., Kabisch, N., Karle, S.J., Lafortezza, R., Nastran, M., Nielsen, A.B., van der Jagt, A.P., Vierikko, K., Kowarik, I., 2018. Recreational ecosystem services in European cities: Sociocultural and geographical contexts matter for park use. Ecosyst. Serv. 31, 455–467. https://doi.org/10.1016/j.ecoser.2018.01.015

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

Foltête, J.-C., Ingensand, J., Blanc, N., 2020. Coupling crowd-sourced imagery and visibility modelling to identify landscape preferences at the panorama level. Landsc. Urban Plan. 197, 103756. https://doi.org/10.1016/j.landurbplan.2020.103756

Foursquare, 2019. Places Database [WWW Document]. URL https://developer.foursquare.com/docs/data (accessed 4.17.19).

Fox, N., Graham, L.J., Eigenbrod, F., Bullock, J.M., Parks, K.E., 2021a. 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

Fox, N., Graham, L.J., Eigenbrod, F., Bullock, J.M., Parks, K.E., 2021b. Reddit: A novel data source for cultural ecosystem service studies. Ecosyst. Serv. 50, 101331. https://doi.org/10.1016/j.ecoser.2021.101331

Frank, S., Fürst, C., Koschke, L., Witt, A., Makeschin, F., 2013. Assessment of landscape aesthetics—Validation of a landscape metrics-based assessment by visual estimation of the scenic beauty. Ecol. Indic. 32, 222–231. https://doi.org/10.1016/j.ecolind.2013.03.026

Fuller, R.A., Irvine, K.N., Devine-Wright, P., Warren, P.H., Gaston, K.J., 2007. Psychological benefits of greenspace increase with biodiversity. Biol. Lett. 3, 390–394. https://doi.org/10.1098/rsbl.2007.0149

G7, 2022. G7 Climate, Energy and Environment Ministers' Communiqué. Schloss Elmau.

Gandomi, A., Haider, M., 2015. Beyond the hype: Big data concepts, methods, and analytics. Int. J. Inf. Manage. 35, 137–144. https://doi.org/10.1016/j.ijinfomgt.2014.10.007

Gao, Q., Abel, F., Houben, G.-J., Yu, Y., 2012. A Comparative Study of Users' Microblogging Behavior on Sina Weibo and Twitter, in: Masthoff, J., Mobasher, B., Desmarais, M.C., Nkambou, R. (Eds.), User Modeling, Adaptation, and Personalization. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 88–101.

Garneau, D., 2018. Electric Beads: On Indigenous Digital Formalism. Vis. Anthropol. Rev. 34, 77–86. https://doi.org/10.1111/var.12155

GBIF, 2019. Search Datasets [WWW Document]. URL https://www.gbif.org/dataset/search?q= (accessed 4.17.19).

Geocaching, 2019. Geocaching API [WWW Document]. URL https://api.groundspeak.com/documentation (accessed 4.17.19).

Ghermandi, A., 2016. Analysis of intensity and spatial patterns of public use in natural treatment systems using geotagged photos from social media. Water Res. 105, 297–304. https://doi.org/10.1016/j.watres.2016.09.009

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., 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., Sinclair, M., 2019. Passive crowdsourcing of social media in environmental research: A systematic map. Glob. Environ. Chang. 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. Chang. 65, 102189. https://doi.org/10.1016/j.gloenvcha.2020.102189

Giddy, J.K., Webb, N.L., 2018. The influence of the environment on adventure tourism: from motivations to experiences. Curr. Issues Tour. 21, 2124–2138. https://doi.org/10.1080/13683500.2016.1245715

Ginsburg, F., 2008. Rethinking the digital age, in: Hesmondhalgh, D., Toynbee, J. (Eds.), The Media and Social Theory. Routledge, London, pp. 141–158. https://doi.org/10.4324/9780203930472

Gliozzo, G., Pettorelli, N., Haklay, M. (Muki), 2016. Using crowdsourced imagery to detect cultural ecosystem services: a case study in South Wales, UK. Ecol. Soc. 21. https://doi.org/10.5751/ES-08436-210306

Glueck, J., 2018. Foursquare's Third Consecutive Year of 50% Revenue Growth or Better [WWW Document]. URL https://medium.com/foursquare-direct/foursquares-third-consecutive-year-of-50-revenue-growth-or-better-adfca92d733 (accessed 4.17.19).

Go, A., Bhayani, R., Huang, L., 2009. Twitter sentiment classification using distant supervision. CS224N Proj. report, Stanford 1.

Gobster, P.H., Nassauer, J.I., Daniel, T.C., Fry, G., 2007. The shared landscape: what does aesthetics have to do with ecology? Landsc. Ecol. 22, 959–972. https://doi.org/10.1007/s10980-007-9110-x

Gómez-Baggethun, E., Barton, D.N., 2013. Classifying and valuing ecosystem services for urban planning. Ecol. Econ. 86, 235–245. https://doi.org/10.1016/j.ecolecon.2012.08.019

Gómez-Baggethun, E., de Groot, R., Lomas, P.L., Montes, C., 2010. The history of ecosystem services in economic theory and practice: From early notions to markets and payment schemes. Ecol. Econ. 69, 1209–1218. https://doi.org/10.1016/j.ecolecon.2009.11.007

Goodchild, M.F., 2007. Citizens as sensors: the world of volunteered geography. GeoJournal 69, 211–221. https://doi.org/10.1007/s10708-007-9111-y

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., Adams, A., Vivanco, L., 2020a. Looking into the dragons of cultural ecosystem services. Ecosyst. People 16, 257–272. https://doi.org/10.1080/26395916.2020.1815841

Gould, R.K., Bremer, L.L., Pascua, P., Meza-Prado, K., 2020b. Frontiers in Cultural Ecosystem Services: Toward Greater Equity and Justice in Ecosystem Services Research and Practice. Bioscience 70, 1093–1107. https://doi.org/10.1093/biosci/biaa112

Gould, R.K., Morse, J.W., Adams, A.B., 2019a. Cultural ecosystem services and decision-making: How researchers describe the applications of their work. People Nat. 1, 457–475. https://doi.org/10.1002/pan3.10044

Gould, R.K., Pai, M., Muraca, B., Chan, K.M.A., 2019b. He 'ike 'ana ia i ka pono (it is a recognizing of the right thing): how one indigenous worldview informs relational values and social values. Sustain. Sci. 14, 1213–1232. https://doi.org/10.1007/s11625-019-00721-9

GPSies, 2019. Extended search [WWW Document]. URL https://www.gpsies.com/trackList.do (accessed 4.17.19).

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

Graves, R.A., Pearson, S.M., Turner, M.G., 2017. Species richness alone does not predict cultural ecosystem service value. Proc. Natl. Acad. Sci. 114, 3774 LP – 3779. https://doi.org/10.1073/pnas.1701370114

Griffin, G.P., Jiao, J., 2015. Where does bicycling for health happen? Analysing volunteered geographic information through place and plexus. J. Transp. Heal. 2, 238–247. https://doi.org/10.1016/j.jth.2014.12.001

Grizzetti, B., Liquete, C., Pistocchi, A., Vigiak, O., Zulian, G., Bouraoui, F., De Roo, A., Cardoso, A.C., 2019. Relationship between ecological condition and ecosystem services in European rivers, lakes and coastal waters. Sci. Total Environ. 671, 452–465. https://doi.org/10.1016/j.scitotenv.2019.03.155

Guerrero, P., Møller, M.S., Olafsson, A.S., Snizek, B., 2016. Revealing Cultural Ecosystem Services through Instagram Images: The Potential of Social Media Volunteered Geographic Information for Urban Green Infrastructure Planning and Governance. Urban Plan. 1, 1. https://doi.org/10.17645/up.v1i2.609

Guerry, A.D., Polasky, S., Lubchenco, J., Chaplin-Kramer, R., Daily, G.C., Griffin, R., Ruckelshaus, M., Bateman, I.J., Duraiappah, A., Elmqvist, T., Feldman, M.W., Folke, C., Hoekstra, J., Kareiva, P.M., Keeler, B.L., Li, S., McKenzie, E., Ouyang, Z., Reyers, B., Ricketts, T.H., Rockström, J., Tallis, H., Vira, B., 2015. Natural capital and ecosystem services informing decisions: From promise to practice. Proc. Natl. Acad. Sci. 112, 7348–7355. https://doi.org/10.1073/pnas.1503751112

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/DOI: 10.1017/CBO9780511750458.007

Haines-Young, R., Potschin, M.B., 2018. Common International Classification of Ecosystem Services (CICES) V5.1: Guidance on the Application of the Revised Structure. Nottingham, United Kingdom.

Hall, D.K., Riggs, G.A., 2015. MODIS/Terra Snow Cover Monthly L3 Global 0.05Deg CMG, Version 6 [WWW Document]. NASA Natl. Snow Ice Data Cent. Distrib. Act. Arch. Cent. https://doi.org/https://doi.org/10.5067/MODIS/MOD10CM.006

Hansen, R., Pauleit, S., 2014. From Multifunctionality to Multiple Ecosystem Services? A Conceptual Framework for Multifunctionality in Green Infrastructure Planning for

Urban Areas. Ambio 43, 516–529. https://doi.org/10.1007/s13280-014-0510-2

Hartig, T., Evans, G.W., Jamner, L.D., Davis, D.S., Gärling, T., 2003. Tracking restoration in natural and urban field settings. J. Environ. Psychol. 23, 109–123. https://doi.org/10.1016/S0272-4944(02)00109-3

Hartig, T., Mitchell, R., de Vries, S., Frumkin, H., 2014. Nature and Health. Annu. Rev. Public Health 35, 207–228. https://doi.org/10.1146/annurev-publhealth-032013-182443

Hausmann, A., Slotow, R., Burns, J.K., Di Mini, E., 2016. The ecosystem service of sense of place: benefits for human well-being and biodiversity conservation. Environ. Conserv. 43, 117–127. https://doi.org/10.1017/S0376892915000314

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., Bogaart, P.W., Hein, L., Tuia, D., 2020. Defining and spatially modelling cultural ecosystem services using crowdsourced data. Ecosyst. Serv. 43, 101091. https://doi.org/10.1016/j.ecoser.2020.101091

Havinga, I., Hein, L., 2021. MAIA working paper: Exploring aesthetic ecosystem service measures using big data and machine learning. Wageningen.

Havinga, I., Marcos, D., Bogaart, P.W., Hein, L., Tuia, D., 2021a. 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

Havinga, I., Marcos, D., Bogaart, P.W., Hein, L., Tuia, D., 2021b. Geo-Data for Mapping Scenic Beauty: Exploring the Potential of Remote Sensing and Social Media, in: 2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS. pp. 188–191. https://doi.org/10.1109/IGARSS47720.2021.9553417

He, K., Zhang, X., Ren, S., Sun, J., 2016. Deep Residual Learning for Image Recognition. Proc. IEEE Conf. Comput. Vis. pattern Recognit. 770–778.

Heikinheimo, V., Tenkanen, H., Bergroth, C., Järv, O., Hiippala, T., Toivonen, T., 2020. Understanding the use of urban green spaces from user-generated geographic information. Landsc. Urban Plan. 201, 103845. https://doi.org/10.1016/j.landurbplan.2020.103845

Hein, L., Bagstad, K.J., Obst, C., Edens, B., Schenau, S., Castillo, G., Soulard, F., Brown, C., Driver, A., Bordt, M., Steurer, A., Harris, R., Caparrós, A., 2020a. Progress in natural capital accounting for ecosystems. Science (80-.). 367, 514 LP – 515. https://doi.org/10.1126/science.aaz8901

Hein, L., Obst, C., Edens, B., Remme, R.P., 2015. Progress and challenges in the development of ecosystem accounting as a tool to analyse ecosystem capital. Curr. Opin. Environ. Sustain. 14, 86–92. https://doi.org/10.1016/j.cosust.2015.04.002

Hein, L., Remme, R.P., Schenau, S., Bogaart, P.W., Lof, M.E., Horlings, E., 2020b. Ecosystem accounting in the Netherlands. Ecosyst. Serv. 44, 101118. https://doi.org/10.1016/j.ecoser.2020.101118

Hein, L., van Koppen, K., de Groot, R.S., van Ierland, E.C., 2006. Spatial scales, stakeholders and the valuation of ecosystem services. Ecol. Econ. 57, 209–228. https://doi.org/10.1016/j.ecolecon.2005.04.005

Hermes, J., Albert, C., von Haaren, C., 2018. Assessing the aesthetic quality of landscapes in Germany. Ecosyst. Serv. 31, 296–307. https://doi.org/10.1016/j.ecoser.2018.02.015

Hernández-Morcillo, M., Plieninger, T., Bieling, C., 2013. An empirical review of cultural ecosystem service indicators. Ecol. Indic. 29, 434–444. https://doi.org/10.1016/j.ecolind.2013.01.013

Herzog, T.R., Strevey, S.J., 2008. Contact With Nature, Sense of Humor, and Psychological Well-Being. Environ. Behav. 40, 747–776. https://doi.org/10.1177/0013916507308524

Hevia, V., Martín-López, B., Palomo, S., García-Llorente, M., de Bello, F., González, J.A., 2017. Trait-based approaches to analyze links between the drivers of change and ecosystem services: Synthesizing existing evidence and future challenges. Ecol. Evol. 7, 831–844. https://doi.org/10.1002/ece3.2692

Hill, R., Díaz, S., Pascual, U., Stenseke, M., Molnár, Z., Van Velden, J., 2021. Nature's contributions to people: Weaving plural perspectives. One Earth 4, 910–915. https://doi.org/10.1016/j.oneear.2021.06.009

Hirons, M., Comberti, C., Dunford, R., 2016. Valuing Cultural Ecosystem Services. Annu. Rev. Environ. Resour. 41, 545–574. https://doi.org/10.1146/annurev-environ-110615-085831

Hirschberg, J., Manning, C.D., 2015. Advances in natural language processing. Science (80-.). 349, 261–266. https://doi.org/10.1126/science.aaa8685

Hirshleifer, J., Glazer, A., Hirshleifer, D., 2005. Product quality and product variety, in: Price Theory and Applications: Decisions, Markets, and Information. Cambridge, New York.

Hollenstein, L., Purves, R., 2010. Exploring place through user-generated content: Using Flickr tags to describe city cores. J. Spat. Inf. Sci. 1, 21–48.

Holt, C.A., Hewson, C.M., Fuller, R.J., 2012. The Nightingale in Britain: status, ecology and conservation needs. Br. Birds 105, 172–187.

Hoyle, H., Hitchmough, J., Jorgensen, A., 2017. All about the 'wow factor'? The relationships between aesthetics, restorative effect and perceived biodiversity in designed urban planting. Landsc. Urban Plan. 164, 109–123. https://doi.org/10.1016/j.landurbplan.2017.03.011

Hoyle, H., Norton, B., Dunnett, N., Richards, J.P., Russell, J.M., Warren, P., 2018. Plant species or flower colour diversity? Identifying the drivers of public and invertebrate response to designed annual meadows. Landsc. Urban Plan. 180, 103–113. https://doi.org/10.1016/j.landurbplan.2018.08.017

Hu, W., Fey, M., Zitnik, M., Dong, Y., Ren, H., Liu, B., Catasta, M., Leskovec, J., 2020. Open Graph Benchmark: Datasets for Machine Learning on Graphs, in: Larochelle, H., Ranzato, M., Hadsell, R., Balcan, M.F., Lin, H. (Eds.), Advances in Neural Information Processing Systems. Curran Associates, Inc., pp. 22118–22133.

Huertas Herrera, A., Toro Manríquez, M., Soler, R., Lorenzo, C., Lencinas, M.V., Martínez Pastur, G., 2021. Assessing Socio-ecological Systems Using Social Media Data: An Approach for Forested Landscapes in Tierra del Fuego, Argentina. Soc. Indic. Res. 157, 817–839. https://doi.org/10.1007/s11205-021-02678-8

Hundepool, A., de Wolf, P.-P., 2012. Method Series: Statistical Disclosure Control. The Hague/Heerlen.

Hurrell, H.G., 1951. The movements of Swifts in summer. Br. Birds 44, 146–151.

Ilieva, R.T., McPhearson, T., 2018. Social-media data for urban sustainability. Nat. Sustain. 1, 553–565. https://doi.org/10.1038/s41893-018-0153-6

iNaturalist, 2019. API reference [WWW Document]. URL https://www.inaturalist.org/pages/api+reference (accessed 4.17.19).

International Telecommunication Union, 2018. Measuring the Information Society Report 2018: Volume 1. Geneva.

InVEST, 2017. InVEST Documentation – Visitation: Recreation and Tourism [WWW Document]. URL http://data.naturalcapitalproject.org/nightly-build/invest-users-guide/html/recreation.html

IPBES, 2022. Methodological assessment of the diverse values and valuation of nature of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services. IPBES secretariat, Bonn, Germany. https://doi.org/doi.org/10.5281/zenodo.6522522

IPBES, 2019. Global assessment report on biodiversity and ecosystem services of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services. Bonn, Germany. https://doi.org/10.5281/zenodo.3831673

Jacobs, C., Zipf, A., 2017. Completeness of citizen science biodiversity data from a volunteered geographic information perspective. Geo-spatial Inf. Sci. 20, 3–13. https://doi.org/10.1080/10095020.2017.1288424

Jenkins, A., Croitoru, A., Crooks, A.T., Stefanidis, A., 2016. Crowdsourcing a Collective Sense of Place. PLoS One 11, e0152932.

Jessel, B., 2006. Elements, characteristics and character – Information functions of landscapes in terms of indicators. Ecol. Indic. 6, 153–167. https://doi.org/10.1016/j.ecolind.2005.08.009

JNCC, 2020. Special Areas of Conservation spatial boundaries.

Joglekar, S., Quercia, D., Redi, M., Aiello, M.L., Kauer, T., Sastry, N., 2020. FaceLift: a transparent deep learning framework to beautify urban scenes. R. Soc. Open Sci. 7. https://doi.org/10.1098/rsos.190987

Johnson, M.L., Campbell, L.K., Svendsen, E.S., McMillen, H.L., 2019. Mapping Urban Park Cultural Ecosystem Services: A Comparison of Twitter and Semi-Structured Interview Methods. Sustain. . https://doi.org/10.3390/su11216137

Jordan, M.I., Mitchell, T.M., 2015. Machine learning: Trends, perspectives, and prospects. Science (80-.). 349, 255–260. https://doi.org/10.1126/science.aaa8415

Jurado Rota, J., Pérez Albert, M.Y., Serrano Giné, D., 2019. Visitor monitoring in protected areas: an approach to Natura 2000 sites using Volunteered Geographic Information (VGI). Geogr. Tidsskr. J. Geogr. 1–15. https://doi.org/10.1080/00167223.2019.1573409

Kadykalo, A.N., López-Rodriguez, M.D., Ainscough, J., Droste, N., Ryu, H., Ávila-Flores, G., Le Clec'h, S., Muñoz, M.C., Nilsson, L., Rana, S., Sarkar, P., Sevecke, K.J., Harmáčková,

Z. V, 2019. Disentangling 'ecosystem services' and 'nature's contributions to people.' Ecosyst. People 15, 269–287. https://doi.org/10.1080/26395916.2019.1669713

Kaplan, R., Kaplan, S., 1989. The Experience of Nature. Cambridge University Press, Cambridge.

Karasov, O., Vieira, A.A.B., Külvik, M., Chervanyov, I., 2020. Landscape coherence revisited: GIS-based mapping in relation to scenic values and preferences estimated with geolocated social media data. Ecol. Indic. 111, 105973. https://doi.org/10.1016/j.ecolind.2019.105973

Kashyap, R., Nahapetian, A., 2014. Tweet analysis for user health monitoring, in: 2014 4th International Conference on Wireless Mobile Communication and Healthcare - Transforming Healthcare Through Innovations in Mobile and Wireless Technologies (MOBIHEALTH). pp. 348–351. https://doi.org/10.1109/MOBIHEALTH.2014.7015983

Keeler, B.L., Wood, S.A., Polasky, S., Kling, C., Filstrup, C.T., Downing, J.A., 2015. Recreational demand for clean water: evidence from geotagged photographs by visitors to lakes. Front. Ecol. Environ. 13, 76–81. https://doi.org/10.1890/140124

Kellert, S.R., Wilson, E.O., 1993. The Biophilia Hypothesis. Island Press/Shearwater Books, Washington, DC.

Kemp, S., 2019. Digital 2019: Global Digital Yearbook.

Keniger, L.E., Gaston, K.J., Irvine, K.N., Fuller, R.A., 2013. What are the Benefits of Interacting with Nature? Int. J. Environ. Res. Public Heal. . https://doi.org/10.3390/ijerph10030913

Kenter, J.O., Bryce, R., Christie, M., Cooper, N., Hockley, N., Irvine, K.N., Fazey, I., O'Brien, L., Orchard-Webb, J., Ravenscroft, N., Raymond, C.M., Reed, M.S., Tett, P., Watson, V., 2016. Shared values and deliberative valuation: Future directions. Ecosyst. Serv. 21, 358–371. https://doi.org/10.1016/j.ecoser.2016.10.006

Kenter, J.O., O'Brien, L., Hockley, N., Ravenscroft, N., Fazey, I., Irvine, K.N., Reed, M.S., Christie, M., Brady, E., Bryce, R., Church, A., Cooper, N., Davies, A., Evely, A., Everard, M., Fish, R., Fisher, J.A., Jobstvogt, N., Molloy, C., Orchard-Webb, J., Ranger, S., Ryan, M., Watson, V., Williams, S., 2015. What are shared and social values of ecosystems? Ecol. Econ. 111, 86–99. https://doi.org/10.1016/j.ecolecon.2015.01.006

Kim, Y., Kim, C., Lee, D.K., Lee, H., Andrada, R.I.I.T., 2019. Quantifying nature-based tourism in protected areas in developing countries by using social big data. Tour. Manag. 72,

249–256. https://doi.org/10.1016/j.tourman.2018.12.005

King, G., 2011. Ensuring the Data-Rich Future of the Social Sciences. Science (80-.). 331, 719 LP – 721. https://doi.org/10.1126/science.1197872

King, H.P., Morris, J., Graves, A., Bradbury, R.B., McGinlay, J., Bullock, J.M., 2017. Biodiversity and cultural ecosystem benefits in lowland landscapes in southern England. J. Environ. Psychol. 53, 185–197. https://doi.org/10.1016/j.jenvp.2017.08.002

Kingma, D.P., Ba, J., 2014. Adam: A Method for Stochastic Optimization. https://doi.org/10.48550/ARXIV.1412.6980

Kirchhoff, T., 2019. Abandoning the Concept of Cultural Ecosystem Services, or Against Natural–Scientific Imperialism. Bioscience 69, 220–227. https://doi.org/10.1093/biosci/biz007

Klain, S.C., Chan, K.M.A., 2012. Navigating coastal values: Participatory mapping of ecosystem services for spatial planning. Ecol. Econ. 82, 104–113. https://doi.org/10.1016/j.ecolecon.2012.07.008

Kokil, J., Salvatore, G., Andrew, S.H., L., K.M., H., U.L., C., E.J., 2020. Estimating geographic subjective well-being from Twitter: A comparison of dictionary and data-driven language methods. Proc. Natl. Acad. Sci. 117, 10165–10171. https://doi.org/10.1073/pnas.1906364117

Koylu, C., Zhao, C., Shao, W., 2019. Deep Neural Networks and Kernel Density Estimation for Detecting Human Activity Patterns from Geo-Tagged Images: A Case Study of Birdwatching on Flickr. ISPRS Int. J. Geo-Information 8. https://doi.org/10.3390/ijgi8010045

Krafte Holland, K., Larson, L.R., Powell, R.B., 2018. Characterizing conflict between humans and big cats Panthera spp: A systematic review of research trends and management opportunities. PLoS One 13, e0203877.

Kremen, C., Merenlender, A.M., 2018. Landscapes that work for biodiversity and people. Science (80-.). 362, eaau6020. https://doi.org/10.1126/science.aau6020

Kuo, F.E., Sullivan, W.C., 2001. Aggression and Violence in the Inner City: Effects of Environment via Mental Fatigue. Environ. Behav. 33, 543–571. https://doi.org/10.1177/00139160121973124

La Notte, A., D'Amato, D., Mäkinen, H., Paracchini, M.L., Liquete, C., Egoh, B., Geneletti, D.,

Crossman, N.D., 2017. Ecosystem services classification: A systems ecology perspective of the cascade framework. Ecol. Indic. 74, 392–402. https://doi.org/10.1016/j.ecolind.2016.11.030

La Rosa, D., Spyra, M., Inostroza, L., 2016. Indicators of Cultural Ecosystem Services for urban planning: A review. Ecol. Indic. 61, 74–89. https://doi.org/10.1016/j.ecolind.2015.04.028

Labib, S.M., Huck, J.J., Lindley, S., 2021. Modelling and mapping eye-level greenness visibility exposure using multi-source data at high spatial resolutions. Sci. Total Environ. 755, 143050. https://doi.org/10.1016/j.scitotenv.2020.143050

Ladle, R.J., Correia, R.A., Do, Y., Joo, G.-J., Malhado, A.C.M., Proulx, R., Roberge, J.-M., Jepson, P., 2016. Conservation culturomics. Front. Ecol. Environ. 14, 269–275. https://doi.org/10.1002/fee.1260

Lahsen, M., 2020. Should AI be Designed to Save Us From Ourselves?: Artificial Intelligence for Sustainability. IEEE Technol. Soc. Mag. 39, 60–67. https://doi.org/10.1109/MTS.2020.2991502

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., Gómez-Baggethun, E., Haase, D., Scheuer, S., Elmqvist, T., 2016. Bridging the gap between ecosystem service assessments and land-use planning through Multi-Criteria Decision Analysis (MCDA). Environ. Sci. Policy 62, 45–56. https://doi.org/https://doi.org/10.1016/j.envsci.2016.02.013

Lary, D.J., Alavi, A.H., Gandomi, A.H., Walker, A.L., 2016. Machine learning in geosciences and remote sensing. Geosci. Front. 7, 3–10. https://doi.org/10.1016/j.gsf.2015.07.003

LeCun, Y., Bengio, Y., Hinton, G., 2015. Deep learning. Nature 521, 436–444. https://doi.org/10.1038/nature14539

Lee, H., Seo, B., Cord, A.F., Volk, M., Lautenbach, S., 2022. Using crowdsourced images to study selected cultural ecosystem services and their relationships with species richness

and carbon sequestration. Ecosyst. Serv. 54, 101411. https://doi.org/10.1016/j.ecoser.2022.101411

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.

Levering, A., Marcos, D., Tuia, D., 2021. On the relation between landscape beauty and land cover: A case study in the U.K. at Sentinel-2 resolution with interpretable AI. ISPRS J. Photogramm. Remote Sens. 177, 194–203. https://doi.org/10.1016/j.isprsjprs.2021.04.020

Levin, N., Kark, S., Crandall, D., 2015. Where have all the people gone? Enhancing global conservation using night lights and social media. Ecol. Appl. 25, 2153–2167. https://doi.org/10.1890/15-0113.1

Levin, N., Lechner, A.M., Brown, G., 2017. An evaluation of crowdsourced information for assessing the visitation and perceived importance of protected areas. Appl. Geogr. 79, 115–126. https://doi.org/10.1016/j.apgeog.2016.12.009

Li, D., Zhou, X., Wang, M., 2018. Analyzing and visualizing the spatial interactions between tourists and locals: A Flickr study in ten US cities. Cities 74, 249–258. https://doi.org/10.1016/j.cities.2017.12.012

Li, L., Goodchild, M.F., Xu, B., 2013. Spatial, temporal, and socioeconomic patterns in the use of Twitter and Flickr. Cartogr. Geogr. Inf. Sci. 40, 61–77. https://doi.org/10.1080/15230406.2013.777139

Li, S., Dragicevic, S., Castro, F.A., Sester, M., Winter, S., Coltekin, A., Pettit, C., Jiang, B., Haworth, J., Stein, A., Cheng, T., 2016. Geospatial big data handling theory and methods: A review and research challenges. ISPRS J. Photogramm. Remote Sens. 115, 119–133. https://doi.org/10.1016/j.isprsjprs.2015.10.012

Li, Z., Hoiem, D., 2016. Learning Without Forgetting, in: European Conference on Computer Vision. pp. 614–629.

Lindemann-Matthies, P., Junge, X., Matthies, D., 2010. The influence of plant diversity on people's perception and aesthetic appreciation of grassland vegetation. Biol. Conserv. 143, 195–202. https://doi.org/10.1016/j.biocon.2009.10.003

Liu, J., Li, J., Li, W., Wu, J., 2016. Rethinking big data: A review on the data quality and usage issues. ISPRS J. Photogramm. Remote Sens. 115, 134–142. https://doi.org/10.1016/j.isprsjprs.2015.11.006

Liu, X., He, J., Yao, Y., Zhang, J., Liang, H., Wang, H., Hong, Y., 2017. Classifying urban land use by integrating remote sensing and social media data. Int. J. Geogr. Inf. Sci. 31, 1675–1696. https://doi.org/10.1080/13658816.2017.1324976

Liu, Y., Ott, M., Goyal, N., Du, J., Joshi, M., Chen, D., Levy, O., Lewis, M., Zettlemoyer, L., Stoyanov, V., 2019. RoBERTa: A Robustly Optimized BERT Pretraining Approach. https://doi.org/10.48550/ARXIV.1907.11692

Loff, J., Reis, M., Martins, B., 2015. Predicting Well-Being with Geo-Referenced Data Collected from Social Media Platforms, in: Proceedings of the 30th Annual ACM Symposium on Applied Computing, SAC '15. Association for Computing Machinery, New York, NY, USA, pp. 1167–1173. https://doi.org/10.1145/2695664.2695939

Longley, P.A., Adnan, M., Lansley, G., 2015. The Geotemporal Demographics of Twitter Usage. Environ. Plan. A Econ. Sp. 47, 465–484. https://doi.org/10.1068/a130122p

Lopez, B., Minor, E., Crooks, A., 2020. Insights into human-wildlife interactions in cities from bird sightings recorded online. Landsc. Urban Plan. 196, 103742. https://doi.org/10.1016/j.landurbplan.2019.103742

Lothian, A., 1999. Landscape and the philosophy of aesthetics: is landscape quality inherent in the landscape or in the eye of the beholder? Landsc. Urban Plan. 44, 177–198. https://doi.org/10.1016/S0169-2046(99)00019-5

Loureiro, D., Barbieri, F., Neves, L., Anke, L.E., Camacho-Collados, J., 2022. TimeLMs: Diachronic Language Models from Twitter. https://doi.org/10.48550/ARXIV.2202.03829

MA, 2005. Ecosystems and Human well-being: synthesis, Millennium Ecosystem Assessment (MA). Washington, D.C.

Maes, J., Egoh, B., Willemen, L., Liquete, C., Vihervaara, P., Schägner, J.P., Grizzetti, B., Drakou, E.G., Notte, A. La, Zulian, G., Bouraoui, F., Luisa Paracchini, M., Braat, L., Bidoglio, G., 2012. Mapping ecosystem services for policy support and decision making

in the European Union. Ecosyst. Serv. 1, 31–39. https://doi.org/10.1016/j.ecoser.2012.06.004

Maes, Joachim, Hauck, J., Paracchini, M.L., Ratamäki, O., Hutchins, M., Termansen, M., Furman, E., Pérez-Soba, M., Braat, L., Bidoglio, G., 2013. Mainstreaming ecosystem services into EU policy. Curr. Opin. Environ. Sustain. 5, 128–134. https://doi.org/10.1016/j.cosust.2013.01.002

Maes, J., Teller, A., Erhard, M., Liquete, C., Braat, L., Berry, P., Egoh, B., Puydarrieux, P., Fiorina, C., Santos, F., Paracchini, M.L., Keune H, Wittmer H, Hauck J, Fiala I, Verburg PH, Condé S, Schägner JP, San Miguel J, Estreguil C, O.O., Barredo JI, Pereira HM, Stott A, Laporte V, Meiner A, Olah B, Royo Gelabert E, Spyropoulou R, Petersen JE, M., C, Zal N, Achilleos E, Rubin A, Ledoux L, Brown C, Raes C, Jacobs S, Vandewalle M, Connor D, B.G., 2013. Mapping and Assessment of Ecosystems and their Services. An analytical framework for ecosystem assessments under Action 5 of the EU Biodiversity Strategy to 2020. Luxembourg. https://doi.org/10.2779/12398

Malik, M.M., Pfeffer, J., 2016. Identifying Platform Effects in Social Media Data. Tenth Int. AAAI Conf. Web Soc. Media.

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

Mancini, F., Coghill, G.M., Lusseau, D., 2018. Using social media to quantify spatial and temporal dynamics of nature-based recreational activities. PLoS One 13, e0200565.

Mandle, L., Shields-Estrada, A., Chaplin-Kramer, R., Mitchell, M.G.E., Bremer, L.L., Gourevitch, J.D., Hawthorne, P., Johnson, J.A., Robinson, B.E., Smith, J.R., Sonter, L.J., Verutes, G.M., Vogl, A.L., Daily, G.C., Ricketts, T.H., 2021. Increasing decision relevance of ecosystem service science. Nat. Sustain. 4, 161–169. https://doi.org/10.1038/s41893-020-00625-y

Manikonda, L., Meduri, V.V., Kambhampati, S., 2021. Tweeting the Mind and Instagramming the Heart: Exploring Differentiated Content Sharing on Social Media. Proc. Int. AAAI Conf. Web Soc. Media 10, 639–642.

MapMyFitness, 2019. Search for fitness training routes [WWW Document]. URL https://www.mapmyfitness.com/routes/search (accessed 4.17.19).

Marcos, D., 2020. Contextual Semantic Interpretability. ECCV.

Marcos, D., Fong, R., Lobry, S., Flamary, R., Courty, N., Tuia, D., 2020. Contextual Semantic Interpretability. arXiv:2009.08720.

Martínez-Harms, M.J., Balvanera, P., 2012. Methods for mapping ecosystem service supply: a review. Int. J. Biodivers. Sci. Ecosyst. Serv. Manag. 8, 17–25. https://doi.org/10.1080/21513732.2012.663792

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

Massimino, D., Johnston, A., Noble, D.G., Pearce-Higgins, J.W., 2015. Multi-species spatially-explicit indicators reveal spatially structured trends in bird communities. Ecol. Indic. 58, 277–285. https://doi.org/10.1016/j.ecolind.2015.06.001

McArthur, D.P., Hong, J., 2019. Visualising where commuting cyclists travel using crowdsourced data. J. Transp. Geogr. 74, 233–241. https://doi.org/10.1016/j.jtrangeo.2018.11.018

McClure, E.C., Sievers, M., Brown, C.J., Buelow, C.A., Ditria, E.M., Hayes, M.A., Pearson, R.M., Tulloch, V.J.D., Unsworth, R.K.F., Connolly, R.M., 2020. Artificial Intelligence Meets Citizen Science to Supercharge Ecological Monitoring. Patterns 1, 100109. https://doi.org/10.1016/j.patter.2020.100109

McGinlay, J., Parsons, D.J., Morris, J., Hubatova, M., Graves, A., Bradbury, R.B., Bullock, J.M., 2017. Do charismatic species groups generate more cultural ecosystem service benefits? Ecosyst. Serv. 27, 15–24. https://doi.org/10.1016/j.ecoser.2017.07.007

Medrouk, L., Pappa, A., 2017. Deep Learning Model for Sentiment Analysis in Multi-lingual Corpus, in: Liu, D., Xie, S., Li, Y., Zhao, D., El-Alfy, E.-S.M. (Eds.), Neural Information Processing. Springer International Publishing, Cham, pp. 205–212.

Mehrabi, N., Morstatter, F., Saxena, N., Lerman, K., Galstyan, A., 2021. A Survey on Bias and Fairness in Machine Learning. ACM Comput. Surv. 54. https://doi.org/10.1145/3457607

Methorst, J., Bonn, A., Marselle, M., Böhning-Gaese, K., Rehdanz, K., 2021. Species richness is positively related to mental health – A study for Germany. Landsc. Urban Plan. 211, 104084. https://doi.org/10.1016/j.landurbplan.2021.104084

Middleton, S.E., Middleton, L., Modafferi, S., 2014. Real-time crisis mapping of natural disasters using social media. IEEE Intell. Syst. 29, 9–17.

https://doi.org/10.1109/MIS.2013.126

Milcu, A.I., Hanspach, J., Abson, D., Fischer, J., 2013. Cultural ecosystem services: A literature review and prospects for future research. Ecol. Soc. 18, 44–88. https://doi.org/10.5751/ES-05790-180344

Miller, H.J., Goodchild, M.F., 2015. Data-driven geography. GeoJournal 80, 449–461. https://doi.org/10.1007/s10708-014-9602-6

Miller, J.R., 2005. Biodiversity conservation and the extinction of experience. Trends Ecol. Evol. 20, 430–434. https://doi.org/10.1016/j.tree.2005.05.013

Missemer, A., 2018. Natural Capital as an Economic Concept, History and Contemporary Issues. Ecol. Econ. 143, 90–96. https://doi.org/10.1016/j.ecolecon.2017.07.011

Mitchell, L., Frank, M.R., Harris, K.D., Dodds, P.S., Danforth, C.M., 2013. The Geography of Happiness: Connecting Twitter Sentiment and Expression, Demographics, and Objective Characteristics of Place. PLoS One 8, e64417.

Mocanu, D., Baronchelli, A., Perra, N., Gonçalves, B., Zhang, Q., Vespignani, A., 2013. The Twitter of Babel: Mapping World Languages through Microblogging Platforms. PLoS One 8, e61981.

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

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

Nahuelhual, L., Benra Ochoa, F., Rojas, F., Díaz, G.I., Carmona, A., 2016. Mapping social values of ecosystem services: What is behind the map? Ecol. Soc. 21. https://doi.org/10.5751/ES-08676-210324

Nahuelhual, L., Carmona, A., Laterra, P., Barrena, J., Aguayo, M., 2014. A mapping approach to assess intangible cultural ecosystem services: The case of agriculture heritage in Southern Chile. Ecol. Indic. 40, 90–101. https://doi.org/10.1016/j.ecolind.2014.01.005

Naik, N., Kominers, S.D., Raskar, R., Glaeser, E.L., Hidalgo, C.A., 2017. Computer vision

uncovers predictors of physical urban change. Proc. Natl. Acad. Sci. 114, 7571 LP – 7576. https://doi.org/10.1073/pnas.1619003114

Nasar, J.L., 2000. The evaluative image of places., in: Person–Environment Psychology: New Directions and Perspectives, 2nd Ed. Lawrence Erlbaum Associates Publishers, Mahwah, NJ, US, pp. 117–168.

Nasar, J.L., Li, M., 2004. Landscape mirror: the attractiveness of reflecting water. Landsc. Urban Plan. 66, 233–238. https://doi.org/https://doi.org/10.1016/S0169-2046(03)00113-0

Natural England, 2019. Monitor of Engagement with the Natural Environment 2009-19 [WWW Document]. URL http://publications.naturalengland.org.uk/publication/2248731?category=47018

Nature – Editorial, 2020. The United Nations must get its new biodiversity targets right. Nature 578, 337–338. https://doi.org/10.1038/d41586-020-00450-5

NBTC-NIPO, 2015. ContinuVrijeTijdsOnderzoek 2015. The Hague, The Netherlands.

Nenzén, H.K., Araújo, M.B., 2011. Choice of threshold alters projections of species range shifts under climate change. Ecol. Modell. 222, 3346–3354. https://doi.org/10.1016/j.ecolmodel.2011.07.011

Newton, A.C., Stewart, G.B., Myers, G., Diaz, A., Lake, S., Bullock, J.M., Pullin, A.S., 2009. Impacts of grazing on lowland heathland in north-west Europe. Biol. Conserv. 142, 935–947. https://doi.org/10.1016/j.biocon.2008.10.018

Niemiller, K.D.K., Davis, M.A., Niemiller, M.L., 2021. Addressing 'biodiversity naivety' through project-based learning using iNaturalist. J. Nat. Conserv. 64, 126070. https://doi.org/10.1016/j.jnc.2021.126070

Nilsen, E.B., Milner-Gulland, E.J., Schofield, L., Mysterud, A., Stenseth, N.C., Coulson, T., 2007. Wolf reintroduction to Scotland: public attitudes and consequences for red deer management. Proc. R. Soc. B Biol. Sci. 274. https://doi.org/10.1098/rspb.2006.0369

NOMIS, 2011. Table population - All usual residents.

Nordh, H., Evensen, K.H., Skår, M., 2017. A peaceful place in the city—A qualitative study of restorative components of the cemetery. Landsc. Urban Plan. 167, 108–117. https://doi.org/10.1016/j.landurbplan.2017.06.004

Norman, P., Pickering, C.M., 2017. Using volunteered geographic information to assess park visitation: Comparing three on-line platforms. Appl. Geogr. 89, 163–172.

https://doi.org/10.1016/j.apgeog.2017.11.001

Norman, P., Pickering, C.M., Castley, G., 2019. What can volunteered geographic information tell us about the different ways mountain bikers, runners and walkers use urban reserves? Landsc. Urban Plan. 185, 180–190. https://doi.org/10.1016/j.landurbplan.2019.02.015

Norton, B., Costanza, R., Bishop, R.C., 1998. The evolution of preferences: Why `sovereign' preferences may not lead to sustainable policies and what to do about it. Ecol. Econ. 24, 193–211. https://doi.org/10.1016/S0921-8009(97)00143-2

Norton, L.R., Inwood, H., Crowe, A., Baker, A., 2012. Trialling a method to quantify the "cultural services" of the English landscape using Countryside Survey data. Land use policy 29, 449–455. https://doi.org/10.1016/j.landusepol.2011.09.002

Obst, C., Hein, L., Edens, B., 2016. National Accounting and the Valuation of Ecosystem Assets and Their Services. Environ. Resour. Econ. 64, 1–23. https://doi.org/10.1007/s10640-015-9921-1

Ode, Å., Tveit, M.S., Fry, G., 2008. Capturing Landscape Visual Character Using Indicators: Touching Base with Landscape Aesthetic Theory. Landsc. Res. 33, 89–117. https://doi.org/10.1080/01426390701773854

Olteanu, A., Castillo, C., Diaz, F., Kıcıman, E., 2019. Social Data: Biases, Methodological Pitfalls, and Ethical Boundaries. Front. Big Data 2. https://doi.org/10.3389/fdata.2019.00013

ONS, 2019. Table SAPE22DT11: Mid-2019 Population Density for Lower Layer Super Output Areas in England and Wales - National Statistics.

ONS, 2014. Income estimates for small areas, England and Wales (2013/14).

Ordnance Survey, 2021. OS Open Green Space.

Ortis, A., Farinella, G.M., Battiato, S., 2020. Survey on visual sentiment analysis. IET Image Process. 14, 1440–1456. https://doi.org/10.1049/iet-ipr.2019.1270

Ostermann, F.O., 2021. Linking Geosocial Sensing with the Socio-Demographic Fabric of Smart Cities. ISPRS Int. J. Geo-Information . https://doi.org/10.3390/ijgi10020052

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. 94, 74–86.

https://doi.org/10.1016/j.ecolind.2017.02.009

Otter, D.W., Medina, J.R., Kalita, J.K., 2021. A Survey of the Usages of Deep Learning for Natural Language Processing. IEEE Trans. Neural Networks Learn. Syst. 32, 604–624. https://doi.org/10.1109/TNNLS.2020.2979670

Owen, J., Owen, D.F., 1975. Suburban Gardens: England's Most Important Nature Reserve? Environ. Conserv. 2, 53–59. https://doi.org/DOI: 10.1017/S0376892900000692

Owiny, S.A., Mehta, K., Maretzki, A.N., 2014. The Use of Social Media Technologies to Create, Preserve, and Disseminate Indigenous Knowledge and Skills to Communities in East Africa. Int. J. Commun. 8.

Padgham, M., Rudis, B., Lovelace, R., Salmon, M., 2017. osmdata. J. Open Source Softw. 2. https://doi.org/10.21105/joss.00305

Palliwoda, J., Kowarik, I., von der Lippe, M., 2017. Human-biodiversity interactions in urban parks: The species level matters. Landsc. Urban Plan. 157, 394–406. https://doi.org/10.1016/j.landurbplan.2016.09.003

Paracchini, M.L., Zulian, G., Kopperoinen, L., Maes, J., Schägner, J.P., Termansen, M., Zandersen, M., Perez-Soba, M., Scholefield, P.A., Bidoglio, G., 2014. Mapping cultural ecosystem services: A framework to assess the potential for outdoor recreation across the EU. Ecol. Indic. 45, 371–385. https://doi.org/10.1016/j.ecolind.2014.04.018

Park, M., Park, J., Baek, Y.M., Macy, M., 2017. Cultural values and cross-cultural video consumption on YouTube. PLoS One 12, e0177865.

Pascual, P., McMillen, H., Ticktin, T., Vaughan, M., Winter, K.B., 2017. Beyond services: A process and framework to incorporate cultural, genealogical, place-based, and indigenous relationships in ecosystem service assessments. Ecosyst. Serv. 26, 465–475. https://doi.org/10.1016/j.ecoser.2017.03.012

Pascual, U., Adams, W.M., Díaz, S., Lele, S., Mace, G.M., Turnhout, E., 2021. Biodiversity and the challenge of pluralism. Nat. Sustain. 4, 567–572. https://doi.org/10.1038/s41893-021-00694-7

Pascual, U., Balvanera, P., Díaz, S., Roth, E., Stenseke, M., Watson, R.T., Ba, E., Islar, M., Kelemen, E., Maris, V., Quaas, M., Subramanian, S.M., Wittmer, H., Adlan, A., Ahn, S., Al-hafedh, Y.S., Amankwah, E., Asah, S.T., Berry, P., Bilgin, A., Breslow, S.J., Bullock, C., Ca, D., Figueroa, E., Golden, C.D., Keune, H., Kumar, R., Ma, K., May, P.H., Mead,

A., Farrell, P.O., Pandit, R., Pengue, W., Pichis-Madruga, R., Popa, F., Preston, S., Pacheco-Balanza, D., Saarikoski, H., Strassburg, B., van den Belt, M., Verma, M., Wickson, F., Yagi, N., 2017. Valuing nature's contributions to people : the IPBES approach. Curr. Opin. Environ. Sustain. 26–27, 7–16. https://doi.org/10.1016/j.cosust.2016.12.006

Patterson, G., Xu, C., Su, H., Hays, J., 2014. The SUN attribute database: Beyond categories for deeper scene understanding. Int. J. Comput. Vis. 108, 59–81.

Pei, T., Sobolevsky, S., Ratti, C., Shaw, S.-L., Li, T., Zhou, C., 2014. A new insight into land use classification based on aggregated mobile phone data. Int. J. Geogr. Inf. Sci. 28, 1988–2007. https://doi.org/10.1080/13658816.2014.913794

Peña, L., Casado-Arzuaga, I., Onaindia, M., 2015. Mapping recreation supply and demand using an ecological and a social evaluation approach. Ecosyst. Serv. 13, 108–118. https://doi.org/10.1016/j.ecoser.2014.12.008

Plieninger, T., Dijks, S., Oteros-Rozas, E., Bieling, C., 2013. Assessing, mapping, and quantifying cultural ecosystem services at community level. Land use policy 33, 118–129. https://doi.org/10.1016/j.landusepol.2012.12.013

Poria, S., Hazarika, D., Majumder, N., Mihalcea, R., 2020. Beneath the Tip of the Iceberg: Current Challenges and New Directions in Sentiment Analysis Research. IEEE Trans. Affect. Comput. 1. https://doi.org/10.1109/TAFFC.2020.3038167

Potschin-Young, M., Haines-Young, R., Görg, C., Heink, U., Jax, K., Schleyer, C., 2018. Understanding the role of conceptual frameworks: Reading the ecosystem service cascade. Ecosyst. Serv. 29, 428–440. https://doi.org/10.1016/j.ecoser.2017.05.015

Quinton, J.M., Duinker, P.N., 2018. Beyond burial: researching and managing cemeteries as urban green spaces, with examples from Canada. Environ. Rev. 27, 252–262. https://doi.org/10.1139/er-2018-0060

Raupach, M.R., 2013. Ecosystem Services and the Global Carbon Cycle, in: Lal, R., Lorenz, K., Hüttl, R.F., Schneider, B.U., Von Braun, J. (Eds.), Ecosystem Services and Carbon Sequestration in the Biosphere. Springer, Dordrecht, pp. 155–181. https://doi.org/10.1007/978-94-007-6455-2

Raymond, C.M., Kenter, J.O., Plieninger, T., Turner, N.J., Alexander, K.A., 2014. Comparing instrumental and deliberative paradigms underpinning the assessment of social values for cultural ecosystem services. Ecol. Econ. 107, 145–156.

https://doi.org/10.1016/j.ecolecon.2014.07.033

Reed, S., Lee, H., Anguelov, D., Szegedy, C., Erhan, D., Rabinovich, A., 2015. Training Deep Neural Networks on Noisy Labels with Bootstrapping.

Remme, R.P., Frumkin, H., Guerry, A.D., King, A.C., Mandle, L., Sarabu, C., Bratman, G.N., Giles-Corti, B., Hamel, P., Han, B., Hicks, J.L., James, P., Lawler, J.J., Lindahl, T., Liu, H., Lu, Y., Oosterbroek, B., Paudel, B., Sallis, J.F., Schipperijn, J., Sosič, R., de Vries, S., Wheeler, B.W., Wood, S.A., Wu, T., Daily, G.C., 2021. An ecosystem service perspective on urban nature, physical activity, and health. Proc. Natl. Acad. Sci. 118, e2018472118. https://doi.org/10.1073/pnas.2018472118

Remme, R.P., Schröter, M., Hein, L., 2014. Developing spatial biophysical accounting for multiple ecosystem services. Ecosyst. Serv. 10, 6–18. https://doi.org/10.1016/j.ecoser.2014.07.006

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

Reyers, B., Biggs, R., Cumming, G.S., Elmqvist, T., Hejnowicz, A.P., Polasky, S., 2013. Getting the measure of ecosystem services: a social–ecological approach. Front. Ecol. Environ. 11, 268–273. https://doi.org/10.1890/120144

Rice, E.S., Haynes, E., Royce, P., Thompson, S.C., 2016. Social media and digital technology use among Indigenous young people in Australia: a literature review. Int. J. Equity Health 15, 81. https://doi.org/10.1186/s12939-016-0366-0

Rice, W.L., Mateer, T.J., Reigner, N., Newman, P., Lawhon, B., Taff, B.D., 2020. Changes in recreational behaviors of outdoor enthusiasts during the COVID-19 pandemic: analysis across urban and rural communities. J. Urban Ecol. 6. https://doi.org/10.1093/jue/juaa020

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

Riordan, B., 2016. Strava Metro: Better Data for Better Cities [WWW Document]. URL https://www.ubdc.ac.uk/media/1416/uofg-training.pdf (accessed 4.17.19).

Robb, D., 2017. Building the Global Heatmap [WWW Document]. URL https://medium.com/strava-engineering/the-global-heatmap-now-6x-hotter-23fc01d301de (accessed 8.21.18).

Roberge, J.-M., 2014. Using data from online social networks in conservation science: which species engage people the most on Twitter? Biodivers. Conserv. 23, 715–726. https://doi.org/10.1007/s10531-014-0629-2

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

Roberts, H.V., 2017. Using Twitter data in urban green space research: A case study and critical evaluation. Appl. Geogr. 81, 13–20. https://doi.org/10.1016/j.apgeog.2017.02.008

Roos, R., van der Wel, N., 2013. Duinen en mensen Texel. Amsterdam.

Rosário, I.T., Rebelo, R., Cardoso, P., Segurado, P., Mendes, R.N., Santos-Reis, M., 2019. Can geocaching be an indicator of cultural ecosystem services? The case of the montado savannah-like landscape. Ecol. Indic. 99, 375–386. https://doi.org/10.1016/j.ecolind.2018.12.003

Roser, M., Ritchie, H., Ortiz-Ospina, E., 2015. Internet [WWW Document]. Our World Data. URL https://ourworldindata.org/internet (accessed 7.25.22).

Royal Meteorological Society, 2010. UK seasonal weather summary – winter 2009/2010. Weather 65, 99. https://doi.org/10.1002/wea.601

Russell, R., Guerry, A.D., Balvanera, P., Gould, R.K., Basurto, X., Chan, K.M.A., Klain, S., Levine, J., Tam, J., 2013. Humans and Nature: How Knowing and Experiencing Nature Affect Well-Being. Annu. Rev. Environ. Resour. 38, 473–502. https://doi.org/10.1146/annurev-environ-012312-110838

Ryo, M., Rillig, M.C., 2017. Statistically reinforced machine learning for nonlinear patterns and variable interactions. Ecosphere 8, e01976. https://doi.org/10.1002/ecs2.1976

Samani, Z.R., Guntuku, S.C., Moghaddam, M.E., Preoţiuc-Pietro, D., Ungar, L.H., 2018. Cross-platform and cross-interaction study of user personality based on images on Twitter and Flickr. PLoS One 13, e0198660. https://doi.org/10.1371/journal.pone.0198660

Sandifer, P.A., Sutton-Grier, A.E., Ward, B.P., 2015. Exploring connections among nature, biodiversity, ecosystem services, and human health and well-being: Opportunities to enhance health and biodiversity conservation. Ecosyst. Serv. 12, 1–15. https://doi.org/10.1016/j.ecoser.2014.12.007

Satterfield, T., Gregory, R., Klain, S., Roberts, M., Chan, K.M., 2013. Culture, intangibles and metrics in environmental management. J. Environ. Manage. 117, 103–114. https://doi.org/10.1016/j.jenvman.2012.11.033

Satz, D., Gould, R.K., Chan, K.M.A., Guerry, A., Norton, B., Satterfield, T., Halpern, B.S., Levine, J., Woodside, U., Hannahs, N., Basurto, X., Klain, S., 2013. The challenges of incorporating cultural ecosystem services into environmental assessment. Ambio 42, 675–684. https://doi.org/10.1007/s13280-013-0386-6

ScenicOrNot, 2015. ScenicOrNot Dataset [WWW Document]. URL http://scenicornot.datasciencelab.co.uk (accessed 5.3.20).

Schifanella, R., Redi, M., Aiello, L.M., 2021. An Image Is Worth More than a Thousand Favorites: Surfacing the Hidden Beauty of Flickr Pictures. Proc. Int. AAAI Conf. Web Soc. Media 9, 397–406.

Schirpke, U., Meisch, C., Marsoner, T., Tappeiner, U., 2018. Revealing spatial and temporal patterns of outdoor recreation in the European Alps and their surroundings. Ecosyst. Serv. 31, 336–350. https://doi.org/10.1016/j.ecoser.2017.11.017

Schirpke, U., Tasser, E., Tappeiner, U., 2013. Predicting scenic beauty of mountain regions. Landsc. Urban Plan. 111, 1–12. https://doi.org/10.1016/j.landurbplan.2012.11.010

Schröter, M., Barton, D.N., Remme, R.P., Hein, L., 2014. Accounting for capacity and flow of ecosystem services: A conceptual model and a case study for Telemark, Norway. Ecol. Indic. 36, 539–551. https://doi.org/10.1016/j.ecolind.2013.09.018

Schröter, M., Kraemer, R., Mantel, M., Kabisch, N., Hecker, S., Richter, A., Neumeier, V., Bonn, A., 2017. Citizen science for assessing ecosystem services: Status, challenges and opportunities. Ecosyst. Serv. 28, 80–94. https://doi.org/10.1016/j.ecoser.2017.09.017

Schröter, M., Remme, R.P., Sumarga, E., Barton, D.N., Hein, L., 2015. Lessons learned for spatial modelling of ecosystem services in support of ecosystem accounting. Ecosyst. Serv. 13, 64–69. https://doi.org/10.1016/j.ecoser.2014.07.003

Schulz, C., Martin-Ortega, J., 2018. Quantifying relational values — why not? Curr. Opin.

Environ. Sustain. 35, 15–21. https://doi.org/10.1016/j.cosust.2018.10.015

Schwartz, A.J., Dodds, P.S., O'Neil-Dunne, J.P.M., Danforth, C.M., Ricketts, T.H., 2019. Visitors to urban greenspace have higher sentiment and lower negativity on Twitter. People Nat. 0. https://doi.org/10.1002/pan3.10045

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. Sci. Total Environ. 799, 149263. https://doi.org/10.1016/j.scitotenv.2021.149263

See, L., Mooney, P., Foody, G., Bastin, L., Comber, A., Estima, J., Fritz, S., Kerle, N., Jiang, B., Laakso, M., Liu, H.-Y., Milčinski, G., Nikšič, M., Painho, M., Pődör, A., Olteanu-Raimond, A.-M., Rutzinger, M., 2016. Crowdsourcing, Citizen Science or Volunteered Geographic Information? The Current State of Crowdsourced Geographic Information. ISPRS Int. J. Geo-Information 5, 23. https://doi.org/10.3390/ijgi5050055

Semenov, A., Mantzaris, A., Nikolaev, A.G., Veremyev, A., Veijalainen, J., Pasiliao, E., Boginski, V., 2018. Exploring Social Media Network Landscape of Post-Soviet Space. IEEE Access 7, 411–426. https://doi.org/10.1109/ACCESS.2018.2885479

Seresinhe, C.I., Moat, H.S., Preis, T., 2017a. Quantifying scenic areas using crowdsourced data. Environ. Plan. B Urban Anal. City Sci. 45, 567–582. https://doi.org/10.1177/0265813516687302

Seresinhe, C.I., Preis, T., MacKerron, G., Moat, H.S., 2019. Happiness is Greater in More Scenic Locations. Sci. Rep. 9, 4498. https://doi.org/10.1038/s41598-019-40854-6

Seresinhe, C.I., Tobias, P., Moat, H.S., 2017b. Using deep learning to quantify the beauty of outdoor places. R. Soc. Open Sci. 4. https://doi.org/10.1098/rsos.170170

Sessions, C., Wood, S.A., Rabotyagov, S., Fisher, D.M., 2016. Measuring recreational visitation at U.S. National Parks with crowd-sourced photographs. J. Environ. Manage. 183, 703–711. https://doi.org/10.1016/j.jenvman.2016.09.018

Sharrock, J.T.R., 1976. The Atlas of Breeding Birds in Britain and Ireland. T & AD Poyser, Calton.

Sinclair, M., Ghermandi, A., Moses, S.A., Joseph, S., 2019. Recreation and environmental quality of tropical wetlands: A social media based spatial analysis. Tour. Manag. 71, 179–186. https://doi.org/10.1016/j.tourman.2018.10.018

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

Singla, A., Weber, I., 2011. Camera Brand Congruence and Camera Model Propagation in the Flickr Social Graph. ACM Trans. Web 5. https://doi.org/10.1145/2019643.2019647

Soga, M., Gaston, K.J., 2016. Extinction of experience: the loss of human–nature interactions. Front. Ecol. Environ. 14, 94–101. https://doi.org/10.1002/fee.1225

Soleymani, M., Garcia, D., Jou, B., Schuller, B., Chang, S.-F., Pantic, M., 2017. A survey of multimodal sentiment analysis. Image Vis. Comput. 65, 3–14. https://doi.org/10.1016/j.imavis.2017.08.003

Soliman, A., Soltani, K., Yin, J., Padmanabhan, A., Wang, S., 2017. Social sensing of urban land use based on analysis of Twitter users' mobility patterns. PLoS One 12, e0181657.

Song, X.P., Richards, D.R., Tan, P.Y., 2020. Using social media user attributes to understand human–environment interactions at urban parks. Sci. Rep. 10, 808. https://doi.org/10.1038/s41598-020-57864-4

Sonter, L.J., Watson, K.B., Wood, S.A., Ricketts, T.H., 2016. Spatial and Temporal Dynamics and Value of Nature-Based Recreation, Estimated via Social Media. PLoS One 11, e0162372.

Spalding, M., Burke, L., Wood, S.A., Ashpole, J., Hutchison, J., zu Ermgassen, P., 2017. Mapping the global value and distribution of coral reef tourism. Mar. Policy 82, 104–113. https://doi.org/10.1016/j.marpol.2017.05.014

Srivastava, S., Vargas Muñoz, J.E., Lobry, S., Tuia, D., 2020. Fine-grained landuse characterization using ground-based pictures: a deep learning solution based on globally available data. Int. J. Geogr. Inf. Sci. 34, 1117–1136. https://doi.org/10.1080/13658816.2018.1542698

Stanbury, A., Eaton, M., Aebischer, N., Balmer, D., Brown, A., Douse, A., Lindley, P., McCulloch, N., Noble, D., Win, I., 2021. The status of our bird populations: the fifth Birds of Conservation Concern in the United Kingdom, Channel Islands and Isle of

Man and second IUCN Red List assessment of extinction risk for Great Britain. Br. Birds 114, 723–747.

Statistics Netherlands, WUR, 2021. Natural Capital Accounting in the Netherlands – Technical report. The Hague.

Statistics Scotland, 2019. Table A: Data zone population, percentage aged 65 and over, mid-2019.

Statistics Scotland, 2014. Local Level Average Household Income Estimates 2014.

Stelzmüller, C., Tanzer, S., Schedl, M., 2021. Cross-City Analysis of Location-Based Sentiment in User-Generated Text, in: Companion Proceedings of the Web Conference 2021, WWW '21. Association for Computing Machinery, New York, NY, USA, pp. 339–346. https://doi.org/10.1145/3442442.3451889

Stevenson, N., Farrell, H., 2018. Taking a hike: exploring leisure walkers embodied experiences. Soc. Cult. Geogr. 19, 429–447. https://doi.org/10.1080/14649365.2017.1280615

Strava, 2018. Strava Global Heatmap [WWW Document]. URL https://www.strava.com/heatmap (accessed 5.22.19).

Sultan, J., Ben-Haim, G., Haunert, J.-H., Dalyot, S., 2017. Extracting spatial patterns in bicycle routes from crowdsourced data. Trans. GIS 21, 1321–1340. https://doi.org/10.1111/tgis.12280

Sun, Y., Du, Y., Wang, Y., Zhuang, L., 2017. Examining associations of environmental characteristics with recreational cycling behaviour by street-level strava data. Int. J. Environ. Res. Public Health 14. https://doi.org/10.3390/ijerph14060644

Tadaki, M., Sinner, J., Chan, K.M.A., 2017. Making sense of environmental values. Ecol. Soc. 22.

TEEB, 2010a. The Economics of Ecosystems and Biodiversity: Mainstreaming the Economics of Nature: A synthesis of the approach, conclusions and recommendations of TEEB.

TEEB, 2010b. The Economics of Ecosystems and Biodiversity Ecological and Economic Foundations. London and Washington.

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

Tengö, M., Hill, R., Malmer, P., Raymond, C.M., Spierenburg, M., Danielsen, F., Elmqvist, T., Folke, C., 2017. Weaving knowledge systems in IPBES, CBD and beyond—lessons learned for sustainability. Curr. Opin. Environ. Sustain. 26–27, 17–25. https://doi.org/10.1016/j.cosust.2016.12.005

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, 1–11. https://doi.org/10.1038/s41598-017-18007-4

The Wildlife Trusts, 2018. Towards a wilder Britain: Creating a nature recovery network to bring back wildlife to every neighbourhood. Newark-on-Trent.

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

Toivonen, T., Heikinheimo, V., Fink, C., Hausmann, A., Hiippala, T., Järv, O., Tenkanen, H., Di Minin, E., 2019. Social media data for conservation science: A methodological overview. Biol. Conserv. 233, 298–315. https://doi.org/10.1016/j.biocon.2019.01.023

Toole, J.L., Ulm, M., González, M.C., Bauer, D., 2012. Inferring Land Use from Mobile Phone Activity, in: Proceedings of the ACM SIGKDD International Workshop on Urban Computing, UrbComp '12. ACM, New York, NY, USA, pp. 1–8. https://doi.org/10.1145/2346496.2346498

Tu, W., Cao, J., Yue, Y., Shaw, S.-L., Zhou, M., Wang, Z., Chang, X., Xu, Y., Li, Q., 2017. Coupling mobile phone and social media data: a new approach to understanding urban functions and diurnal patterns. Int. J. Geogr. Inf. Sci. 31, 2331–2358. https://doi.org/10.1080/13658816.2017.1356464

Tuia, D., Kellenberger, B., Beery, S., Costelloe, B.R., Zuffi, S., Risse, B., Mathis, A., Mathis, M.W., van Langevelde, F., Burghardt, T., Kays, R., Klinck, H., Wikelski, M., Couzin, I.D., van Horn, G., Crofoot, M.C., Stewart, C. V, Berger-Wolf, T., 2022. Perspectives in machine learning for wildlife conservation. Nat. Commun. 13, 792.

https://doi.org/10.1038/s41467-022-27980-y

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

Tveit, M.S., 2009. Indicators of visual scale as predictors of landscape preference; a comparison between groups. J. Environ. Manage. 90, 2882–2888. https://doi.org/10.1016/j.jenvman.2007.12.021

Twitter, 2019. Twitter API: Docs [WWW Document]. URL https://developer.twitter.com/en/docs.html (accessed 4.17.19).

UK NEA, 2014. The UK National Ecosystem Assessment: Synthesis of the Key Findings.

Ulrich, R.S., 1984. View through a Window May Influence Recovery from Surgery. Science (80-.). 224, 420–421.

Ulrich, R.S., 1979. Visual landscapes and psychological well-being. Landsc. Res. 4, 17–23. https://doi.org/10.1080/01426397908705892

UN, 2017. SEEA Experimental Ecosystem Accounting : Technical Recommendations Consultation Draft. New York, USA.

UN, EU, FAO, IMF, OECD, WorldBank, 2014. System of Environmental-Economic Accounting 2012: Experimental Ecosystem Accounting. New York, USA.

United Nations, European Environment Agency, Eurostat, World Bank, FAO, WTO, OECD, IMF, ESAP, CBD, UNEP, 2021. System of Environmental-Economic Accounting— Ecosystem Accounting (SEEA EA). New York.

Uuemaa, E., Antrop, M., Roosaare, J., Marja, R., Mander, Ü., 2009. Landscape metrics and indices : an overview of their use in landscape research. LIVING Rev. Landsc. Res. 3, 1–28.

Uuemaa, E., Mander, Ü., Marja, R., 2013. Trends in the use of landscape spatial metrics as landscape indicators: A review. Ecol. Indic. 28, 100–106. https://doi.org/10.1016/j.ecolind.2012.07.018

Väisänen, T., Heikinheimo, V., Hiippala, T., Toivonen, T., 2021. Exploring human–nature interactions in national parks with social media photographs and computer vision. Conserv. Biol. 35, 424–436. https://doi.org/10.1111/cobi.13704

van der Maarel, E., Dauvellier, P.L., 1978. Naar een Globaal Ecologisch Model voor de

ruimtelijke ontwikkeling van Nederland. s'Gravenhage.

Van Horn, G., Mac Aodha, O., Song, Y., Cui, Y., Sun, C., Shepard, A., Adam, H., Perona, P., Belongie, S., 2018. The INaturalist Species Classification and Detection Dataset, in: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR).

van Loenen, S., 2016. Acht maanden hoogseizoen op Texel. NRC.

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. U. S. A. 113, 12974–12979. https://doi.org/10.1073/pnas.1614158113

Venter, Z.S., Barton, D.N., Gundersen, V., Figari, H., Nowell, M., 2020. Urban nature in a time of crisis: recreational use of green space increases during the COVID-19 outbreak in Oslo, Norway. Environ. Res. Lett. 15, 104075. https://doi.org/10.1088/1748-9326/abb396

Venter, Z.S., Sadilek, A., Stanton, C., Barton, D.N., Aunan, K., Chowdhury, S., Schneider, A., Iacus, S.M., 2021. Mobility in Blue-Green Spaces Does Not Predict COVID-19 Transmission: A Global Analysis. Int. J. Environ. Res. Public Heal. . https://doi.org/10.3390/ijerph182312567

Venturelli, P.A., Hyder, K., Skov, C., 2017. Angler apps as a source of recreational fisheries data: opportunities, challenges and proposed standards. Fish Fish. 18, 578–595. https://doi.org/10.1111/faf.12189

Vinuesa, R., Sirmacek, B., 2021. Interpretable deep-learning models to help achieve the Sustainable Development Goals. Nat. Mach. Intell. 3, 926. https://doi.org/10.1038/s42256-021-00414-y

Walden-Schreiner, C., Rossi, S.D., Barros, A., Pickering, C., Leung, Y.F., 2018. Using crowd-sourced photos to assess seasonal patterns of visitor use in mountain-protected areas. Ambio 47, 781–793. https://doi.org/10.1007/s13280-018-1020-4

Wartmann, F.M., Acheson, E., Purves, R.S., 2018. Describing and comparing landscapes using tags, texts, and free lists: an interdisciplinary approach. Int. J. Geogr. Inf. Sci. 32, 1572–1592. https://doi.org/10.1080/13658816.2018.1445257

Wartmann, F.M., Tieskens, K.F., van Zanten, B.T., Verburg, P.H., 2019. Exploring tranquillity experienced in landscapes based on social media. Appl. Geogr. 113, 102112.
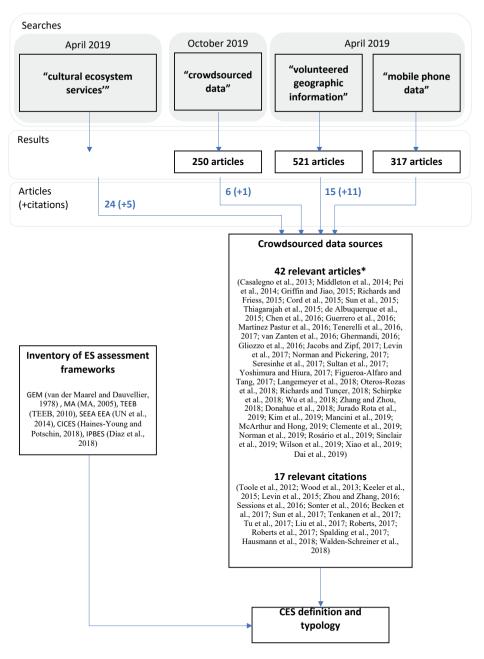
https://doi.org/10.1016/j.apgeog.2019.102112

Waterloo, S.F., Baumgartner, S.E., Peter, J., Valkenburg, P.M., 2017. Norms of online expressions of emotion: Comparing Facebook, Twitter, Instagram, and WhatsApp. New Media Soc. 20, 1813–1831. https://doi.org/10.1177/1461444817707349

Weibo, 2019. API [WWW Document]. URL https://open.weibo.com/wiki/API文档/en (accessed 4.17.19).

Weinstein, N., Balmford, A., DeHaan, C.R., Gladwell, V., Bradbury, R.B., Amano, T., 2015. Seeing Community for the Trees: The Links among Contact with Natural Environments, Community Cohesion, and Crime. Bioscience 65, 1141–1153. https://doi.org/10.1093/biosci/biv151

Wesolowski, A., Eagle, N., Noor, A.M., Snow, R.W., Buckee, C.O., 2013. The impact of biases in mobile phone ownership on estimates of human mobility. J. R. Soc. Interface 10. https://doi.org/10.1098/rsif.2012.0986

White, M.P., Pahl, S., Ashbullby, K., Herbert, S., Depledge, M.H., 2013. Feelings of restoration from recent nature visits. J. Environ. Psychol. 35, 40–51. https://doi.org/10.1016/j.jenvp.2013.04.002

Wiedmann, T., Lenzen, M., Keyßer, L.T., Steinberger, J.K., 2020. Scientists' warning on affluence. Nat. Commun. 11, 3107. https://doi.org/10.1038/s41467-020-16941-y

Wikiloc, 2019. Search [WWW Document]. URL https://www.wikiloc.com/wikiloc/find.do (accessed 4.17.19).

Wilkins, E.J., Van Berkel, D., Zhang, H., Dorning, M.A., Beck, S.M., Smith, J.W., 2022. Promises and pitfalls of using computer vision to make inferences about landscape preferences: Evidence from an urban-proximate park system. Landsc. Urban Plan. 219, 104315. https://doi.org/10.1016/j.landurbplan.2021.104315

Willemen, L., Cottam, A.J., Drakou, E.G., Burgess, N.D., 2015. Using social media to measure the contribution of red list species to the nature-based tourism potential of african protected areas. PLoS One 10, 1–14. https://doi.org/10.1371/journal.pone.0129785

Wilson, T., Lovelace, R., Evans, A.J., 2019. A Path Toward the Use of Trail Users' Tweets to Assess Effectiveness of the Environmental Stewardship Scheme: An Exploratory Analysis of the Pennine Way National Trail. Appl. Spat. Anal. Policy 12, 71–99. https://doi.org/10.1007/s12061-016-9201-7

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. n/a. https://doi.org/10.1002/pan3.10382

Wolf, I.D., Wohlfart, T., 2014. Walking, hiking and running in parks: A multidisciplinary assessment of health and well-being benefits. Landsc. Urban Plan. 130, 89–103. https://doi.org/10.1016/j.landurbplan.2014.06.006

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. https://doi.org/10.1038/srep02976

Wood, S.A., Winder, S.G., Lia, E.H., White, E.M., Crowley, C.S.L., Milnor, A.A., 2020. Next-generation visitation models using social media to estimate recreation on public lands. Sci. Rep. 10, 15419. https://doi.org/10.1038/s41598-020-70829-x

Workman, S., Souvenir, R., Jacobs, N., 2017. Understanding and Mapping Natural Beauty. 2017 IEEE Int. Conf. Comput. Vis. 4, 5590–5599.

Wu, H., Liu, L., Yu, Y., Peng, Z., 2018. Evaluation and Planning of Urban Green Space Distribution Based on Mobile Phone Data and Two-Step Floating Catchment Area Method. Sustainability. https://doi.org/10.3390/su10010214

Wu, X., Zhu, X., Wu, G.-Q., Ding, W., 2014. Data Mining with Big Data. IEEE Trans. Knowl. Data Eng. 26, 97–107. https://doi.org/10.1109/TKDE.2013.109

Xiao, Y., Wang, D., Fang, J., 2019. Exploring the disparities in park access through mobile phone data: Evidence from Shanghai, China. Landsc. Urban Plan. 181, 80–91. https://doi.org/10.1016/j.landurbplan.2018.09.013

Yan, T., Liu, F., 2021. Sentiment Analysis and Effect of COVID-19 Pandemic using College SubReddit Data. https://doi.org/10.48550/ARXIV.2112.04351

Yoshimura, N., Hiura, T., 2017. Demand and supply of cultural ecosystem services: Use of geotagged photos to map the aesthetic value of landscapes in Hokkaido. Ecosyst. Serv. 24, 68–78. https://doi.org/10.1016/j.ecoser.2017.02.009

Yuan, Y., Wei, G., Lu, Y., 2018. Evaluating gender representativeness of location-based social media: a case study of Weibo. Ann. GIS 24, 163–176. https://doi.org/10.1080/19475683.2018.1471518

Yves, G., Yoshua, B., 2006. Entropy Regularization, in: Semi-Supervised Learning. The MIT Press. https://doi.org/10.7551/mitpress/9780262033589.003.0009

Zhang, F., Zhou, B., Ratti, C., Liu, Y., 2020. Discovering place-informative scenes and objects using social media photos. R. Soc. Open Sci. 6, 181375. https://doi.org/10.1098/rsos.181375

Zhang, S., Zhou, W., 2018. Recreational visits to urban parks and factors affecting park visits: Evidence from geotagged social media data. Landsc. Urban Plan. 180, 27–35. https://doi.org/10.1016/j.landurbplan.2018.08.004

Zhou, B., Lapedriza, A., Khosla, A., Oliva, A., Torralba, A., 2017. Places: A 10 million Image Database for Scene Recognition. IEEE Trans. Pattern Anal. Mach. Intell.

Zhou, L., Pan, S., Wang, J., Vasilakos, A. V, 2017. Machine learning on big data: Opportunities and challenges. Neurocomputing 237, 350–361. https://doi.org/10.1016/j.neucom.2017.01.026

Zhou, X., Zhang, L., 2016. Crowdsourcing functions of the living city from Twitter and Foursquare data. Cartogr. Geogr. Inf. Sci. 43, 393–404. https://doi.org/10.1080/15230406.2015.1128852

Zielstra, D., Hochmair, H.H., 2013. Positional accuracy analysis of Flickr and Panoramio images for selected world regions. J. Spat. Sci. 58, 251–273. https://doi.org/10.1080/14498596.2013.801331

Zvaríková, M., Prokop, P., Zvarík, M., Ježová, Z., Medina-Jerez, W., Fedor, P., 2021. What Makes Spiders Frightening and Disgusting to People? Front. Ecol. Evol. 9. https://doi.org/10.3389/fevo.2021.694569

Supplementary materials

Supplementary material for Chapter 2

Figure S1. Literature search diagram.

Supplementary material for Chapter 3
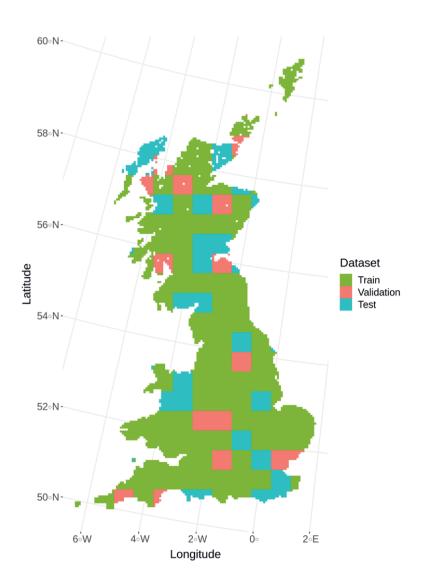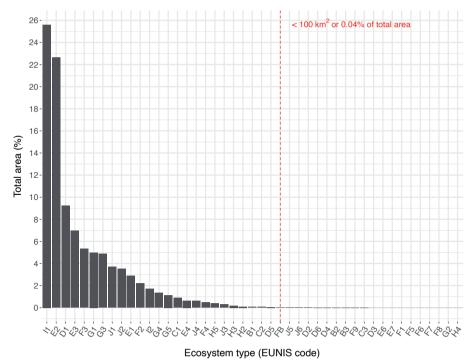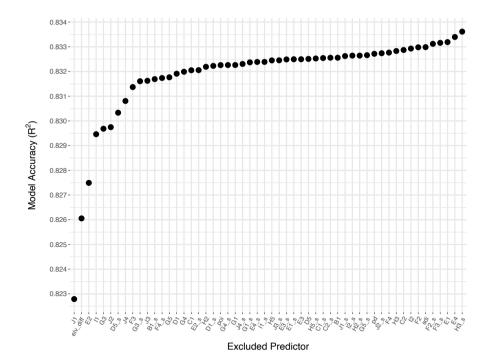
Figure S2. The 70% training, 10% validation and and 20% test split used in the study.

Figure S3. Threshold analysis of ecosystem types in GB. B = coastal, C = water, D = mires/bogs, E = Grasslands, F = heathland, G = woodland, H = inland scree/bare surface, I = Arable land and market gardens, J = buildings. A threshold point at shrub plantations (FB) onwards was selected, after which very little or none of the ecosystem types are present in the country. Table S3 contains a full list of ecosystem code and class descriptions.

Figure S4. Model accuracy (R²) per excluded indicator. B = coastal, C = water, D = mires/bogs, E = Grasslands, elv_diff = relief, F = heathland, G = woodland, H = inland scree/bare surface, I = Arable land and market gardens, J = buildings. "s" denotes surrounding ecosystem indicator. Supplementary Table S7 contains a full list of ecosystem code and class descriptions.
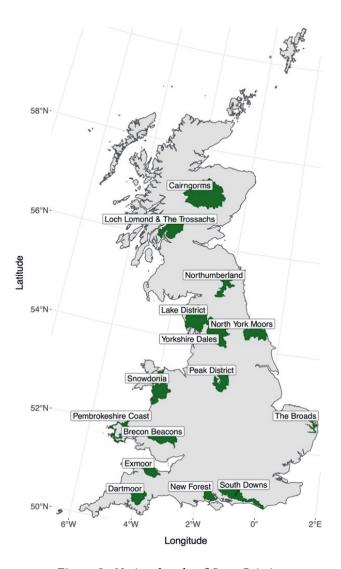
Figure S5. National parks of Great Britain.
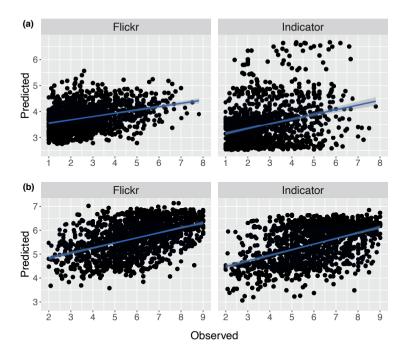
Figure S6. Observed versus predicted values in (a) the Greater London area and (b) the Lake District. A Kendall's tau correlation test resulted in a 0.223 correlation for the Flickr model versus 0.175 for the indicator model in Greater London, and correlations of 0.334 versus 0.330 in the Lake District.
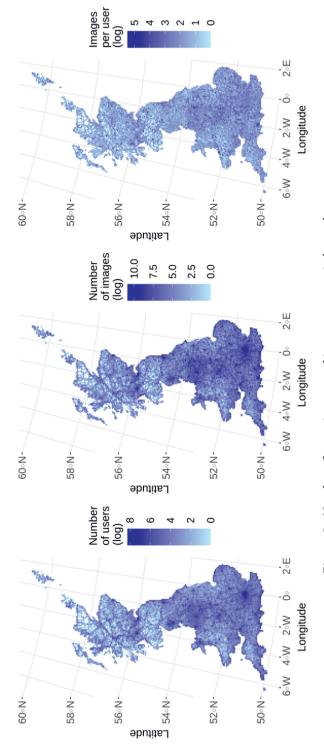
Figure S7. Number of users, images and images per user in log scale.

Table S1. Environmental indicators of aesthetic landscape quality.

Visual concept	Theory	Indicator(s)	Description	Dataset	Source
Naturalness	Important visual factor related to nature's restorative effects on mental health (Ulrich, 1984, 1979) and the innate biological need to affiliate with nature(Kellert and Wilson, 1993). The aesthetic value of water, in particular, is linked to its perceived naturalness (Kaplan and Kaplan, 1989; Nasar, 2000; Nasar and Li, 2004).	% ecosystem type	The % of ecosystem types per grid cell	EEA ecosystem type map at $100 \times 100m$	(EEA, 2019)
Visual scale	A key driver of peoples' aesthetic experience of the landscape. Landscapes that are both open and offer refuge are said to be more attractive because of our evolutionary history as both predator and prey (Appleton, 1975). Thus, higher elevation areas and differences in the landscape are likely to offer a greater aesthetic appeal.	Relief (m)	The difference in elevation within each grid cell	EU DEM at $25 \times 25m$	(EEA, 2017)
Complexity	According to Kaplan's Informational Processing Theory, complexity satisfies our physiological need to explore, providing content and things to think about (Kaplan and Kaplan, 1989). Complexity in the landscape can manifest itself in terms of the number and distribution of landscape attributes.	Patch Density Index (PDI)	Fragmentation, number of distinct ecosystem patches	EEA ecosystem type map at $100 \times 100m$	(EEA, 2019)
		Shannon Diversity Index (SDI)	Number of ecosystems and their spatial proportion	EEA ecosystem type map at $100 \times 100m$	(EEA, 2019)

Table S1. Environmental indicators of aesthetic landscape quality.

	Indicators to represent landscape complexity therefore frequently draw upon landscape metrics in landscape ecology such as the PDI and SDI (Ode et al., 2008).				
Uniqueness	Takes into account the distinctiveness of an area (Jessel, 2006). For example, a natural feature can hold a much larger aesthetic value in the urban environment than in a more natural context. Uniqueness is also related to concepts of imageability and historicity which recognise the impression landscape elements with a cultural significance can have on the viewer (Ode et al., 2008; Tveit et al., 2006).	% ecosystem type versus surrounding area	Relative difference in the percentage area of ecosystem types in grid cells within 10km	EEA ecosystem type map at 100 × 100m	(EEA, 2019)
		Historic POI	Number of historic points of interest per grid cell[1]	OSM	(Padgham et al., 2017)

[1]*The OSM API was used to calculate historical point features per grid cell. This included archaeological sites, ruins, castles and churches (a full list can be found in Table S10). All spatial features returned by the API query that were not points were converted to point features by calculating their centroids*

Table S2. Places365 scene classes.

airfield	bowling alley	drugstore	industrial area	parking garage / outdoor	subway station / platform
airplane cabin	boxing ring	elevator / door	inn / outdoor	parking lot	supermarket
airport terminal	bridge	elevator lobby	islet	pasture	sushi bar
alcove	building facade	elevator shaft	jacuzzi / indoor	patio	swamp
alley	bullring	embassy	jail cell	pavilion	swimming hole
amphitheater	burial chamber	engine room	japanese garden	pet shop	swimming pool / indoor
amusement arcade	bus interior	entrance hall	jewelry shop	pharmacy	swimming pool / outdoor
amusement park	bus station / indoor	escalator / indoor	junkyard	phone booth	synagogue / outdoor
apartment building / outdoor	butchers shop	excavation	kasbah	physics laboratory	television room
aquarium	butte	fabric store	kennel / outdoor	picnic area	television studio
aqueduct	cabin / outdoor	farm	kindergarden classroom	pier	temple / asia
arcade	cafeteria	fastfood restaurant	kitchen	pizzeria	throne room
arch	campsite	field / cultivated	lagoon	playground	ticket booth
archaelogical excavation	campus	field / wild	lake / natural	playroom	topiary garden
archive	canal / natural	field road	landfill	plaza	tower
arena / hockey	canal / urban	fire escape	landing deck	pond	toyshop
arena / performance	candy store	fire station	laundromat	porch	train interior
arena / rodeo	canyon	fishpond	lawn	promenade	train station / platform
army base	car interior	flea market / indoor	lecture room	pub / indoor	tree farm
art gallery	carrousel	florist shop / indoor	legislative chamber	racecourse	tree house
art school	castle	food court	library / indoor	raceway	trench
art studio	catacomb	football field	library / outdoor	raft	tundra
artists loft	cemetery	forest / broadleaf	lighthouse	railroad track	underwater / ocean deep
assembly line	chalet	forest path	living room	rainforest	utility room
athletic field / outdoor	chemistry lab	forest road	loading dock	reception	valley

Table S2. Places365 scene classes.

atrium / public	childs room	formal garden	lobby	recreation room	vegetable garden
attic	church / indoor	fountain	Lock chamber	repair shop	veterinarians office
auditorium	church / outdoor	galley	locker room	residential neighborhood	viaduct
auto factory	classroom	garage / indoor	mansion	restaurant	village
auto showroom	clean room	garage / outdoor	manufactured home	restaurant kitchen	vineyard
badlands	cliff	gas station	market / indoor	restaurant patio	volcano
bakery / shop	closet	gazebo / exterior	market / outdoor	rice paddy	volleyball court / outdoor
balcony / exterior	clothing store	general store / indoor	marsh	river	waiting room
balcony / interior	coast	general store / outdoor	martial arts gym	rock arch	water park
ball pit	cockpit	gift shop	mausoleum	roof garden	water tower
ballroom	coffee shop	glacier	medina	rope bridge	waterfall
bamboo forest	computer room	golf course	mezzanine	ruin	watering hole
bank vault	conference center	greenhouse / indoor	moat / water	runway	wave
banquet hall	conference room	greenhouse / outdoor	mosque / outdoor	sandbox	wet bar
bar	construction site	grotto	motel	sauna	wheat field
barn	corn field	gymnasium / indoor	mountain	schoolhouse	wind farm
barndoor	corral	hangar / indoor	mountain path	science museum	windmill
baseball field	corridor	hangar / outdoor	mountain snowy	server room	yard
basement	cottage	harbor	movie theater / indoor	shed	youth hostel
basketball court / indoor	courthouse	hardware store	museum / indoor	shoe shop	zen garden
bathroom	courtyard	hayfield	museum / outdoor	shopfront	
bazaar / indoor	creek	heliport	music studio	shopping mall / indoor	
bazaar / outdoor	crevasse	highway	natural history museum	shower	
beach	crosswalk	home office	nursery	ski resort	
beach house	dam	home theater	nursing home	ski slope	
beauty salon	delicatessen	hospital	oast house	sky	
bedchamber	department store	hospital room	ocean	skyscraper	
bedroom	desert / sand	hot spring	office	slum	

Table S2. Places365 scene classes.

beer garden	desert / vegetation	hotel / outdoor	office building	snowfield
beer hall	desert road	hotel room	office cubicles	soccer field
berth	diner / outdoor	house	oilrig	stable
biology laboratory	dining hall	hunting lodge / outdoor	operating room	stadium / baseball
boardwalk	dining room	ice cream parlor	orchard	stadium / football
boat deck	discotheque	ice floe	orchestra pit	stadium / soccer
boathouse	doorway / outdoor	ice shelf	pagoda	stage / indoor
bookstore	dorm room	ice skating rink / indoor	palace	stage / outdoor
booth / indoor	downtown	ice skating rink / outdoor	pantry	staircase
botanical garden	dressing room	iceberg	park	storage room
bow window / indoor	driveway	igloo	parking garage / indoor	street

Table S3. SUN image attributes.

boating	competing	vegetation	marble	rusty
driving	sports	shrubbery	glass	warm
biking	exercise	foliage	surf	cold
transporting	playing	leaves	ocean	natural
sunbathing	gaming	flowers	running water	man-made
touring	spectating	asphalt	still water	open area
hiking	farming	pavement	ice	semi-enclosed area
climbing	constructing	shingles	snow	enclosed area
camping	shopping	carpet	clouds	far-away horizon
reading	medical activity	brick	smoke	no horizon
studying	working	& tiles	fire	rugged scene
training	using tools	concrete	natural light	vertical components
research	digging	metal	sunny	horizontal components
diving	conducting business	paper	indoor lighting	symmetrical
swimming	praying	wood	aged	cluttered space
bathing	fencing	vinyl	glossy	scary
eating	railing	plastic	matte	soothing
cleaning	wire	cloth	sterile	stressful
socializing	railroad	sand	moist	
congregating	trees	rock	dry	
waiting in line	grass	dirt	dirty	

Table S4. SoN ResNet-50 test statistics. Model accuracy is reported using root mean squared error (RMSE) and Kendall's τ, a ranking correlation coefficient.

Epoch	RMSE	Kendall's τ
1	0.6998	0.6299
2	0.7008	0.6339
3	0.7079	0.6381
4	0.6909	0.6361
5	0.7546	0.6368
6	0.6926	0.6375
7	0.6997	0.6328
8	0.7491	0.6275
9	0.7189	0.6215
10	0.7325	0.6172

Table S5. Most correlated indicators. "(s)" denotes an ecosystem in surrounding area variable.

Indicator	2nd indicator	Pearson's R
I1 farmland	I1 farmland (s)	0.904
J2 low density buildings (s)	I2 gardens and parks (s)	0.887
J1 cities, towns and villages (s)	I2 gardens and parks (s)	0.886
G3 coniferous woodland (s)	G5 lines of trees (s)	0.858
E2 mesic grasslands	E2 mesic grasslands (s)	0.819
F2 alpine shrub	F2 alpine shrub (s)	0.816
I2 gardens and parks (s)	J4 roads (s)	0.802
J1 cities, towns and villages (s)	J4 roads (s)	0.793
D1 bogs	D1 bogs (s)	0.777
J1 cities, towns and villages (s)	J2 low density buildings (s)	0.760
J2 low density buildings (s)	J4 roads (s)	0.752
F2 alpine shrub (s)	E4 alpine grasslands (s)	0.748
G1 deciduous woodland	G1 deciduous woodland (s)	0.746
J2 low density buildings	J2 low density buildings (s)	0.744
I2 gardens and parks	I2 gardens and parks (s)	0.713
G3 coniferous woodland	G3 coniferous woodland (s)	0.713
J1 cities, towns and villages	I2 gardens and parks	0.704

Table S6. Time-series analysis - additional data sources.

Dataset	Source
National Parks (England)	https://naturalengland-defra.opendata.arcgis.com/
Cairngorms National Park Designated Boundary	https://spatialdata.gov.scot/
Loch Lomond and The Trossachs National Park Designated Boundary	https://spatialdata.gov.scot/
National Parks (Wales)	https://lle.gov.wales/
MOD10CM.V6	https://nsidc.org/ (Hall and Riggs, 2015)

Table S7. EEA ecosystem types.

EUNIS code	EUNIS Class name	Area (km²)	Area (%)
B1	Coastal dunes and sandy shores	205.05	0.09
B2	Coastal shingle	15.75	0.01
B3	Rock cliffs, ledges and shores, including the supralittoral	9.79	0.00
C1	Surface standing waters	2027.55	0.88
C2	Surface running waters	177.16	0.08
C3	Littoral zone of inland surface waterbodies	3.74	0.00
D1	Raised and blanket bogs	21249.21	9.24
D2	Valley mires, poor fens and transition mires	23.34	0.01
D3	Aapa, palsa and polygon mires	0	0.00
D4	Base-rich fens and calcareous spring mires	17.31	0.01
D5	Sedge and reedbeds, normally without free-standing water	114.05	0.05
D6	Inland saline and brackish marshes and reedbeds	18.44	0.01
E1	Dry grasslands	6630.9	2.88
E2	Mesic grasslands	52083.24	22.64
E3	Seasonally wet and wet grasslands	16040.37	6.97
E4	Alpine and subalpine grasslands	1465.75	0.64
E6	Inland salt steppes	0	0.00
E7	Sparsely wooded grasslands	0	0.00
F1	Tundra	0	0.00
F2	Arctic, alpine and subalpine shrub	5106.45	2.22
F3	Temperate and mediterranean-montane scrub	12265.09	5.33
F4	Temperate shrub heathland	1146.42	0.50
F5	Maquis, arborescent matorral and thermo-Mediterranean brushes	0	0.00
F6	Garrigue	0	0.00
F7	Spiny Mediterranean heaths (phrygana, hedgehog-heaths and related coastal cliff vegetation)	0	0.00
F8	Thermo-Atlantic xerophytic scrub	0	0.00
F9	Riverine and fen scrubs	7.65	0.00
FB	Shrub plantation	51.22	0.02
G1	Broadleaved deciduous woodland	11485.08	4.99
G2	Broadleaved evergreen woodland	0	0.00
G3	Coniferous woodland	11202.43	4.87
G4	Mixed deciduous and coniferous woodland	3047.2	1.32
G5	Lines of trees, small anthropogenic woodlands, recently felled woodland, early-stage woodland and coppice	2619.83	1.14
H2	Screes	219.63	0.10
H3	Inland cliffs, rock pavements and outcrops	430.22	0.19

Table S7. EEA ecosystem types.

H4	Snow or ice-dominated habitats	0	0.00
H5	Miscellaneous inland habitats with very sparse or no vegetation	889.47	0.39
I1	Arable land and market gardens	58901.8	25.61
I2	Cultivated areas of gardens and parks	3895.57	1.69
J1	Buildings of cities, towns and villages	8526.9	3.71
J2	Low density buildings	8052.28	3.50
J3	Extractive industrial sites	674.15	0.29
J4	Transport networks and other constructed hard-surfaced areas	1385.46	0.60
J5	Highly artificial man-made waters and associated structures	26.75	0.01
J6	Waste deposits	23.85	0.01
Total		**230039.1**	**100**

Table S8. Scenicness model accuracy results without the user limitation.

Model	Places365 scene classes	SUN attributes	Scenic rating distribution	Environmental indicators	r^2	RMSE	Kendall's τ
Flickr							
1	–	–	✓	–	0.672	0.627	0.613
2	–	✓	–	–	0.739	0.558	0.654
3	–	✓	✓	–	0.746	0.552	0.660
4	✓	–	–	–	0.756	0.542	0.674
5	✓	✓	✓	–	0.760	0.537	0.674
6	✓	–	✓	–	0.757	0.540	0.674
7	✓	✓	–	–	0.762	0.534	0.675
Indicator							
8	–	–	–	✓	0.819	0.468	0.730
Combination							
9	✓	✓	–	✓	0.827	0.458	0.731
10	✓	✓	✓	✓	0.827	0.458	0.732
11	–	✓		✓	0.829	0.455	0.732
12	✓	–	–	✓	0.830	0.456	0.734
13	–	–	✓	✓	**0.831**	**0.453**	**0.738**

Table S9. Summary statistics for largest differences in image attribute scores with unfiltered dataset based on ten random image selections per user per day per grid cell.

Attribute	min	0.25	median	0.75	max
grass	-0.0129345	-0.012813	-0.012728	-0.0126741	-0.0125904
cloth	-0.0117806	-0.0117536	-0.0117219	-0.0116848	-0.0116245
playing	-0.0082253	-0.0081799	-0.00814	-0.0081338	-0.0081115
competing	-0.0080414	-0.0079843	-0.0079614	-0.0079484	-0.0079092
sports	-0.0080318	-0.0079829	-0.0079552	-0.0079414	-0.0078951
vegetation	-0.0080157	-0.0078309	-0.0078205	-0.0077516	-0.0075968
no horizon	-0.0079613	-0.0078365	-0.0077178	-0.0076277	-0.0075967
exercise	-0.0070634	-0.0070209	-0.0069846	-0.0069786	-0.0069431
foliage	-0.0068866	-0.0067719	-0.0067143	-0.006672	-0.0064665
sunny	-0.0065354	-0.0064305	-0.0063678	-0.0063338	-0.0062988
railroad	0.00125414	0.00129332	0.00129991	0.00130359	0.00134532
swimming	0.00144828	0.00147526	0.00154538	0.001581	0.00161854
enclosed area	0.00188263	0.0019101	0.0019217	0.0019345	0.00200661
transporting	0.00230039	0.00233472	0.00236526	0.00239926	0.0024206
natural	0.00271528	0.00278886	0.00285209	0.00304828	0.0031844
boating	0.00280333	0.00284384	0.00291285	0.00296349	0.00302866
ocean	0.00295043	0.00301037	0.00308272	0.00311155	0.00313657
indoor lighting	0.00367905	0.00371899	0.00374535	0.0037538	0.00378158
far-away horizon	0.00531631	0.005401	0.00546001	0.00560656	0.00575712
clouds	0.00646776	0.00654812	0.00665955	0.0066942	0.00684807
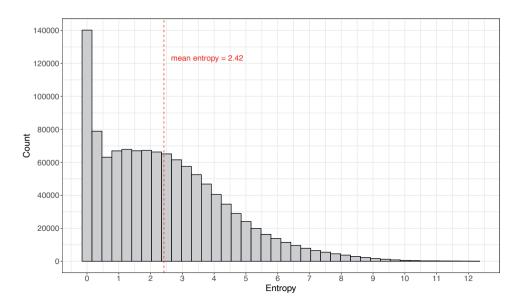
Table S10. OSM historic POI.

Category	Description
aqueduct	A historic structure to convey water
archaeological site	A place in which evidence of past activity is preserved.
building	Unspecified historic building.
castle	Used for various kinds of castles, palaces, fortresses, manors, stately homes, kremlins, shiros and other.
castle wall	A fortification surrounding the bailey of a castle
church	A building with historical value for Christian religious activities, particularly for worship services.
city gate	A city gate within a city wall
citywalls	A citywall is a fortification used to defend a city.
farm	A historical farm, kept in its original state.
fort	A military fort, a stand-alone defensive structure which differs from a castle in that there is no permanent residence
manor	Historic manors/mansions having different use today \\
monastery	Building/place that was a monastery.
monument	A memorial object, which is especially large, built to remember, show respect to a person or group of people or to commemorate an event.
ruins	Remains of structures that were once complete, but have fallen into partial or complete disrepair.
rune stone	Stones, boulders or bedrock with historical runic inscriptions.
tower	This property distinguishes a tower as historic
wayside cross	A historical cross, symbol of christian faith.
wayside shrine	A shrine often showing a religious depiction. Also for modern shrines.
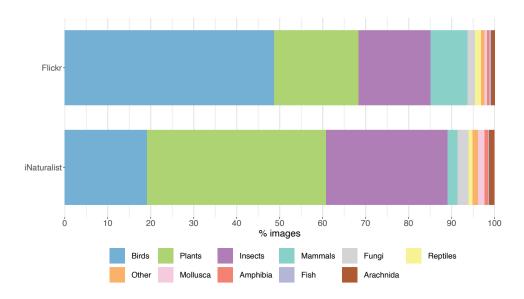
Supplementary material for Chapter 4

Figure S8. European sample grid at 25km resolution to download the Flickr and iNaturalist image training dataset.

Figure S9. Distribution of iNaturalist observation image entropy scores based on the species classification models' predictions.

Figure S10. The percentage of images per species "supercategory" in Flickr species images and the images of iNaturalist observations, as predicted by the species classification model.

Table S11. Randomly sampled images (hyperlinks) of the species interaction model's predictions using different beta coefficients. Confidence bands reflect the confidence of the image being a species image (species image => 0.5, max=1).

Confidence band	Beta=1	Beta=0.1	Beta=0.01	Beta=0.001
(0.9,1]	[1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20]	[1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20]	[1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20]	[1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20]
(0.8, 0.9]	[1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20]	[1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20]	[1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20]	[1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20]"
(0.7, 0.8]	[1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20]	[1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20]	[1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20]	[1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20]
(0.6, 0.7]	[1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20]	[1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20]	[1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20]	[1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20]
(0.5, 0.6]	[1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20]	[1], [2], [3], [4], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19] , [20]	[1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20]	[1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20]
(0.4,0.5]	[1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20]	[1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20]	[1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20]	[1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20]

Table S11. Randomly sampled images (hyperlinks) of the species interaction model's predictions using different beta coefficients. Confidence bands reflect the confidence of the image being a species image (species image => 0.5, max=1).

(0.3, 0.4]	[1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20]	[1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [NA], [16], [17], [18], [19], [20]	[1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20]	[1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20]
(0.2, 0.3]	[1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20]	[1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20]	[1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20]	[1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20]
(0.1, 0.2]	[1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20]	[1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20]	[1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20]	[1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20]
(0, 0.1]	[1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20]	[1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20]	[1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20]	[1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20]

Table S12. Overall accuracy of the species classification model at different taxonomic levels.

Taxonomic level	Overall accuracy (no filter)	Overall accuracy (<2.42 entropy filter)
Genus	32.4%	49.6%
Family	47.0%	65.9%
Order	59.1%	76.3%
Phylum	89.1%	94.7%

Table S13. Overall accuracy of the species classification model with a <2.42 entropy filter on the iNaturalist observation dataset for the most frequent genera predicted on Flickr and iNaturalist.

Genus	Common name	Total predicted	Genus OA (%)	Family OA (%)	Order OA (%)	Phylum OA (%)	Top misclassification (% of total predictions)
Aglais	Tortoiseshells	5,435	99.6	99.8	99.9	99.9	Bumblebee (0.18)
Erithacus	Robins	3,470	99.1	99.1	99.9	100	Bumblebee (0.09)
Sciurus	Squirrels	3,385	91.5	91.5	92.4	98.9	Thrushes (3.28)
Larus	Gulls	3,887	87.4	95.1	95.5	99.9	Fulmars (3.09)
Cygnus	Swans	5,664	87.4	94.3	94.3	99.6	Gulls (2.61)
Ardea	Herons	3,409	85.9	90.5	90.8	99.7	Swans (4.81)
Turdus	Thrushes	5,419	85.7	85.7	98.2	99.8	Moorhens (0.87)
Anas	Dabbling Ducks	7,121	85.1	95.4	95.4	99.8	Coots (2.49)
Branta	Black Geese	4,043	84.5	94.2	94.2	98.7	Coots (2.08)
Pieris	Garden Whites	5,706	83.5	89.9	94.1	94.6	Wood sorrels (0.7)
Geranium	Geraniums	7,951	78.8	79.1	79.1	97.8	Mallow (6.55)
Vanessa	Red Admiral	7,742	78.4	95.6	98.3	99.7	Bumblebee (1.47)
Anser	Grey/white Geese	3,078	73.2	91.0	91.0	97.0	Gulls (1.92)
Harmonia	Ladybugs	7,402	72.2	97.2	98.1	99.7	Froghoppers (0.51)
Trifolium	Clover	6,535	62.8	64.2	64.2	96.1	Anacamptis (8.28)
Apis	Honey bees	7,214	32.1	47.0	61.0	98.2	Hoverflies (20.6)
Odocoileus	Deer (Americas)	1,911	0	80.3	80.6	96.9	Foxes (5.18)

Table S14. Bird density and species model class groupings to conduct the biodiversity comparison.

Species	Bird density maps	Species model grouping	Species model classes*	Conservation status[†]	Grouping justification
Blue Tit	Blue Tit	*Cyanistes*	*Cyanistes caeruleus* (3,016)	Green	None - only one species class available within the genus.
Bullfinch	Bullfinch	*Pyrrhula*	*Pyrrhula pyrrhula* (599)	Amber	None - only one species class available within the genus.
Buzzard	Buzzard	*Buteo*	*Buteo augur* (2)	Green	The available species classes within the genus are visually similar.
			Buteo buteo (274)		
			Buteo galapagoensis (31)		
			Buteo jamaicensis (1,866)		
			Buteo lagopus (5)		
			Buteo lineatus (452)		
			Buteo plagiatus (131)		
			Buteo platypterus (71)		
			Buteo regalis (64)		
			Buteo rufinus (7)		
			Buteo swainsoni (147)		
Chaffinch	Chaffinch	*Fringilla*	*Fringilla coelebs* (2,685)	Green	None - only one species class available within the genus.
Coal Tit	Coal Tit	*Periparus*	*Periparus ater* (415)	Green	None - only one species class available within the genus.
Collared Dove	Collared Dove	*Streptopelia*	*Streptopelia capicola* (13)	Green	The available species classes within the genus are visually similar.
			Streptopelia chinensis (104)		
			Streptopelia decaocto (957)		
			Streptopelia decipiens (52)		
			Streptopelia (24)		
			Streptopelia senegalensis (33)		
Crows	Carrion Crow	*Corvus*	*Corvus brachyrhynchos* (784)	Amber	Genus is visually similar. Conservation status has been set to amber to reflect amber
	Jackdaw		*Corvus corax* (721)		
	Rook		*Corvus cornix* (73)		
			Corvus corone (123)		

Table S14. Bird density and species model class groupings to conduct the biodiversity comparison.

			Corvus frugilegus (58)		status of Rook.
			Corvus monedula (585)		
Curlew	Curlew	*Numenius*	*Numenius americanus* (266)	Red	The available species classes within the genus are visually similar.
			Numenius madagascariensis (458)		
			Numenius phaeopus (356)		
Dunnock	Dunnock	*Prunella*	*Prunella collaris* (22)	Amber	The available species classes within the genus are visually similar.
			Prunella modularis (1,151)		
Goldcrest	Goldcrest	*Regulus*	*Regulus calendula* (618)	Green	The available species classes within the genus are visually similar.
			Regulus satrapa (218)		
Goldfinch	Goldfinch	*Carduelis*	*Carduelis carduelis* (1,614)	Green	None - only one species class available within the genus.
Great Spotted Woodpecker	Great Spotted Woodpecker	*Dendrocopos*	*Dendrocopos major* (1,297)	Green	The available species classes within the genus are visually similar.
			Dendrocopos medius (94)		
			Dendrocopos minor (2)		
			Dendrocopos syriacus (23)		
Great Tit	Great Tit	*Parus*	*Parus major* (2,021)	Green	The available species classes within the genus are visually similar.
			Parus minor (31)		
Green Woodpecker	Green Woodpecker	*Picus*	*Picus canus* (82)	Green	None - only one species class available within the genus.
Greenfinch	Greenfinch	*Chloris*	*Chloris chloris* (960)	Red	The available species classes within the genus are visually similar.
			Chloris cucullata (9)		
			Chloris sinica (84)		
House Martin, Swallow	House Martin, Swallow	*Hirundinidae*	*Cecropis abyssinica* (3)	Amber	Due to the visual similarity of species at the family level, the bird densities were combined and compared to
			Delichon urbicum (13)		
			Hirundo neoxena (7)		
			Hirundo rustica (972)		

Table S14. Bird density and species model class groupings to conduct the biodiversity comparison.

			Hirundo tahitica (3)		the models' predictions at family level. Conservation status was set to amber to reflect the House Martin's red list status.
			Petrochelidon pyrrhonota (205)		
			Progne subis (34)		
			Ptyonoprogne rupestris (5)		
			Pygochelidon cyanoleuca (1)		
			Riparia riparia (38)		
			Stelgidopteryx ruficollis (11)		
			Stelgidopteryx serripennis (209)		
			Tachycineta albiventer (7)		
			Tachycineta bicolor (68)		
			Tachycineta thalassina (29)		
House Sparrow	House Sparrow	*Passer*	*Passer diffusus* (26)	Red	The available species classes within the genus are visually similar.
			Passer domesticus (4127)		
			Passer griseus (12)		
			Passer hispaniolensis (35)		
			Passer melanurus (33)		
			Passer montanus (505)		
Jay	Jay	*Garrulus*	*Garrulus glandarius* (447)	Green	None - only one species class available within the genus.
Kestrel	Kestrel	*Falco*	*Falco cenchroides* (58)	Amber	Excluded Merlins (Falco columbarius), Peregrine (*Falco peregrinus*) and gyrfalcon (*Falco rusticolus*) from species model classes as too visually dissimilar.
			Falco naumanni (60)		
			Falco sparverius (454)		
			Falco tinnunculus (1,790)		
Lapwing	Lapwing	*Vanellus*	*Vanellus albiceps* (9)	Red	The available species classes within the genus are visually similar.
			Vanellus chilensis (91)		
			Vanellus coronatus (41)		
			Vanellus senegallus (21)		
			Vanellus vanellus (486)		
Long-tailed Tit	Long-tailed Tit	*Aegithalos*	*Aegithalos caudatus* (489)	Green	None - only one species class available within the genus.
Magpie	Magpie	*Pica*	*Pica hudsonia* (469)	Green	The available species classes

Table S14. Bird density and species model class groupings to conduct the biodiversity comparison.

			Pica nuttalli (10)		within the genus are visually similar.
			Pica pica (570)		
Mallard	Mallard	*Anas*	*Anas acuta* (984)	Amber	The available species classes within the genus are visually similar.
			Anas castanea (5)		
			Anas crecca (1,550)		
			Anas erythrorhyncha (64)		
			Anas flavirostris (116)		
			Anas fulvigula (210)		
			Anas georgica (8)		
			Anas platyrhynchos (11,900)		
			Anas poecilorhyncha (20)		
			Anas rubripes (124)		
			Anas superciliosa (61)		
			Anas undulata (41)		
			Anas zonorhyncha (1)		
Meadow Pipit	Meadow Pipit	*Anthus*	*Anthus cervinus* (67)	Amber	The available species classes within the genus are visually similar.
			Anthus petrosus (243)		
			Anthus rubescens (495)		
			Anthus rufulus (11)		
			Anthus spinoletta (3)		
			Anthus spragueii (60)		
			Anthus trivialis (9)		
Moorhen	Moorhen	*Gallinula*	*Gallinula chloropus* (893)	Amber	The available species classes within the genus are visually similar.
			Gallinula galeata (1,041)		
			Gallinula tenebrosa (56)		
Nuthatch	Nuthatch	*Sitta*	*Sitta canadensis* (253)	Green	Excluded
			Sitta europaea (1,154)		White-breasted nuthatch (*Sitta carolinensis*) and Pygmy nuthatch (*Sitta pygmaea*) from species model classes as too visually dissimilar.
Pied/White Wagtail	Pied/White Wagtail	*Motacilla*	*Motacilla alba* (1,035)	Green	Excluded Grey wagtail (*Motacilla cinerea*) from species model classes as too visually
			Motacilla capensis (12)		
			Motacilla maderaspatensis (20)		

					dissimilar.
Pigeons	Stock Dove Woodpigeon	*Columba*	*Columba guinea* (43) *Columba livia* (1,916) *Columba oenas* (18) *Columba palumbus* (1,198)	Amber	Genus is visually similar so bird densities and species classes have been combined.
Robin	Robin	*Erithacus*	*Erithacus rubecula* (9,804)	Green	None - only one species class available within the genus.
Skylark	Skylark	*Alauda*	*Alauda arvensis* (240)	Red	None - only one species class available within the genus.
Starling	Starling	*Sturnus*	*Sturnus unicolor* (4) *Sturnus vulgaris* (1,753)	Red	The available species classes within the genus are visually similar.
Swift	Swift	*Apodidae*	*Aeronautes saxatalis* (15) *Chaetura pelagica* (9) *Streptoprocne zonaris* (58)	Red	Species model classes not available within *Apus* genus so classifications taken at family level which includes visually similar species.
Thrushes	Blackbird Mistle Thrush Song Thrush	*Turdus*	*Turdus amaurochalinus* (28) *Turdus assimilis* (2) *Turdus eunomus* (34) *Turdus falcklandii* (14) *Turdus fuscater* (35) *Turdus grayi* (177) *Turdus iliacus* (8) *Turdus leucomelas* (12) *Turdus libonyana* (14) *Turdus merula* (3,404) *Turdus migratorius* (194) *Turdus philomelos* (1,033) *Turdus pilaris* (309) *Turdus rufiventris* (5) *Turdus rufopalliatus* (46)	Amber	Genus is visually similar so bird densities and species classes have been combined. Conservation status is set to amber because of the red list status of the Mistle Thrush.

Table S14. Bird density and species model class groupings to conduct the biodiversity comparison.

			Turdus torquatus (35)		
Warblers	Chiffchaff Blackcap Garden Warbler Whitethroat	*Phylloscopus* *Sylvia*	*Phylloscopus collybita* (252) *Sylvia atricapilla* (110) *Sylvia communis* (270) *Sylvia melanocephala* (2)	Amber	The available species classes within the *Sylvia* genus are visually similar. The Chiffchaff is also included due to visual similarities, having formally formed part of the same taxonomic family *Sylviidae*. Conservation status is set to amber because of the amber status of the Whitethroat.
Wren	Wren	*Troglodytes*	*Troglodytes aedon* (870) *Troglodytes pacificus* (26)	Amber	The available species classes within the genus are visually similar.
Yellowhammer	Yellowhammer	*Emberiza*	*Emberiza citrinella* (666)	Red	Excluded other Eberiza species classes *Emberiza cia*, *Emberiza cirlus*, *Emberiza elegans*, *Emberiza melanocephala* and *Emberiza rustica* due to the visual uniqueness of the Yellowhammer within this genus.

*Number of species class predictions in parentheses

†Source: BTO BirdFacts. Url: https://www.bto.org/understanding-birds/birdfacts

Supplementary material for Chapter 5

Table S15. The relationship between the levels of reported well-being per statement in the MENE survey and the sentiment estimated by the three NLP models in Flickr image text within a 1km radius of the surveyed trips.

Model	Statement correlation (Pearson's r)					
	I enjoyed it	It made me feel calm and relaxed	It made me feel refreshed and revitalised	I took time to appreciate my surroundings	I learned something new about the natural world	I felt close to nature
Hedonometer	**0.05218**	**0.03776**	**0.03480**	**0.05070**	**0.01392**	**0.06013**
Sentiment140	0.02105	0.00980	0.00762	0.01913	-0.00902	0.00531
RoBERTa	0.04401	0.02831	0.01604	0.03213	0.00506	0.01901

Table S16. Correlation (Pearson's R) between aesthetic quality ratings and sentiment estimated by the three NLP models on an individual image basis.

Model	Aesthetic quality (1-10)	Aesthetic quality (<6)	Aesthetic quality (>6)
Hedonometer	**0.142**	0.156	0.0289
Sentiment140	0.0526	0.0571	0.0201
RoBERTa	0.0897	0.0859	0.0467

Table S17. Correlation (Pearson's R) between species interactions and sentiment estimated by the three NLP models on an individual image basis.

Model	Species interactions
Hedonometer	0.124
Sentiment140	0.003
RoBERTa	0.033

Table S18. Correlations between aesthetic quality in Flickr images and the level of agreement with the well-being statements associated with trips within 1km reported in the MENE survey.

Statement	Correlation (Pearson's R)
I enjoyed it	0.0885
It made me feel calm and relaxed	0.0835
It made me feel refreshed and revitalised	0.0898
I took time to appreciate my surroundings	0.151
I learnt something new about the natural world	0.0718
I felt close to nature	0.163

Table S19. Correlations between the number of species interactions in Flickr images and the level of agreement with the well-being statements associated with trips within 1km reported in the MENE survey.

Statement	Correlation (Pearson's R)
I enjoyed it	0.0244
It made me feel calm and relaxed	0.0353
It made me feel refreshed and revitalised	0.0199
I took time to appreciate my surroundings	0.0306
I learnt something new about the natural world	0.0232
I felt close to nature	0.0581

Summary

Machine learning and crowdsourced data offer new ways in which to generate measures of Cultural Ecosystem Services (CES) in ecosystem service assessments. As a result, demonstrating the use of these novel techniques can help better integrate the ecosystem service concept into decision-making, especially at large-scales.

This thesis aims to explore the potential of crowdsourced data and machine learning to measure CES through the following research questions:

1. How can CES be defined and spatially modelled in the context of crowdsourced data?

2. How can social media and deep learning capture the aesthetic quality of the landscape in support of aesthetic ecosystem service models?

3. What do social media and deep learning-based indicators of biodiversity-related CES capture in comparison to citizen science and ecological measures?

4. How can social media and natural language processing capture the positive experiences associated with different CES measures?

The thesis contains six chapters:

Chapter 1: General introduction

This chapter introduces the existing challenges and knowledge gaps facing CES assessment using crowdsourced data and machine learning, as well as the research questions.

Chapter 2: Defining and spatially modelling CES using crowdsourced data

This chapter presents a conceptual exercise in which the CES concept is reconsidered in the context of existing, established conceptualisations and sources of crowdsourced data. At the same time, three spatial models of CES are presented for the island of Texel to further inform the conceptualisation.

Chapter 3: Social media and deep learning capture the aesthetic quality of the landscape

In this chapter, a measure of landscape aesthetics is generated for Great Britain using Flickr images and deep learning. The accuracy of the model is assessed using a national, crowdsourced database of landscape aesthetics and compared to a traditional indicator model. The final model uses a full, image-based semantic prediction of landscape aesthetic quality, produced by a deep learning model trained for the study.

Chapter 4: Deep learning and social media reveal specific cultural contributions of biodiversity

This chapter explores the potential of deep learning and social media to develop CES measures of biodiversity. A deep learning model is trained on a large database of images to generate predictions of human-species interactions in images. This model is applied to Flickr images in Great Britain and the spatial distributions are compared with citizen science data. User activity is explored versus key socio-environmental factors and further comparisons are made with ecological measures of biodiversity.

Chapter 5: Understanding the sentiment generated by CES using social media and natural language processing

In this chapter, the connection between peoples' positive experiences and CES measures produced using social media and natural language processing, including machine learning, is explored. A number of sentiment models are applied to the textual data associated with Flickr images in Great Britain and compared with different CES measures of landscape aesthetics and individual interactions with different species.

Chapter 6: Synthesis

Finally, this chapter presents a synthesis of the main findings, a discussion of the methods, relevancy of the findings for key ecosystem service frameworks, research outlook and concluding remarks.

Acknowledgements

Doing a PhD is quite an individual mind-game. When you're so much in your head, you sometimes forget how much you rely on the people around you: your partner, your friends and your colleagues, and how much patience they have for your distracted musings! Many a time have I been caught mumbling something or other to myself, running to my laptop midway through cooking dinner, or simply seen staring into space as I contemplate the effects of switching two steps in an experimental workflow. Many a fellow PhD student would also sympathise with the small graveyard of ideas, left-behind lines of code and _v2, v_3, v_II manuscript pages piled up in the documents folder. A PhD is a living thing, with a million evolving reference points, from papers in the scientific literature, colleagues at the coffee machine, to heated discussions over a beer (or two), the invaluable feedback of your supervision team and the constant support of family and loved ones.

So, first of, I'd like to thank my supervisors. Lars for providing me with the opportunity, helping me to secure the funding for my PhD through WIMEK and the European MAIA project, while providing many challenging intellectual debates and allowing me the freedom to fully explore the research set out in this thesis. I'd also like to thank Devis for his never-ending support, enthusiasm and humour. I could not have gotten through some of the most difficult points of my PhD journey without you. Your love of research and rock-solid support of the people in your team is inspiring and I hope to carry that on into my own professional life. In the end, deep learning became a big part of my thesis and I'm very proud of our collective contributions to the ecosystem services literature, much of which came from our inspiring discussions. Patrick, I'd like to thank you for a long-running collaboration, your wide-ranging knowledge and sharp analytical thinking. This lead to many productive conceptual discussions which formed the basis of the conceptual work laid out in this thesis. Last but not least, I want to thank Diego, supervisor all in but name. You were the research buddy I needed: while I was lost in the details, you could steer the ship straight with a simple comment or two. Thanks for putting up with my chart spamming on slack for 4 years.
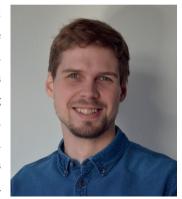
Although the covid pandemic made physical contact challenging for two years, I have many fond memories of working in both the Environmental Systems Analysis Group and the Laboratory of Geo-information Science and Remote Sensing. Highlights include the adventurous ESA outings and inspiring writing week organised by Rik, where the pressure was on, to write and to cook. Education through Karen's encouragement in the ESA group

was also a great experience, where my own critical thinking saw great improvements through many an interesting exchange with students. In the GRS group, I am especially indebted to Beni and Danius for their technical assistance with the servers and my own computer. Squash with the GRS group also got me whacking balls voraciously at walls once a week, with a few well-deserved beers after, what a way to blow off steam. The Veluwe run was also a highlight, where despite our best efforts as geospatial experts, we saw much more of the Veluwe than originally planned. Spending time in both groups also meant I got to meet a lot of inspiring people from all corners of the world with many helpful encounters that fed back into my research. What a privilege this has been! Special thanks go out to Aritta and Arnan for being my paranymphs on the day.

Finally, for their enduring support, I would like to express my sincerest gratitude to my family and partner Chataine. My mother especially for her straightforward, practical advice and my father for the boundless optimism and fantastic ambitions that guided me through this process. Thank you for your constant motivation and emotional support. Chataine: what a crazy time this has been, and as we go on new adventures, I know I have someone very special by my side.

About the author

Ilan Havinga was born in Utrecht, the Netherlands on 21 April 1992. He soon left the country at 5 months old to live in England with his parents, spending his childhood growing up in the rolling hills of the Cotswolds. Trade was a preoccupation at school, with a booming sweet selling business. This led to his BSc in Business Studies at Oxford Brookes University in 2010 where he focused on sustainability in business and graduated with First Class Honours. Building on a placement year at Sky media group, Ilan joined their sustainability team after graduating from his Bachelors. Here he became responsible for their corporate environmental reporting and was involved in a broad variety of initiatives from improving accessibility to working with suppliers on their environmental impact.

Desiring to expand his knowledge in environmental reporting but at country-level, Ilan decided to begin a Masters at Wageningen University in 2016, where he joined the MSc Climate Studies programme and graduated two years later Cum Laude. His master thesis focused on developing ecosystem accounting in Costa Rica in the context of their national payments for ecosystem services programme, utilising remote sensing and machine learning to model ecosystem service supply. Wishing to continue in academia, Ilan began a PhD at the Environmental Systems Analysis Group partly funded by the WIMEK Graduate Programme and the European MAIA project. His research focused on applying machine learning, including deep learning, and big data – termed crowdsourced data – to measure cultural ecosystem services. Alongside his research, Ilan also contributed to teaching at the university including lectures, group work and individual thesis supervision.

Since 2022, Ilan now lives in London and works for Allianz Global Investors. In his role at the company, Ilan supports the development of their impact investing measurement and reporting approach.

List of publications

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

Havinga, I., Marcos, D., Bogaart, P.W., Hein, L. and Tuia, D., 2021. Geo-Data for Mapping Scenic Beauty: Exploring the Potential of Remote Sensing and Social Media. In *2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS* (pp. 188-191). https://doi.org/10.1109/IGARSS47720.2021.9553417.

Levering, A., Marcos, D., **Havinga, I.** and Tuia, D., 2021. Cross-Modal Learning of Housing Quality in Amsterdam. In *Proceedings of the 4th ACM SIGSPATIAL International Workshop on AI for Geographic Knowledge Discovery* (pp. 1-4). https://doi.org/10.1145/3486635.3491067.

Havinga, I., Bogaart, P.W., Hein, L. and Tuia, D., 2020. Defining and spatially modelling cultural ecosystem services using crowdsourced data. *Ecosystem Services*, 43, 101091. https://doi.org/10.1016/j.ecoser.2020.101091.

Havinga, I., Hein, L., Vega-Araya, M. and Languillaume, A., 2020. Spatial quantification to examine the effectiveness of payments for ecosystem services: A case study of Costa Rica's Pago de Servicios Ambientales. *Ecological Indicators*, 108, 105766. https://doi.org/10.1016/j.ecolind.2019.105766.

Barton, D.N., Obst, C., Day, B., Caparrós, A., Dadvand, P., Fenichel, E., **Havinga, I.**, Hein, L., McPhearson, T., Randrup, T. and Zulian, G., 2019. Discussion paper 10: recreation services from ecosystems. *Paper submitted to the Expert Meeting on Advancing the Measurement of Ecosystem Services for Ecosystem Accounting, New York, January*.

SENSE

Netherlands Research School for the
Socio-Economic and Natural Sciences of the Environment

D I P L O M A

for specialised PhD training

The Netherlands research school for the
Socio-Economic and Natural Sciences of the Environment
(SENSE) declares that

Ilan Havinga

born on 21 April 1992 in Utrecht, The Netherlands

has successfully fulfilled all requirements of the
educational PhD programme of SENSE.

Wageningen, 18 January 2023

Chair of the SENSE board

Prof. dr. Martin Wassen

The SENSE Director

Prof. Philipp Pattberg

The SENSE Research School has been accredited by the Royal Netherlands Academy of Arts and Sciences (KNAW)

K O N I N K L I J K E   N E D E R L A N D S E
A K A D E M I E   V A N   W E T E N S C H A P P E N

The SENSE Research School declares that **Ilan Havinga** has successfully fulfilled all requirements of the educational PhD programme of SENSE with a work load of 35.9 EC, including the following activities:

SENSE PhD Courses

o Environmental research in context (2019)
o Selected topics in mathematics (2019)
o Research in context activity: 'Landscape quality media campaign' (2020)

Other PhD and Advanced MSc Courses

o Machine learning for spatial data, PE&RC and WIMEK (2019)
o Linear Models, PE&RC & WIMEK (2020)
o Generalized Linear Models, PE&RC & WIMEK (2020)
o Mixed Linear Models, PE&RC & WIMEK (2020)

Management and Didactic Skills Training

o Teaching in the MSc courses 'Introduction to Climate Change in a Global Change Context' (2019), Environmental Quality and Governance' (2021) and 'Integrated Ecosystem Assessment in Regional Management' (2021)
o Co-supervising MSc student with thesis entitled 'Characterising urban green space area in the Randstad metropolitan area through social media' (2020)
o Designing and creating materials for 'Integrated Ecosystem Assessment in Regional Management' (2020)

Oral Presentations

o *Cultural value of ecosystems using VGI*. ESP conference 2019, 21-25 October 2019, Hannover, Germany
o *Exploring the potential of Flickr metadata for recreational modelling*. ACES conference 10 December 2020, Gainesville, United State of America (online)
o *Geo-Data for Mapping Scenic Beauty: Exploring the Potential of Remote Sensing and Social Media*. IGARSS 2021, 11-16 July, 2021, Brussels, Belgium (online)
o *Modelling the aesthetic contributions of ecosystems using social media and machine learning*. ESP Europe Conference, 7-10 June 2021, Tartu, Estonia (online)

SENSE coordinator PhD education

Dr. ir. Peter Vermeulen