Ecosystem Services 43 (2020) 101091

Contents lists available at ScienceDirect

Ecosystem Services

journal homepage: www.elsevier.com/locate/ecoser

Defining and spatially modelling cultural ecosystem services using crowdsourced data

Ilan Havinga[a,*], Patrick W. Bogaart[b], Lars Hein[a], Devis Tuia[c]

[a] Environmental Systems Analysis Group, Wageningen University, PO Box 47, 6700 AA Wageningen, the Netherlands
[b] National Accounts Department, Statistics Netherlands, Henri Faasdreef 312, 2492 JP The Hague, the Netherlands
[c] Laboratory of Geo-information Science and Remote Sensing, Wageningen University, PO Box 47, 6700 AA Wageningen, the Netherlands

ARTICLE INFO

Keywords:
Ecosystem services
Cultural ecosystem services
Spatial analysis
Volunteered geographic information
Social media
Big 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.

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 (Norton et al., 2012; Hernández-Morcillo et al., 2013; Schröter et al., 2015) and spatial models have tended to rely on proxies such as land cover (Eigenbrod et al., 2010; Chan et al., 2011; Maes et al., 2013). As a

* Corresponding author.
E-mail address: ilan.havinga@wur.nl (I. Havinga).

https://doi.org/10.1016/j.ecoser.2020.101091
Received 19 July 2019; Received in revised form 9 March 2020; Accepted 13 March 2020
Available online 04 April 2020
2212-0416/ © 2020 The Authors. Published by Elsevier B.V. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/BY-NC-ND/4.0/).

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., 2012; 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 (Hein et al., 2006; Barbier, 2011; 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' (Elwood and Leszczynski, 2011; Elwood et al., 2012; Crampton et al., 2013). In line with the terminology used in recent studies (Gliozzo et al., 2016; See et al., 2016; Tenerelli et al., 2016; Sinclair et al., 2018; Calcagni et al., 2019; Ghermandi and Sinclair, 2019), 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 (Richards and Friess, 2015; Willemen et al., 2015; Martínez Pastur et al., 2016). 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

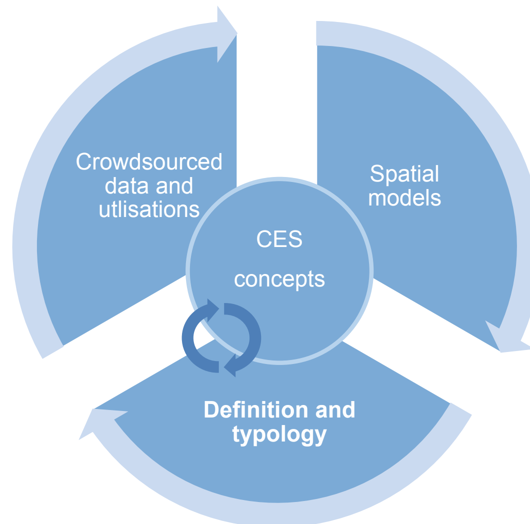

Fig. 1. Conceptual process followed to develop the CES definition and typology. The proposed definition and typology were developed following an iterative process which considered crowdsourced data and utilisations, the authors' experience developing CES models using these sources as well as established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

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 (Fig. 1). In Section 2 of this paper, CES concepts and sources of crowdsourced data are considered in an inventory of ES assessment frameworks and utilisations of crowdsourced data. In Section 3 and 4, we outline our CES definition and suggest a general typology of eight services. In Section 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 6, we discuss our conceptualisation of CES, taking into account the representativeness of the data, measurement uncertainties and ethical considerations. Section 7 summarises the main conclusions of the paper.

2. Inventories of established CES concepts and crowdsourced data

2.1. Methods

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 (Gómez-Baggethun et al., 2010; La Notte et al., 2017; Díaz et al., 2018; Hein et al., 2020). 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).

2.1.2. 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 (Goodchild, 2007; Connors et al., 2012). “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 17 studies to the inventory. A more detailed overview of the literature selection process can be found in the supplementary materials, Appendix A.

2.2. Results

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 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. 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 (Tenerelli et al., 2016; van Zanten et al., 2016; Yoshimura and Hiura, 2017; Kim et al., 2019) and the content of the images (Richards and Friess, 2015; Thiagarajah et al., 2015; Richards and Tunçer, 2018), 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

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 et al., 2014, p. 42; UN, 2017)	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

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 (Middleton et al., 2014; de Albuquerque et al., 2015; Chen et al., 2016), 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 (Zhou and Zhang, 2016; Roberts et al., 2017).

(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 (Norman and Pickering, 2017; Jurado Rota et al., 2019; Norman et al., 2019).

(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 (Toole et al., 2012; Pei et al., 2014). 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 (Toole et al., 2012; Pei et al., 2014; Tu et al., 2017) and determine the accessibility of urban green space (Wu et al., 2018; Xiao et al., 2019).

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

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
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

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.

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 1 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 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 (UN, 2017; Díaz et al., 2018; Haines-Young and Potschin, 2018). 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, 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 (MA, 2005; TEEB, 2010b; Haines-Young and Potschin, 2018). 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 (van der Maarel and Dauvellier, 1978; UN, 2017; Díaz et al., 2018). 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 (TEEB, 2010b; Díaz et al., 2018). 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

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

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

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 (Thiagarajah et al., 2015; Roberts, 2017). 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 (MA, 2005; TEEB, 2010b; Díaz et al., 2018). Sacred sites can vary in scale, from pilgrimage routes and mountain ranges to small spaces of vegetation (MA, 2005; Haines-Young and Potschin, 2018). 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.

5. Spatial CES models

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.

5.1.1. Study area

Texel is an island of 160 km^2 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 (Fig. 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).

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

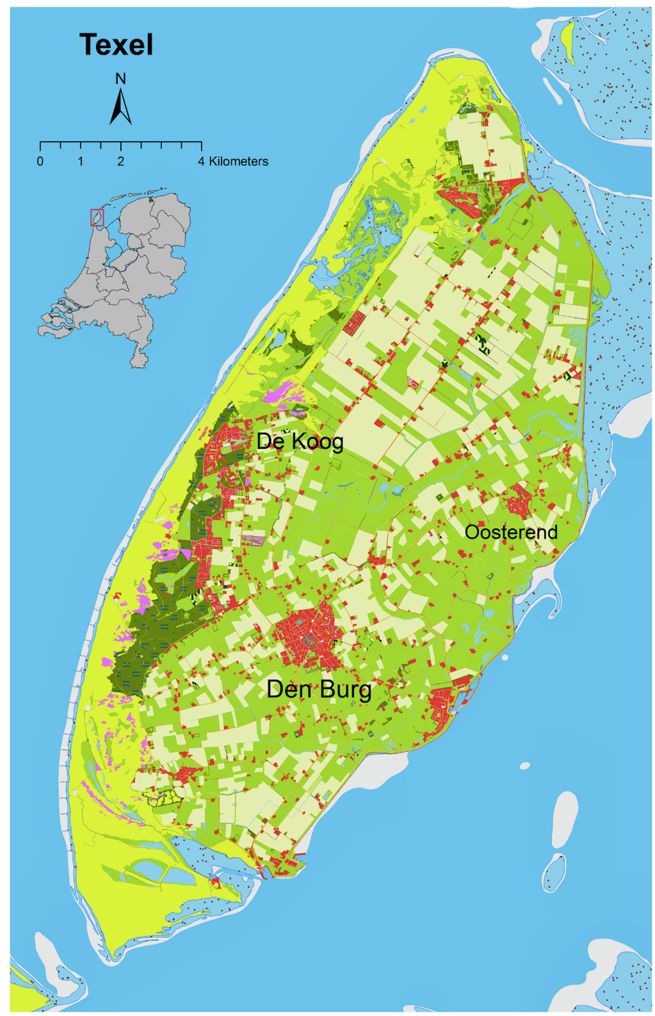

Fig. 2. Topographic map of Texel.

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

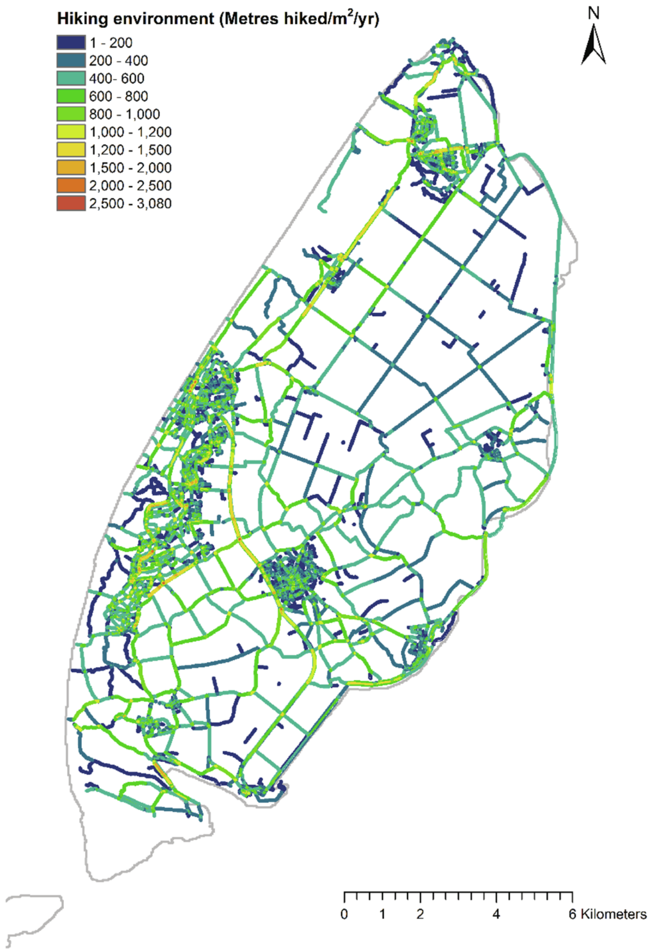

Fig. 3. Hiking environment (Metres hiked/m^2/yr).

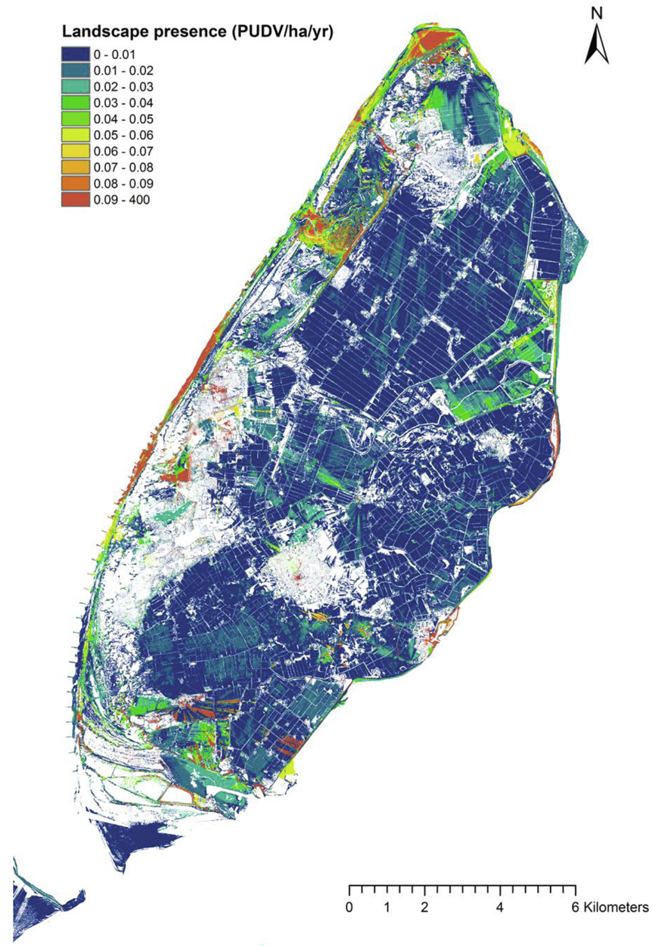

Fig. 4. Landscape presence (PUDV/ha/yr).

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:

$$I_i = \frac{N \bullet D}{L_i} \bullet \frac{S_i \bullet L_i}{\sum_{j=1}^{n} (S_j \bullet L_j)} \tag{1}$$

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 50 m area:

$$H_i = I_i \bullet \frac{L_i}{A_i} \tag{2}$$

where H_i is the hiking environment as an ES, measured in metres hiked/m^2/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 50 m along the length of the road in m^2. 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.

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.

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 m^2 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 m^2 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.

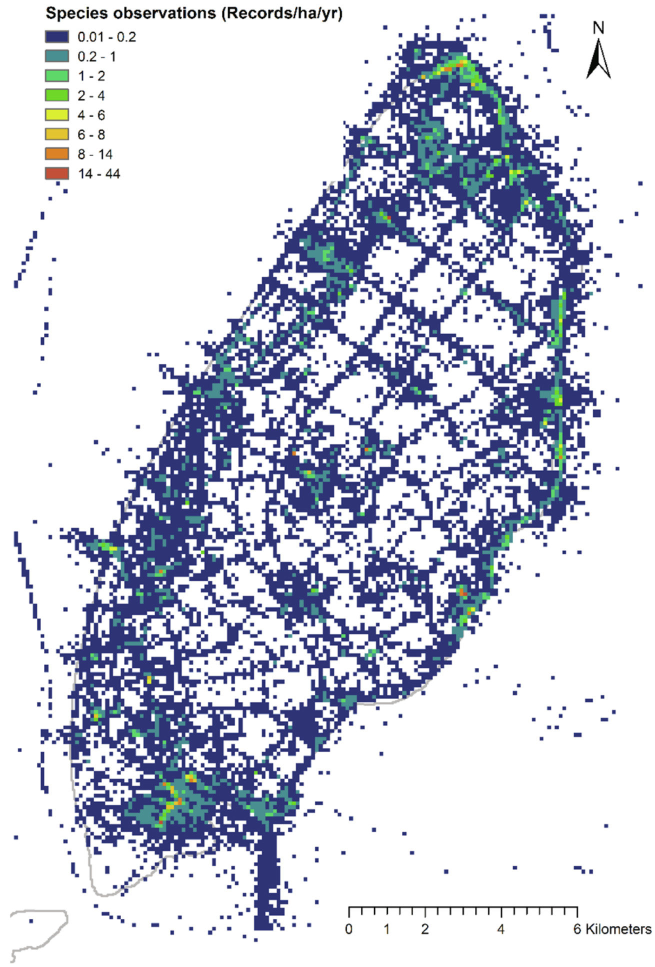

Fig. 5. Species observations (Records/ha/yr).

5.2. *Results*

5.2.1. *Activity services – hiking environment*

Fig. 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/m^2/yr and 3080 m hiked/m^2/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.

5.2.2. *Aesthetic services – landscape presence*

Fig. 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.

5.2.3. *Naturalist services – species observations*

The distribution of naturalist services measured using species observations on Texel is shown in Fig. 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.

6. Discussion

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., 2012; 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., 2012). 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.

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 (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 (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.

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.

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).

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.

Declaration of Competing Interest

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

Acknowledgments

The authors would like to thank Carl Obst, David Barton and Rolf Groeneveld for some initial discussions that helped shape the research at an early stage. We would also like to extend our thanks to two anonymous reviewers whose highly constructive feedback helped us to significantly improve a previous version of the manuscript.

Funding

This research was supported by EU Horizon 2020 grant 817527 (MAIA) and the WIMEK Graduate Programme of Wageningen University.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.ecoser.2020.101091.

References

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.

AHN, 2014. AHN3. Amersfoort.

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.

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.

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.

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.

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

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.

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.

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.

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. DOI: 10.1093/acprof:oso/9780199588992.003.0012.

Chan, K.M.A., Satterfield, T., Goldstein, J., 2012. 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.

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.

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.

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.

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.

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.

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.

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.

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., 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.

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).

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., 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.

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.

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. Manage. 60, 266–281. https://doi.org/10.1080/09640568.2016.1151772.

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.

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

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

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. DOI: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).

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.

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

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.

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.

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. 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.

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.

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., 2020. Progress in natural capital accounting for ecosystems. Science (80-.). 367, 514 LP – 515. DOI:10.1126/science.aaz8901.

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.

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.

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

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.

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.

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.

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.

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

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. Manage. 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. DOI:10.1126/science.1197872.

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.

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.

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.

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, 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, 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.
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, 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.
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.
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, 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. DOI:10.2779/12398.
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.
MapMyFitness, 2019. Search for fitness training routes [WWW Document]. URL https://www.mapmyfitness.com/routes/search (accessed 4.17.19).
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.
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.
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.
NBTC-NIPO, 2015. ContinuVrijeTijdsOnderzoek 2015. The Hague, The Netherlands.
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, 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.
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.
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.
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.
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.
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.
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.
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).
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.
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.
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.
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.
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.
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.
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., 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.
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.
Seresinhe, C.I., Moat, H.S., Preis, T., 2017. Quantifying scenic areas using crowdsourced data. Environ. Plan. B Urban Anal. City Sci. 45, 567–582. https://doi.org/10.1177/0265813516687302.
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.
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., Ghermandi, A., Moses, S.A., Joseph, S., 2019. Recreation and environmental quality of tropical wetlands: a social media based spatial analysis. Tour. Manage. 71, 179–186. https://doi.org/10.1016/j.tourman.2018.10.018.
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.
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.
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.
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.
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.
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. DOI: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.
Twitter, 2019. Twitter API: Docs [WWW Document]. URL https://developer.twitter.com/en/docs.html (accessed 4.17.19).
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.
van der Maarel, E., Dauvellier, P.L., 1978. Naar een Globaal Ecologisch Model voor de ruimtelijke ontwikkeling van Nederland. s'Gravenhage.
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.
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.
Weibo, 2019. API [WWW Document]. URL https://open.weibo.com/wiki/API文档/en (accessed 4.17.19).
Wikiloc, 2019. Search [WWW Document]. URL https://www.wikiloc.com/wikiloc/find.do (accessed 4.17.19).
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.
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.
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.
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.
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, 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.