UNDERSTANDING THE RELATIONAL VALUES BETWEEN PEOPLE AND NATURE THROUGH THE OBSERVATION OF VIRTUAL COMMUNITIES

SUMARI

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1. Introduction

In light of the ever-increasing need for nature conservation to take into account the multiple linkages that characterize human-nature interactions, the Ecosystem Services (ES) framework has attracted growing interest in recent decades. This concept has been embraced by international studies, working groups and regulations such as the Economics of Ecosystem Services and Biodiversity (TEEB, 2010), the Intergovernmental Platform for Biodiversity and Ecosystem Services (IPBES), the Ecosystem Services Partnership (ESP) and, more recently, the European Biodiversity Strategy (2020). As defined by the Millennium Ecosystem Assessment (MEA, 2005), ES are the benefits people obtain from ecosystems, be they material or non-material. Material benefits include the so-called 'provisioning' services such as food, water and energy supplies, 'regulating' services including climate regulation, runoff mitigation and carbon sequestration, and 'supporting' services such as soil formation, nutrient cycling and primary production. Non-material benefits, on the other hand, are provided by cultural ES (CES) that include aesthetics, recreation, spiritual values, cultural identity and environmental learningamong others.. The inherent intangibility, subjectivity and incommensurability of CES make their contribution to human wellbeing difficult to quantify and so are problematical to implement in landscape and urban planning (Langemeyer et al., 2018). In 2005, approximately 70% of the CES worldwide were found to be declining in quality (MEA, 2005) and the regional assessments performed by the IPBES showed similar figures in 2018 (IPBES, 2018). In addition, current trends in global population growth and urbanization (Dickinson & Hobbs, 2017) are placing increasing pressure on natural ecosystems and, due to the ever-decreasing opportunities for interacting with nature (Dickinson & Hobbs, 2017; Gaston & Soga, 2020; Miller, 2005), human societies are now thought to rely more and more on CES for their wellbeing (Guo et al., 2010). Finally, certain social-ecological interactions can lead to a loss of environmental CES values and stewardship, which will eventually affect ES co-production.

1.1. Relational CES values for sustainability

Compared to other Ecosystem Services, CES are assumed to be more cognitively accessible (Andersson et al., 2015), less substitutable by technical or other means, and ever more essential within a context of great economic growth (Guo et al., 2010) combined with rising urbanization rates (Dickinson & Hobbs, 2017). Moreover, CES have proven to be generally resistant to commodification practices and generate intrinsic motivations for conservation (Arias-Arévalo et al., 2018). These qualities arise because CES are place-specific and linked to subjective human values and identities (Chan et al., 2016).

Recent studies have linked CES to the concept of relational values (Chan et al., 2016). The relational dimension of environmental values improves the predominant binary understanding that links nature conservation to either intrinsic or instrumental motivations. Relational values highlight the significance of social components such as justice, reciprocity and collective flourishment in guiding people's behaviour towards nature, and are assumed to contribute to living a profitable community life in accordance with moral principles – cf. fundamental and eudaimonic values (Arias-Arévalo et al., 2018; Chan et al., 2016). Within this framework, nature is understood as an integral part of social-ecological systems resulting from the actions and interactions between a wide variety of species, including humans (Dickinson & Hobbs, 2017). Therefore, relational CES values have the potential to be key drivers of local green stewardship and pro-environmental behaviour and activities (Andersson et al., 2015; Martinez-Harms et al., 2018), as well as a gateway to sustainable and just social-ecological transitions (see Chan et al., 2016). Nevertheless, recent studies have also highlighted the need to assess the distribution of relational CES values in different social groups, as well as at different spatial and temporal scales (Calcagni et al., 2019).

1.2. Crowdsourced data for assessing relational CES values

The assessment of CES values using social media (SM) data analysis is gaining momentum as a new field in research (Calcagni et al., 2019; Ghermandi and Sinclair, 2019). SM data reflecting societal values and individual relationships with and within nature and expressed via non-deliberative and collective processes on digital platforms (see Guerrero et al., 2016) are presumed to reveal the relational dimension of values (Calcagni et al., 2019). In addition, and in accordance with feminist geography scholarship, local values cannot be separated from the situated embodied positionality of the individual who holds them (Leszczynski & Elwood, 2015). Likewise, in the digital environment subjectivities are negotiated and forms of power reproduced, while everyday life and perceptions of space are mediated and interlaced with relational socio-spatial processes of gender, race, class and age (Elwood & Leszczynski, 2018). SM data, which contain metadata including geotags, time stamps and user demographics such as name and hometown, prove valuable in analysing the distribution of relational CES values over space, time and social groups (Ilieva & McPhearson, 2018; Martinez-Harms et al., 2018).

Therefore, SM offers promising opportunities for internalizing epistemological plurality and opening pathways for better inclusiveness in the assessment of relational CES values (Calcagni et al., 2019; Leszczynski & Elwood, 2015). Consequently, the analysis of crowdsourced data can facilitate a more comprehensive assessment of ecosystem services in general, thereby providing a critical foundation for inclusive planning processes in a context of diverging nature values.

1.3. Mapping relational CES values for just and sustainable landscape planning and management

The mapping and assessing of ES are rapidly becoming vital tasks in the biodiversity conservation and environmental protection proposed by protocols such as the European Biodiversity Strategy 2030 (European Commission, 2020). Their aim is to improve knowledge of the links between biodiversity, climate change and environmental degradation while taking into account the natural and cultural heritage embodied in landscapes that forms an essential part of individual and collective human well-being. Mapping ES enables this knowledge to be transferred to spatial planning endeavours. Although some ES – especially supporting and regulating ES – operate on a global scale (e.g. carbon sequestration affects climate regulation for everyone), most services operate at smaller scales and require spatially explicit assessment (Geneletti, 2016).

Given that the ultimate goal is to inform and improve land-use policy, the process of ES delivery to people distinguishes between 'potential' and 'flow'. ES potential is the hypothetical maximum yield of selected ES and is determined by the biophysical landscape and its features. ES flow, on the other hand, is defined as the actual amount of benefits accrued through social-ecological interactions (Baró et al., 2016). While land-use policies are classically based on assessments of ES potential, recently ES flow and potential vs. flow comparison analyses have provided useful insights in land-use policy and planning (Baró et al., 2016; Langemeyer et al., 2018).

Building on recent studies relying on crowdsourced data for assessing the flow of relational CES values (Langemeyer et al., 2018; Oteros-Rozas et al., 2017), in this article we aim to explore the potential of this novel methodology and data source to provide policy recommendations at different scales in the fields of both ecological and social planning (Geneletti, 2016). To highlight the potential of SM analysis in the assessment of relational CES in a spatially explicit manner, we use a case study of three nested geographical scales: (a) Catalonia, (b) Barcelona Province and (c) the city of Barcelona.

2. Case studies

2.1. Catalonia

The region of Catalonia is located on the north-east Mediterranean coast of Spain and has a surface area of 32,049 km^2. Its population is very unevenly distributed since 70% of people live in the metropolitan area of Barcelona (less than 10% of the whole territory), thereby reflecting the urban nature of contemporary Catalan society (Nogué & Vicente, 2004). Catalonia possesses one of the most diverse and richest landscapes in the whole of Europe (Nogué et al., 2016) as a result of its climate, ecosystems, historical legacy and cultural identity. Such richness is reflected in the Landscape Catalogues, a work developed by the *Observatori del Paisatge*, which differentiates 135 landscapes within the region. A spatially explicit assessment of relational CES at this scale is urgently needed since the Natural Heritage and Biodiversity Strategy adopted by the Catalan Government's Acord GOV/54/2018 establishes the goal of developing full ES cartography for the region to help identify the landscape's multifunctionality and, in turn, guide landscape planning and management.

2.2. Barcelona Province

Barcelona Province in Catalonia has a surface area of 7726.4 km^2 and, with a total current population of 5.5 million people mainly concentrated within and around the city of Barcelona, is one of the most densely populated urban regions in Europe (717 inhab./km^2). Drastic changes in land cover and land use have had a direct impact on the provision of ecosystem services in the province (MAES, 2016). Therefore, in recent years the Barcelona Provincial Council (*Diputació de Barcelona*) has fomented land-use policies aimed at developing a capillary and multifunctional green infrastructure network for maintaining ecosystem services. It has thus promoted the development of a territorial information system and ES mapping (Project SITxell[1], acronym in Catalan of Territorial Information System for the Network of Open Areas in Barcelona province) to support regional and local policymaking (MAES, 2016). However, to date, this mapping only covers food and forest biomass provision, global climate regulation, erosion control, habitat for species and recreational facilities; this thus confirms the abovementioned lack of consideration of the full scope of CES in policy-making and underscores the need for developing innovative methods for mapping relational CES values, as developed by Langemeyer et al. (2018).

2.3. Barcelona City

Barcelona is the capital of Catalonia. Administratively divided into ten districts, the city is home to 1.62 million people within its 102 km^2, making it one of the densest and most compact cities in Europe. The city

[1] http://www.sitxell.eu/en/mapes.asp

of Barcelona is characterized by a lack of green space availability per capita (on average 7 m^2/inhabit.), which is relatively low in comparison to the European average. Here we focus particularly on 18 urban parks using the findings of Amorim Maia et al. (2020) to highlight the potential of analysing SM data at a micro scale. We aim to gain a differentiated understanding of relational CES values and provide critical insights for urban planning in the city as a whole, in particular in light of the gentrification processes being triggered by urban greening.

In addition, we look at the 8,300-ha peri-urban park of Collserola on the outskirts of city, declared a Natural Park in 2010. The Special Plan for the Protection of the Natural Environment and Landscape of Collserola Natural Park (PEPNat), although still pending its final approval, aims to ensure the conservation of its biodiversity, habitats and ecological processes while favouring the social use of this protected area (e.g. running, cycling, etc.), (Comissió institucional del Pla Especial de Collserola, 2019). If Collserola is included among the green spaces that are accessible to the citizens of Barcelona, the availability of green spaces rises to 17.62 m^2/inhabit., which highlights the relevance of Collserola to this study. However, questions regarding the trade-offs between its accessibility and the attractiveness of its diverse benefits for different social groups must also be tackled (Depietri et al., 2016; Turkelboom et al., 2018).

3. Data & methods

In order to assess the relational CES flow at the different spatial scales analysed in this study, we retrieved publicly available data from the photosharing social media platform Flickr[2] (via its Application Programming Interface). For the regional-scale analysis, data was automatically downloaded by the open-source software InVEST[3]. Finally, for the provincial- and city-scale analyses, the script for executing the download was written in ECMAScript 6 on Github[4]. In compliance with the General Data Protection Regulation (*General Data Protection Regulation*, 2016), to guarantee the anonymity of Flickr users we applied special security precautions on the only computer containing all the data, individual data and spatial data were stored separately. Personal data such as a user's hometown, when retrieved, were removed once the assessment had finished.

3.1. Catalonia

For Catalonia, we assessed both the flow and the potential of the relational CES *outdoor recreation* by retrieving data from 2005–2017 using the InVEST recreation model[5]. The purpose of this model is to predict the impact of recreation- and tourism-based person-days on locations including natural habitats and built features, and accessibility, that factor into people's decisions about where to recreate.

[2] https://www.flickr.com/

[3] https://www.naturalcapitalproject.org/invest/

[4] available at this link: https://github.com/JALB91/queries/blob/9985026257b7f8cfbf86c5d866889b9686bfec61/flickr/index.js

[5] Available at this link: http://releases.naturalcapitalproject.org/invest-userguide/latest/recreation.html

The model calculates the correlation coefficients between Flickr data and a number of landscape components chosen as predictor variables. It displays the rate of visitation in landscapes (grid cells) and computes a regression to estimate the relative contribution of each landscape component using the following formula:

$$y_i = \beta_0 + \beta_1 x_{i1} + \ldots + \beta_p x_{ip} \qquad \text{for } i = 1 \ldots n \qquad \text{(eq. 1)}$$

where y_i is the visitation rate and x_{ip} is the coverage of each landscape component in each cell or polygon (hereafter called 'cell') *i* within an Area of Interest (AOI) containing *n* cells, and β_p estimates are the regression coefficients for each landscape component chosen as predictor variable, *p*. We defined the administrative boundaries of Catalonia as the Area of Interest. This input is a single polygon shapefile of Catalonia projected onto linear units in ETRS_1989_UTM_Zone_31N coordinate systems.

As a first output of the regression model, the *outdoor recreation flow* (ORF) was calculated as the average number of Flickr photo-user-days (PUD) geotagged in 2005–2017 in Catalonia. The calculation resulted in a grid shapefile with a 500x500 m resolution and n = 270,364 cells. One photo-user-day at a location (see Wood et al. 2013) corresponds to a single photographer who took at least one photo on a particular day. This variable aims to compensate for the users that upload many pictures taken in the same place on the same day in order to avoid overestimating the visitation rate.

In order to calculate the *outdoor recreation potential* (ORP), we chose the following landscape components as predictor variables for running the regression model:

a. Land cover

b. Nature Protection Areas

c. Geomorphological features

d. Tourism sport settings

e. Tourism facilities

f. Accessibility

g. Urban predictors

We deliberately excluded contingent events (festivals, fairs, concerts, events, etc.) and took into account only the recreational value of the landscape's natural and anthropogenic components. Although we used natural components, tourist facilities and accessibility predictors for calculating the ORP as in previous studies (see Baró et al. 2016), we also included urban components in the regression analysis to account for their relative impact on the actual visitation rate. By excluding contingent events from ORP calculations, we corrected the imbalance of photo density in urban areas and highlighted the effects of natural, tourist-related features and their accessibility on visitation rates, thereby visualizing their potential throughout the whole area of the case study.

Once the x_{ip} values have been calculated, the regression is computed and results take the form of a table reporting the βp estimates per each predictor variable and the corresponding standard errors (SE), as well as the variance and the significance levels based on whether or not one of the extremes of the variance interval or the full interval change sign. The variance, showing where 95% of the βp estimates are likely to fall, is calculated with the following equation (see eq. 2):

$$z = \beta_p \pm 1.96\, SE \qquad \text{(eq. 2)}$$

The β_p estimates indicate the relationship between each predictor variable and the visitation rate y_i, after accounting for all other predictor variables included in the regression. Therefore, they represent the respective explanatory values of the predictor variable for the presence or absence of photographs taken in the surrounding area.

In order to map this value in each cell i ($e_{i,p}$), we divided the Area of Interest into a raster with the same resolution and number of cells as the ORF and applied the following equation (eq. 3) using the tool *Map Algebra*:

$$e_{i,p} = \beta_p \cdot x_{i,p} \qquad \text{for i = 1...n} \qquad \text{(eq. 3)}$$

where $e_{i,p}$ is the explanatory value of each predictor variable p to the ORF in each cell i within the Area of Interest that has n cells, β_p are the regression estimates for each predictor variable p, and $x_{i,p}$ is the spatial distribution of each predictor variable p in each cell i. When $e_{i,\ p} < 0$ we took the absolute number.

Finally, for the calculation of the aggregated ORP, we applied the following equation (eq. 4) using the tool *Map Algebra*:

$$orp_i = \sum_{p=1}^{25} \beta_p \cdot x_{i,p} \qquad \text{for i = 1...n} \qquad \text{(eq. 4)}$$

The number of predictor variables to be included in this calculation (25) was calculated by subtracting from the total number of predictor variables each of the following concepts: the urban predictors returning a non-significant β_p estimate (i.e. *slope, rocks, crops, picnic areas, shelters, ski stations* and *interest areas*) and those resulting in an inverse distribution of ORP, that is, those increasing with the distance from the predictor variable (i.e. *forests, protected watersheds, PEIN areas* and *beach)*.

3.2. Barcelona Province

We determined both the *landscape aesthetics* (LA) flow and potential for Barcelona province. To assess the LA flow, we retrieved 131,507 pictures uploaded in 2015 by 4,356 different users. A sub-sample of 13,460 photographs randomly chosen from the entire study area was manually coded by progressive visual-content screening following a protocol based on previous studies (Oteros-Rozas et al., 2017; Tenerelli et al., 2016) and modified during this assessment. Photos that did not depict landscapes as the main subject, those of poor quality or with mistaken locations, and duplicates were discarded. The final study sample included 1,262 relevant photographs, corresponding to about 1% of the entire sample, which matches the descriptive studies of dichotomous variables for a confidence level of 99% with a marginal error of 2.06% (cf. Hulley et al., 2007). For geographical interpretations, all coded photos were mapped onto a 2.5×2.5-km-resolution grid using ArcGIS 10.4 software.

The LA-potential assessment was conducted using a spatial multicriteria approach, in which landscape features were used as the evaluation criteria. The assessment was performed by an advisory panel (including four policy-makers from Barcelona Provincial Council and two regional experts from the Catalonia Landscape Observatory) in four main steps: (i) selection of the landscape features to be used as separate evaluation criteria for seven landscape types (LT, aggregation of landscape units, LU, established planning areas used by the Barcelona Provincial Council that share similar geographical characteristics); (ii) expert weighting of the evaluation criteria via an online survey (available at http://goo.gl/forms/z7sFH6hlQOjyNQeY2); (iii) scoring of the evaluation criteria (based on a spatial viewshed analysis performed with ArcGIS 10.4); and (iv) aggregation of criteria scorings through weighted summation (see Eq. 5):

$$P_{i,tot} = \sum_n^N (v_{n,i} \times w_{n,lt}) \qquad \text{(Eq. 5)}$$

where $v_{n,i}$ is the visibility of the landscape feature n in grid cell i, N is the total number of landscape features present in a grid cell, and $w_{n,lt}$, is the weighting factor through a unity-based approach (in a range 0–1) assigned to landscape feature n depending on the landscape type lt in which the cell i is located.

Eq. (2), thus, expresses an aggregate value for the LA potential for each (observation point) grid cell i.

Finally, in order to guide policy-making in the study area, we performed a comparison between LA flow and potential, both calculated at landscape unit (LU) level, using Eq. 6 and 7 respectively:

$$F_{lu} = \frac{mean(\sum_{lu} p_{i,lu})}{A_{lu}} \qquad \text{(Eq. 6)}$$

$$P_{lu} = \frac{mean\ (\sum_n^N (v_{n,i} \times w_{n,lt}))_{lu}}{A_{lu}} \qquad \text{(Eq. 7)}$$

3.3. Barcelona City

At city scale we explored the potential of SM data for revealing the multiple relational values people ascribe to CES and how they relate to social-ecological processes such as green gentrification or eco-tourism. For both urban and peri-urban parks, data was retrieved in 2004– 2017. The data georeferenced in this case study area amounted to 4,320 images from the 18 urban parks and 5,170 from Collserola, the latter group including both pictures and text records. We removed 3,617 photos from the urban park sample by filtering out data with mistaken locations, duplicates and non-relevant content (e.g. selfies, indoors, etc.). For Collserola, we also limited the number of similar units of data to five per owner per location (following Oteros-Rozas et al., 2017) to preclude biases towards 'heavy users' and also to avoid losing a large amount of data as can occur with the 'photo-user-days' approach (cf. Wood et al., 2013). Finally, 1,699 units of data published by 472 single users from Collserola were considered relevant for the analysis.

We adopted a bottom-up, inductive, data-driven approach to customize the CES categories of the analysis to the specific case study. We used the Common International Classification of Ecosystem Services (CICES) version 5.1 (Haines-Young & Potschin, 2018) as a reference. Using only visual content analysis, for the urban park data we classified pictures into three CICES categories: *landscape aesthetics*, *recreation* and *cultural identity*, and added a fourth, *social relations*, which had previously been indicated as missing from the work by Haines-Young & Potschin (2018). In order to represent the broadest possible range of relational CES values, for Collserola both visual and textual content (e.g. tags, texts and descriptions) of the data were manually coded. The coding process included seven CICES categories: *physical recreation, experiential recreation, existence value, cognitive value, natural cultural heritage, landscape aesthetics* and *spiritual value,* and three additional ones, *social relations, built cultural heritage* and *disservices*.

Finally, we attempted to show how relational CES values distributed across space could be linked to social-ecological processes. For urban parks, we used data on green gentrification taken from Anguelovski et al. (2018) and performed a chi-square independence test using IBM SPSS Statistics 24 to verify how this relates to relational CES values portrayed on social media. In Collserola we looked at who is causing gentrification and where. Thus, assuming tourists to be among the primary users responsible for gentrification processes, we manually retrieved information on the hometown of Flickr users and coded the registers as either corresponding to 'locals' (i.e. people living in one of the nine municipalities in the park: Sant Cugat del Vallès, Molins de Rei, El Papiol, Barcelona, Cerdanyola del Vallès, Sant Feliu de Llobregat, Sant Just Desvern, Montcada i Reixac, Esplugues de Llobregat) or 'non-locals' (i.e. people living elsewhere).

Next, we used ArcMap 10.8 to run the Optimized Hot Spot Analysis (Aggregation Method: count incident within fishnet polygons; Bounding Polygon: Collserola; Cell Size: 1000 m) to spatially identify statistically significant clusters of pictures taken by locals and non-locals, and analyse the differences in relational CES values that appeared. Finally, we performed a Chi-square independence test to verify the relationship between CES and users' provenances.

4. Results

4.1. Catalonia

Outdoor recreation flow

The average photo-user-days (PUD) per year, as expected, shows a concentration of pictures in urban areas (see Fig. 1). The number of pictures per pixel ranges from of 0 to over 4,000 in Barcelona.

Outdoor recreation potential

The ORP map has the highest values in mountainous and coastal areas and the lowest in urban centres.

Figure 1. Outdoor recreation flow in Catalonia. Based on the average photo-user-days (PUD) per year in 2005–2017 (Camprubí et al., 2019).

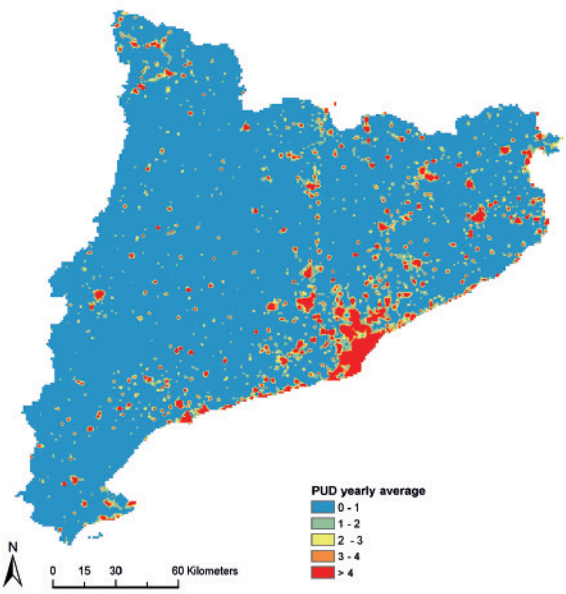
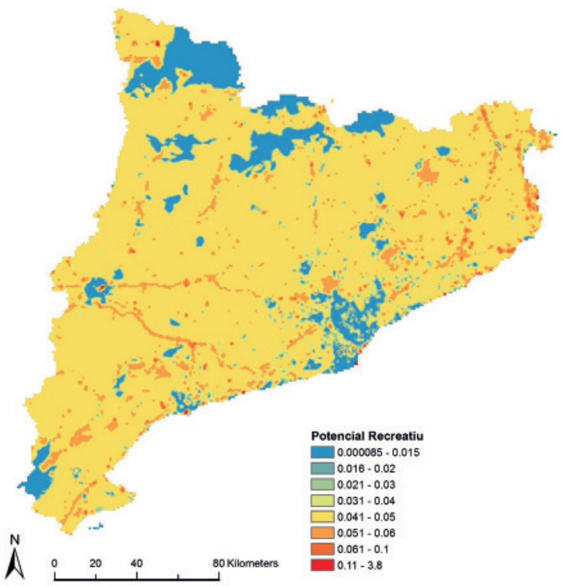


Figure 2. Outdoor recreation potential in Catalonia calculated through a regression analysis between data from social media and predictor variables selected by experts (Camprubí et al., 2019).



4.2. Province of Barcelona

Landscape aesthetics flow

The LA-flow assessment shows a strong bias towards urban settlements in the study area (see Fig. 3), with built infrastructures being the most commonly depicted features in the landscape (present in 41.4% of the coded photographs).

Landscape aesthetics potential

Based on the above-described method, the LA potential was found to be widely distributed throughout

Figure 3. Landscape aesthetic flow, Barcelona Province. Sum of photographs at pixel level (2.5×2.5 km) (Langemeyer et al., 2018).

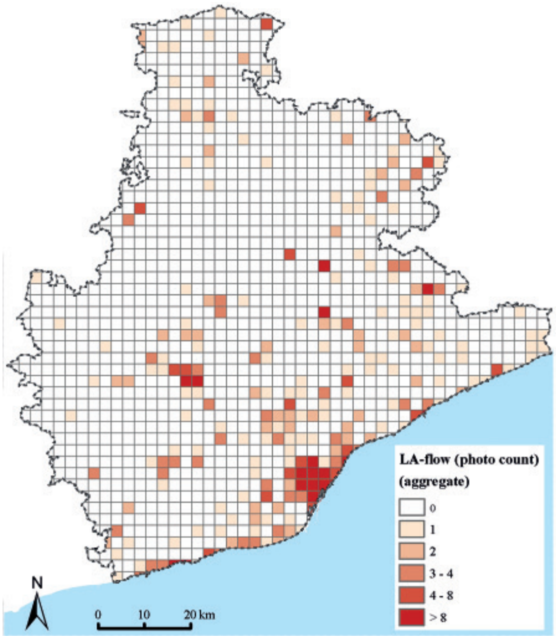


Figure 4. Aggregated landscape aesthetics potential in Barcelona Province. Viewshed analysis and expert weighting computed on a 2.5×2.5 km pixel grid (Langemeyer et al., 2018).

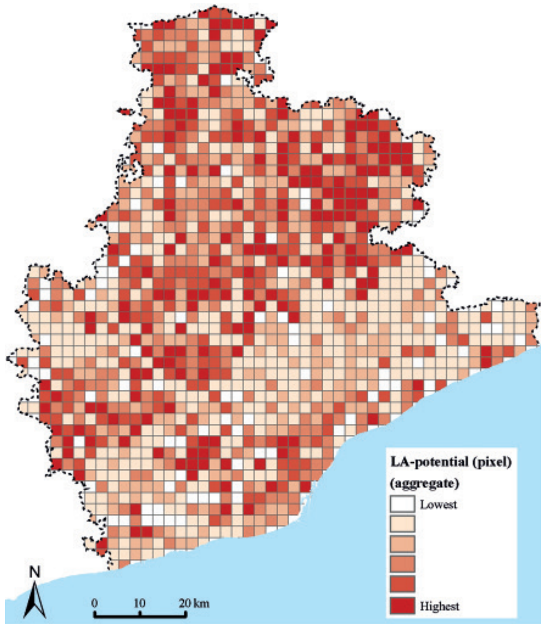
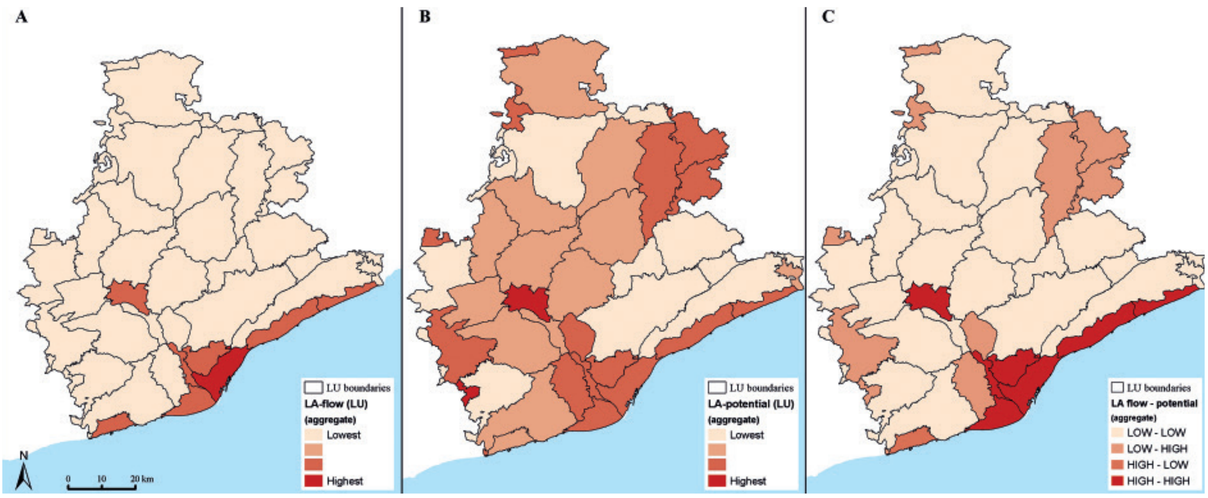


Figure 5. Comparison between LA potential and LA flow at Landscape Unit level. Based on natural breaks (Langemeyer et al., 2018).



the study area. Built infrastructures also have a strong impact on LA potential, although mainly in urban landscapes, while for other landscape types such as littoral-mountainous or coastal landscapes natural features are shown to affect the LA potential the most.

Comparison between LA flow and LA potential

This comparison was performed at Landscape Unit (LU) level. The results show a high LA-potential-flow in urban landscapes in and around the city of Barcelona, in urban-forestry landscapes such as Collserola, and in coastal-mountainous, coastal, and mountainous landscapes. By contrast, most inland upland agroforestry landscapes and agrarian-plain landscapes, as well as urban landscapes (apart from Barcelona), were found to have rather low LA potentials and flows. Of great interest to policy-making is the detection of several landscapes with high but unused LA potential, such as the western mountainous area and the landscapes of the western and central agrarian plain, as well as some of the urbanized-forestry landscapes. LA flow was especially low in the upland agroforestry landscapes in the northern inland areas in Barcelona province.

4.3. Barcelona City

Among the 703 photographs that were found to be significant for this analysis, 85% (594) were taken in parks that were experiencing green gentrification and the remaining 15% (109) in parks that did not (see pie charts in Figure 6). Moreover, parks that experience green gentrification have a clearly higher and statistically significant proportion of photographs that reflect *landscape aesthetics* (88%, p-value = 0.04) or *recreation* (17%, p-value = 0.06) compared to non-gentrified

Figure 6. Distribution of Cultural Ecosystem Services (CES) in relation to green gentrification trends in 18 parks in the city of Barcelona. The size of each pie chart is relative to the total amount of pictures taken in the respective park.

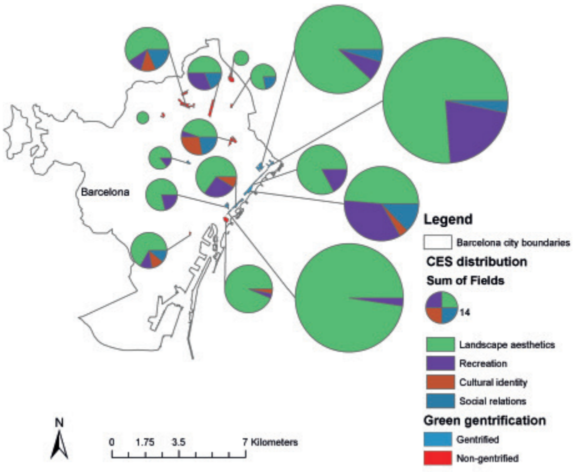
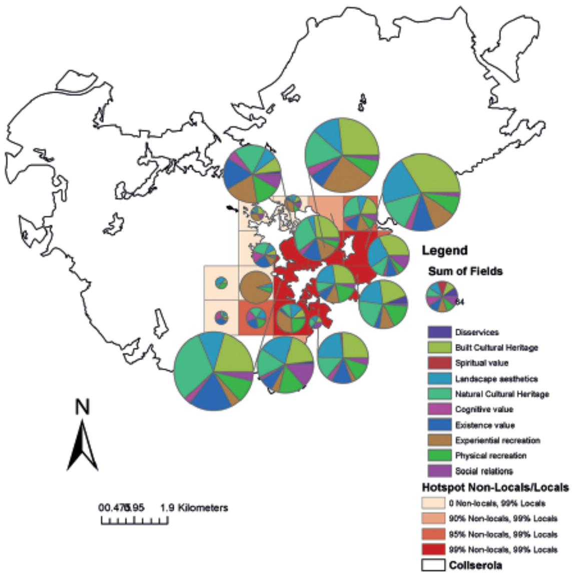


Figure 7. Distribution of Cultural Ecosystem Services (CES) in relation to the clusters of photographs taken by non-locals and locals per grid cell in the peri-urban park of Collserola, Barcelona. The size of each pie chart is relative to the total amount of pictures taken in the respective cell.



parks (79% and 11%, respectively). In turn, there are more photographs of non-gentrified parks showing *cultural identity* (10%, p-value = 0.00) or *social relations* (15%, p-value = 0.00) compared to gentrified parks (1% and 4%, respectively) (see Figure 6). As shown by previous studies (Calcagni et al., 2019; Ghermandi & Sinclair, 2019), *landscape aesthetics* were the most commonly expressed CES, regardless of whether or not a park was associated with green gentrification. Interestingly, elements (i.e. buildings, landscape) located outside the perimeter of the parks were depicted in 7% of the photos taken in gentrified parks and 21% in non-gentrified parks. Both groups of parks presented similar proportions of green (around 20%) and non-green (around 80%) subjects in photographs, confirming previous findings (Langemeyer et al., 2018) on the mainly non-green focus of photos taken within parks.

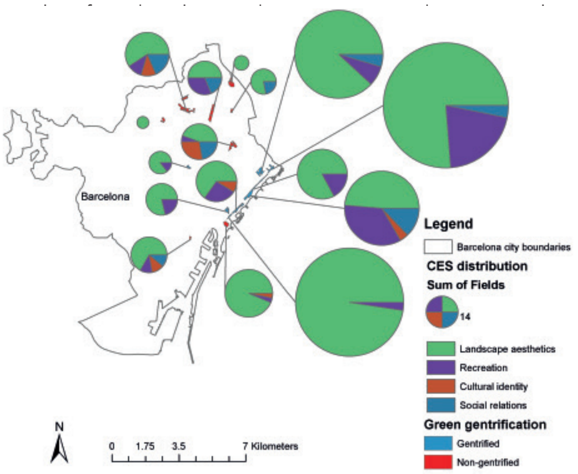
The pictures taken in Collserola cluster around the south-central sector of the park near Tibidabo mountain, a natural landmark in the area and home to a monumental church often visited by tourists.

The Chi-square test confirmed the statistical relevance of the differences between the distribution of the relational CES values shown in Figure 7. In the areas mostly frequented by local people (first three shades of red in Figure 7), there are more pictures categorized as *existence value* (p-value = 0.001365), *cognitive value* (p-value = 0.002005) and *disservices* (p-value = 0.003009). On the other hand, non-locals primarily appreciate *landscape aesthetics* (p-value = 2.20e-16), *built cultural heritage* (p-value = 4.631e-08) and *social relations* (p-value = 1.332e-08). In addition, the findings show that non-locals seem to be less keen to go far from the focal point of Tibidabo.

5. Discussion

5.1. Potential for the integration of relational CES values assessed through SM data in landscape planning and management

The methodologies employed show that SM data are suitable for calculating both relational CES-value flow and potential in a spatially explicit manner. In particular, the aggregated map of *outdoor recreation potential* in Catalonia (Fig. 2) provides useful fine-scale infor-



tional CES-value assessments. The different treatment given to built infrastructures, which had high levels of LA flow in the visual content analysis of the photographs, is thought to be not only related to a potential expert bias towards 'natural' landscapes but also closely tied to aspects regarding accessibility. The LA flow is mainly distributed in coastal, urban and hilly-agroforestry landscape types where most people live. Therefore, policies intended to sustain or enhance LA flow will benefit a larger share of society if they focus on urban green and blue infrastructure. At city scale, the similar portion of pictures depicting built features and parks that experiencing green gentrification and those that do not suggests that there are other underlying aspects to green gentrification that go beyond greenness and the level and/or type of nature present in the space, and are interwoven with structural and social elements both inside and outside the parks. As the Collserola case study confirms, there is a socially mediated pattern of appreciation of relational CES values and access to their respective benefits.

This information is particularly relevant for inclusive and equitable planning and management decisions.

5.2. Opportunities and limitations of the methods

Social media data analysis has proven to be a valuable and novel data source that can be used to assess and quantify relational values ascribed to social-ecological interactions in landscape planning. Given the close and unique perspective it provides on subjective perceptions and non-material values, SM data can enrich our understanding of CES by complementing expert-based assessment with local, wide-ranging and non-authoritative knowledge. SM platforms are the repository of billions of pieces of content shared worldwide, especially in the USA and Europe (Wood et al., 2013). Increasingly available at an unprecedented rate and scale (Ilieva & McPhearson, 2018), SM data permits (near) real-time, high resolution, spatially explicit and, sometimes, global analyses to be undertaken (Tieskens et al., 2018; van Zanten et al., 2016)

While theoretically and methodologically novel, our study does have some methodological caveats. First, the representativeness of social media data depends on the rate of use of the internet, mobile phones and, for the specific cases presented here, Flickr itself. However, the current trend for technologies and social media to spread worldwide across different social groups heralds a promising future for integrating this type of data into research (Guerrero et al., 2016). Yet, SM data may overrepresent types of behaviour and the perceptions of certain profiles and social groups, and to an extent depend on age, gender, social power relations, income levels, education and the ability or motivation to use social networking services (Oteros-Rozas et al., 2017; Tenerelli et al., 2016; Wood et al., 2013). That said, more conventional methods of data collection such as surveys or interviews are likewise not exempt from similar shortcomings (Dunkel, 2015; Tenerelli et al., 2016). To explore which social groups are represented in SM data, we further tested at city scale the analytical potential of this data source by extracting users' demographic information including their hometowns (as in Wood et al., 2013). However, the retrieval and use of SM data imposes important ethical considerations (Boyd & Crawford, 2012; Ghermandi & Sinclair, 2019), especially with reference to personal data (*General Data Protection Regulation*, 2016). Concerns on whether data should be considered public or private is at the heart of an ongoing ethical debate that, to date, restricts data access to SM researchers and makes Flickr the most suited for assessing CES due to its API openness and accessibility for analysis (cf. (Tenerelli et al., 2016).

In the study in Collserola, by combining textual and visual content analysis, as recommended by other scholars (Ilieva & McPhearson, 2018; Oteros-Rozas et al., 2017), we significantly expanded the spectrum of relational CES values retrievable from SM data compared to other analyses (Calcagni et al., 2019; Ghermandi & Sinclair, 2019). Yet, interpretation biases may affect the assessment of what a photograph depicts or what a tag signifies. This spotlights the inherent lack of homogeneity and structure that is the product of the diverse and subjective modes of experiencing and expressing relational CES values, which are still challenging the consistency and time-consumption of SM data analysis. To date, most SM data assessments in environmental sciences are still done manually (Calcagni et al., 2019) and are, in some cases, positively validated using traditional data such as that derived from surveys, PPGIS or official statistics (Upton et al., 2015). Nevertheless, this is changing given the availability of machine learning and related approaches (Ghermandi & Sinclair, 2019) that attain relatively high levels of accuracy compared to manual assessments.

Even so, the production of this type of data cannot be detached from users' specific socio-economic circumstances, which triggers considerations regarding the need to problematize algorithmic epistemology (Boyd & Crawford, 2012; Leszczynski & Elwood, 2015). Thus, scholars argue that automatic digital data processing may in fact merely serve to replicate structural oppressions based on gender, race, class, age, etc., and overexpose already marginalized categories to data discrimination and state surveillance and violence (Elwood & Leszczynski, 2018; Ghermandi & Sinclair, 2019).

5.3. Opportunities for further research

The results of the methodology presented here could be further improved by increasing the quality and variety of the input data. To better assess the recreational use of landscapes, for instance, it might be useful to explore other SM platforms such as those specifically related to recreation (e.g. Wikilocs, Strava, etc.). Assessing the influence of the geographical location, shape and accessibility of green spaces in SM data distribution might become pivotal in revealing infrastructural drivers of social-environmental injustices, as discussed by Ngom, Gosselin, & Blais (2016).

In addition, given that few users share personal information, mainly due to reasons of privacy, future research could benefit from ways of improving our understanding of the social and demographic characteristics of social media users – if the relevant regulations are complied with (van Zanten et al., 2016). Relational CES assessments should be complemented with other methods that enable social actors such as the elderly, poor and other digitally marginalized communities that are underrepresented by social media platforms to be more present in the data. Complementing SM data assessments with more conventional approaches including participant observations, surveys, interviews and participatory mapping (cf. Thiagarajah et al., 2015; Upton et al., 2015) is a promising approach to the need to correct the potential methodological shortcomings of this study.

6. Conclusion

The efforts made in environmental conservation and protection are related to the assessment and mapping of relational CES values that can provide valuable knowledge for sustainable and just landscape planning and management. This work uses novel methods to infer subjective and situated values ascribed to social-ecological interactions in Catalonia, based on the potential of social media data analysis at different spatial scales (i.e. regional, provincial and urban) and planning dimensions (i.e. ecological and social). The proposed methods are valid ways of informing decision-making and landscape planning, and use crowdsourced knowledge to complement expert-based assessments that, for example, can identify the built environment as a potential enabler for beneficial social-ecological interactions. Moreover, the examples presented here act as possible cartographic representations of these interactions, including the multiple values ascribed to them and the planning-relevant information on the people benefitting from them. However, this final frontier of social media data assessments raises concerns over questions of privacy and data protection. As such, in the absence of any clear common ethical framework and given the relevant information that it facilitates, the debate about the scientific use of SM data must continue.

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