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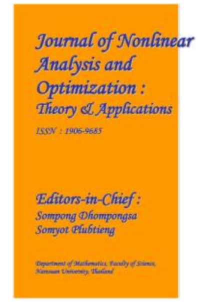

Method creation and application for evaluating cultural ecosystem services in coastal areas using graph theory and social media data

Sandhya Mishra[1], Chetan Kumar Sharma[2]
[1,2]Gandhi Institute for Education & Technology, Bhubaneswar

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A B S T R A C T

Utilizing data from social media platforms (SM) has become a viable method for evaluating cultural ecosystem services (CES). In order to determine the demand for CES, the majority of studies have concentrated on the use of individual SM platforms and photo content analysis.

Here, we present an innovative approach to CES evaluation utilizing SM data by applying graph theory network analyses (GTNA) to hashtags related to SM postings and contrasting it with picture content analysis. The Great Barrier Reef, the Galapagos Islands, and Easter Island are three well-known case study locations throughout the world where we used the suggested methodology on two social media platforms, Instagram and Twitter.

Our findings suggest that the use of graph theory to hashtag analysis provides capabilities like to those of photo content analysis for CES provision evaluation and provider identification. More significantly, GTNA offers improved ability to recognize eudaimonic and relational qualities related to nature—aspects that are difficult to discover for photo content analysis. urthermore, because GTNA is based on user-provided tags, it helps to lessen the interpreter's bias related to photo content assessments. The study also emphasizes how crucial it is to take into account data from various social media platforms because the kinds of users and the information these platforms provide can exhibit disparate characteristics of CES. GTNA is an affordable technique that has the potential to be used on a wide geographic scale due to its simplicity of use and relatively quick computational processing times.

1. Introduction

Humans are deeply connected to the oceans, the largest biome of theplanet. For centuries, humans have lived in coastal communities wherepeople fished, gleaned and hunted for food to support their livelihoods (Erlandson and Rick, 2010). Living by the coast shapes cultures and identities of coastal communities whose actions in turn influence the marine and coastal physical environments (Klain et al., 2014). Marine and coastal ecosystem services (ES), such as food provision, climate regulation or the creation of opportunities for recreation and relaxation, are fundamental elements in the maintenance of human wellbeing (McMichael et al., 2005; Selig et al., 2019). Human interactions with coasts can also affect mental health in many ways, and the forms of evidence include positive effects related to happiness, social interac- tions, social cohesion and engagement; a sense of meaning and purposein life and decreases in mental distress (Bratman et al., 2019).

Cultural ecosystem services (CES) provide some of the benefits people can most directly relate to, since most human-nature interac- tions fall within this category (Garcia Rodrigues et al., 2017; Leenhardt et al., 2015). However, marine ecosystem services, and CES in parti- cular, have been impacted at unprecedented rates by climate change and direct anthropogenic activities (e.g. fishing, pollution and habitat degradation) (IPBES, 2019). In addition, CES are often overlooked in conservation and management schemes for marine and coastal areas (Chan et al., 2012; Everard et al., 2010; Garcia Rodrigues et al., 2017). Defining human-nature interactions in coastal areas and the type of CES offered, e.g. the activities people undertake, what they value, what habitats or species attract most attention, at scales relevant for marine and coastal management is time consuming and often requires re- sources which are not generally available (Waldron et al., 2013). In recent years, social media (SM) data, that is, data created and shared by users on SM platforms, has emerged as a potential useful source of in- formation in environmental research, management and conservation (Di Minin et al., 2015; Ghermandi and Sinclair, 2019; Toivonen et al., 2019). Among the most popular SM networking sites we find Facebook, YouTube, Instagram, Twitter or Flickr (Di Minin et al., 2015; Toivonen et al., 2019). Typically, SM users share data in the form of tags, text, images or videos depending on the platform of choice. As an example, Instagram users generally share images often complemented with a short text and relevant tags selected by the user. In comparison, Twitter works as a micro-blogging platform, where users share short messages (currently limited to 280 characters) sometimes accompanied by an image. In addition to differences in data content type, there are also differences in users' demographic characteristics between SM plat- forms, e.g., the proportion of females, young adults and teenagers is higher in Instagram than in Twitter (PRC, 2019). Despite differences in data content and user types, SM data mining and analysis has proven very valuable as it can provide information on how people interact with their environment, including interactions with nature (Di Minin et al., 2015; Mancini et al., 2018) people's preferences for nature-based ex- periences (Hausmann et al., 2017; Oteros-Rozas et al., 2018), visitation patterns in conservation areas (Tenkanen et al., 2017; Wood et al., 2013) or on mapping CES (Clemente et al., 2019; Richards and Friess, 2015). So far, however, while the number of studies focusing on the terrestrial environment is increasing, few had marine and coastal areas within their scope (Ghermandi and Sinclair, 2019; Toivonen et al.,2019).

Generally, SM data mining studies have restricted their scope to single SM platforms (Ghermandi and Sinclair, 2019; Toivonen et al., 2019), therefore limiting their assessments to particular data formats, to certain sectors of the population (PRC, 2019), or to particular user's needs and behaviours (Manikonda et al., 2016; Tenkanen et al., 2017). Logically, most studies have relied on SM platforms that offer easy data access such as Flickr. Flickr, a SM platform popular among nature photographers with over 90 million monthly active users (2018), allows access to content made publicly available by the user for non-com- mercial use through their Application Programming Interface (API). On the other hand, Instagram, the most popular SM platform (1 billion monthly active users in 2018) after Facebook (2.26 billion users) (Ortiz-Ospina, 2019), has increasingly restricted content access through their API since 2016. As a consequence, the majority of studies have relied on Flickr as a source of data (Ghermandi and Sinclair, 2019; Toivonen et al., 2019). However, due to limited user numbers and post frequency, the amount of observations provided by Flickr is sometimes too low to adequately represent visitor rates in natural areas, as opposed to the higher representativeness achieved through the use of Instagram (Tenkanen et al., 2017). In addition, Flickr predominantly contains nature and wildlife photography, while pictures including people are more frequent in Instagram (Tenkanen et al., 2017). Therefore, limiting analysis to Flickr data could lead to an over-representation of particular CES (e.g. wildlife observation) while under-representing others, such as people actively engaging with nature through an activity (e.g. recrea- tional activities).

Regarding the methodological approaches used in the analysis of SM data, a high proportion of studies have used images as a primary source of information to assess the benefits associated to an area and their spatial distribution (Wood et al., 2013). Geolocation of post images has been used to assess the spatial distribution of the supply and demand of CES (e.g. Clemente et al., 2019), while photo content ana- lysis provides information of the type of CES provided by a particular area. Most studies have relied on the manual classification of photo content; however, this is extremely time consuming. Recently, new methodologies based on artificial intelligence and deep-learning ap- proaches have increasingly facilitated the automatic description of photo content (e.g. Lee et al., 2019), reducing data processing time to a fraction. While the application of artificial intelligence represents a milestone in the analysis of photo content, it still presents some chal- lenges in its application and outcomes (Lee et al., 2019).

To advance in the assessment of CES provided by nature through SM data, we present a novel methodology based on the analysis of text information associated to SM posts (i.e. hashtags) through the appli- cation of graph theory network analysis (GTNA) techniques. Graph theory is defined as the mathematical study of the interaction of a system of connected elements (Berge, 1962; Köning, 1937). By in- vestigating the characteristics and interactions of predominant hashtags through the principles of graph theory, we can widen our under- standing of how social network users perceive the CES provided by nature. We will compare the outcomes of the application of GTNA to image content analysis to assess the suitability and cost-effectiveness of the methods. In addition, to attain a more holistic assessment of CES provision, we will ascertain the diversity and complementarity of the outcomes stemming from different SM platforms.

The study focuses on three worldwide iconic coastal areas as case- studies to illustrate the application of the proposed method, namely the Great Barrier Reef (GBR) Marine Park in Australia, the Galapagos Islands National Park in Ecuador and Easter Island National Park in Chile. These areas include emblematic marine protected areas but also protected terrestrial ecosystems. Two SM platforms, Instagram and Twitter, were used as data sources. The high number of users associated to these platforms and the markedly different content format and user's needs and behaviours between platforms (Manikonda et al., 2016) are expected to illustrate the diversity of CES stemming from the case-study areas.

The main objectives of the study were (i) to illustrate the application of a novel methodology to assess the demand of CES through GTNA, (ii) to compare the proposed methodology to existing image content ana- lysis techniques, and (iii) to explore the complementarity of informa- tion extracted from different SM platforms.

To achieve these objectives, hashtag data from Instagram and Twitter were analysed using graph theory analysis to identify emerging patterns in CES demand. Additionally, manual and automatic identifi- cation of Instagram image content was conducted for comparative purposes to assess the alignment between both approaches. This ex- haustive comparison of remote assessment of CES allows insights into the most cost-efficient techniques to undertake large-scale assessments of social perceptions on ecosystems.

2. Methods

2.1. Data acquisition

In June 2019, ten thousand posts were downloaded from Instagram for each of the three case-study areas; similarly, ten thousand posts were downloaded from Twitter per case study. Instagram and Twitter posts were downloaded through the corresponding application pro- gramming interface (API). Instagram public API is suitable for hashtag-based data extraction using a creator account, while Twitter required a developer premium account to access the full history and volume of tweets. In the case of Twitter only original tweets were retrieved. Post retrieval was done according to the platforms' internal algorithms, which differs according to the type of account owned. While Instagram's post-retrieval using API search appears to be chronological, the company's public documentation does not provide specific in- formation to confirm this. Twitter posts were retrieved chronologically. Nevertheless, the authors of this study did not have complete access to the algorithms' descriptions. For privacy and ethical reasons, no per- sonal information, such as user's names or ids, were used in this study. Results are presented in an aggregate manner so that no information can be traced back to the individual user. A specific development in R was made by the authors for each API and similar data was extracted from the two SM platforms. The API works as a keyword search method. For each case study, a search using the name of the area as query was executed, obtaining a set of 10,000 posts for each area and platform. A sensitivity analysis using accumulation curves, representing the number of accumulated hashtags correlated with the sampling effort, indicated that the retrieval of 10,000 posts was adequate to capture 90% of the most used hashtags in each of the study areas.

Relevant hashtags were used as queries to extract the posts asso- ciated to the case-studies: the hashtags “#greatbarrierreef” and “#ga- lapagos” were used as queries for the GBR Marine Park and the Galapagos Islands National Park, respectively. While, based on the authors’ observations, these hashtags represent the most frequent way SM users refer to these areas in Instagram and Twitter, Easter Island was frequently referred to as “#easterisland”, “#rapanui” and “#isla- depascua”, the last two representing the local names of the area. Therefore, three separate posts’ downloads were performed for Easter Island using each of the three queries. The three data sets for this area were merged for subsequent analysis.

Posts often contain non-relevant information as SM platforms are frequently used as marketing and advertisement tools to reach a wider public and often bots (automated data generating algorithms and ad- vertisements) are used to created large volumes of automated posts. After the downloads were performed, datasets were manually filtered and cleaned in order to retain only relevant information for further analysis (Di Minin et al., 2018; Varol et al., 2017). To maximize the presence of relevant data, three approaches were simultaneously adopted, and data was cleaned at user, post and hashtag level. At user level, those users identified as bots were removed from the database. At post level, irrelevant posts related to advertisement (e.g., posts related to trading marks) were discarded from the analysis. At hashtag level, non-informative hashtags such as #instapic, #instaphoto, #instamood, #like4like, were removed from the database in order to obtain cleaner networks at a later stage.

Since the main aim of the present study was to assess the type of CES provided by the case-study areas, regardless of the user’s nationality, hashtags with a high frequency of appearance were translated to English language. In addition, hashtags were scanned for spelling mis- takes and variations of the same word (e.g. bird - birds, traveller - traveler) in order to standardise the dataset and avoid duplicates.

Networks were build using the first 150 most frequent hashtags in each of the study areas. A sensitivity analysis was performed to de- termine the number of hashtags that were present in over 90% of the 10,000 posts for each of the case study area networks. Results of the analysis indicated that 150 hashtags were sufficient to describe the discourse in each of the areas.

2.2. Image content analysis

For each case study, photos associated to the 10,000 posts were also downloaded and stored for image content analysis. Two types of ana- lyses were performed, and their results compared: a manual procedure, undertaken by the authors of this paper, and an automatic procedure through machine learning technology.

2.2.1. Manual image content analysis

The content of each image was visualised, analysed and classified using an objective coding approach. To classify the CES in the case studies, we adopted and modified the classification developed by Retka et al. (2019) (Table 1). In addition to the CES classification, we re- corded information on whether the photographs were taken above or below water, on specific activities and on predominant habitat types and species appearing on the photographs (Appendix 1).

A random subsample of the photographs was analysed for each of the case-studies. To determine the minimum number of photographs needed to assess the type of CES provided in each case-study, cumu- lative frequency distributions were calculated and plotted for each type of CES per case-study. Random sets of 10 photographs were assessed to quantify the presence of the different CES classes. Additional sets of 10 photographs were sub-sampled and classified until the cumulative average of the percentage of CES classes stabilised.

To assess the consistency of the classification criteria and the level of agreement between the reviewers, a subsample of 75 random photographs across the three case studies was evaluated by each re- viewer. Cohen’s Kappa coefficient (Cohen, 1960) was used to assess the level of agreement between the reviewers.

2.2.2. Automated image content analysis

The same sets of photographs that were analysed manually were assessed through Microsoft Captionbot Computer Vision's REST API (https://azure.microsoft.com/en-gb/services/cognitive-services/ computer-vision/). CaptionBot is a free cognitive tool based onComputerVision, a Microsoft Azure cognitive service that provides re-levant information from images. CaptionBot does not require users tohave experience in machine learning but it provides powerful cap-abilities in content discovery, text extraction and visual data processingto tag content from objects to concepts, or extracting printed or hand-written text. Our intention was to create an AI-based workflow usingtools that were low cost but equally adaptable and flexible. CaptionBotanalyse Image method and Python (https://docs.microsoft.com/en-gb/azure/cognitive-services/Computer-vision/quickstarts/python-disk) were used to obtain a JSON document containing the predictive re-sponse with regards to the image content. The predictive response of the algorithm was extracted in a natural language format (e.g., “I thinkit’s a turtle swimming under water”, “I’m not sure but I think it’s a manwalking on the beach”). Based on the information provided by Captionbot, the authors allocated each of the photographs to one of theestablished CES classes. The level of classification agreement between the manual and automatic classification was assessed using Cohen’sKappa coefficient (Cohen, 1960).

2.3. Graph theory network analysis

The analysis of networks using graph theory can be described as the analysis of existing relationships between the different elements con- tained in a network. The term *vertex* is used to describe the elements in a network, while the term *edge* is used to refer to the connections be- tween the different vertices in a network. In our case, vertices are re- presented by hashtags, while edges illustrate the connections between hashtags (e.g. the hashtags included in the same posts and the fre- quency of those connections).

To assess relationships between hashtags and identify emerging properties within the networks, we used centrality measures and community structure detection algorithms. In networks consisting of several vertices, some of them play a decisive role in facilitating a large number of network connections. Such vertices are central in network organization and are often identified by a range of metrics known as centrality measures. Centrality measures are useful to determine the relative importance of vertices and edges within the overall network (Freeman, 1978). However, there are multiple interpretations of what makes a vertex important and there are therefore many measures of centrality (Freeman, 1978). Some commonly used measures of cen- trality are: Degree; Betweenness; Closeness; Eigenvector centrality; Kleinberg’s hub centrality score (Hub score); Kleinberg’s authority centrality score (Authority score); and Page Rank (Hansen et al., 2020). Conceptually, the simplest form of centrality is *Degree centrality*, which represents the number of edges connected to a vertex. In a SM network, the Degree centrality of a hashtag accounts for the number of connec- tions a hashtag has with other hashtags in the network. However, not all connections are equally important. Connections with well-connected vertices are more important than connections to vertices that are poorly connected to others. Thus, a vertex is important if it is connected to important neighbors, this is defined as Eigenvector centrality. There- fore, it can happen that a vertex with high Degree centrality has low Eigenvector values, e.g. a vertex could have many links (i.e. high De- gree) to poorly connected vertices (i.e. low Eigenvector). Likewise, a vertex with few connections could have a high Eigenvector centrality value if those few connections were to well-connected vertices.

In this study we focus on Eigenvector centrality measure to illustrate

Table 1
Cultural ecosystem service category description used for the classification of photo content.

Cultural Ecosystem Service Category	Description
1. Artistic or cultural expressions and appreciation	Photographs representing people in artistic activities or their products
2. Living cultural heritage	Photographs representing people in cultural activities
3. Gastronomy	Photographs representing typical meals/foods related to the area
4. Historical monuments	Photographs depicting historical infrastructures (e.g. historical buildings, ruins)
5. Landscape appreciation	Photographs for which the main focus is a wide and large scale view of the landscape
6. Nature appreciation	Photographs focusing on fauna or flora
7. Natural structures and monuments	Photographs depicting a specific and well-defined landscape structure (e.g. cliff, cave)
8. Religious, spiritual or ceremonial activities	Photographs representing religious or spiritual monuments or activities (e.g. church, indigenous ritual)
9. Research & education	Photographs showing research or education activities or equipment
10. Social recreation	Photographs representing groups of people in an informal or non-dedicated recreative social environment
11. Activity recreation	Photographs showing people in a specific sports related activity
12. Other	Photographs that do not fit the above criteria

(Source: adapted from Retka et al., 2019).

SM data network structure. Eigenvector is a useful measure for the analysis of hashtags in a SM network because it does not necessarily highlight words with the highest frequency of occurrence (e.g. #in- stagram, #instatravel, #instaphoto, #twitterpic), which might not be necessarily informative. Eigenvector highlights hashtags that are well connected with other hashtags related to the query search, therefore, allows the emergence of relevant hashtags to understand the structure of the network.

In graph theory, a community is defined as a group of vertices where the density of the edges between the vertices inside the group is greater than the connections with the rest of the network. Vertices pertaining to the same community display similar centrality measure values. Generally, connections between vertices within the same com- munity are stronger than connections between vertices of different communities. Here, in order to identify CES bundles, we organized the networks into communities. Graphs depicting the social networks are composed of vertices representing words. Word communities are the grammatical contexts in which these words appear together. If thewords are mentioned frequently in the same context, they will form a community in the graph. If they appear in different contexts, they will move away from each other. To detect these communities, we applied the fast greedy modularity optimization algorithm (Clauset et al., 2004).

Data mining, analyses and graphical outputs were generated using R, a free and open source software (R Core Team, 2019). Specific R packages were used to create hashtags networks, calculate centrality measures and detect community structure (igraph, Csardi and Nepusz, 2006) and to create network visualisations (ggraph v2.0., Pedersen, 2020). In the community graphs, the order and distance of the com- munities to the centre does not imply a greater degree of importance, itis merely a result of the visualisation method.

3. Results

The focus of this study was to develop an innovative methodology for CES assessment using SM and to compare it to existing methodol- ogies. For brevity and clarity, the results section focuses particularly onone of the case-studies (GBR) to fully illustrate the type of information obtained using GTNA, while Galapagos and Easter Island are more succinctly explained (see Appendix 2 for figures).

We first present results for the more direct and traditional metho- dology of manual photo content analysis, move onto the automatic analysis of photographs and finally report on the results obtained through our proposed methodology. Results focus on ascertaining the type of CES provided by each case study.

3.1. *Image analysis*

3.1.1. *Manual image content analysis*

A comparison of the 3 case studies revealed that the proportion of underwater photographs in GBR (45%) was markedly greater than in Easter Island (11%) or Galapagos (8%). The predominant CES classes in GBR were related to activity recreation (33%), the appreciation of the landscape and seascape (26%) and nature (21%), where the main subject of the photographs was either fauna or flora. Snorkelling (14%), wildlife (14%), diving (11%), and habitat appreciation (7%) comprised the most popular activities depicted in the photographs (Fig. 1). Coral reefs were the main habitat in GBR, featuring in approximately 40% of the photographs while fish were identified as the main animal group (17%) (Fig. 1).

In Galapagos, predominant CES classes were nature (49%), land- scape appreciation (19%) and recreational activities (12%). Nature appreciation mainly focused on iconic wild animals: marine iguanas and giant tortoises appeared on 21% of the photographs, birds on 18% and marine mammals on 11% of the photos (Appendix 2, Fig. 1). Of the 3 case-studies, Galapagos was the area with the greatest proportion of pictures focusing on wildlife (Galapagos 57%, GBR 31%, and Easter Island 3%). No particular habitat was frequently depicted, however 27% of photographs focused on the coastal shore fringe.

In Easter Island, a high proportion of photographs (38%) were classified within the historical monuments class (as Easter Island statues featured frequently in photographs), followed by landscape apprecia- tion (13%) and natural structures (11%), such as volcano craters and cliffs. Most photographs depicted grass fields (44%) or shorelines (16%) (Appendix 2, Fig. 2). Inter-reviewer Cohen's kappa coefficient was high(0.87).

3.1.2. *Automated image analysis*

The use of Microsoft Captionbot Computer Vision's REST API for the automatic analysis of photograph content was deemed not satisfactory. Cohen's Kappa coefficient values were low for all three case studies, denoting that the level of agreement between the manual content analysis performed by the authors and that of Captionbot was weak (GBR = 0.51, Galapagos = 0.61, Easter Island = 0.40).

Although overall CES class percentages were similar between the manual and the automatic classification, the classification of individual pictures was different, in GBR 61% of the pictures were equally clas- sified, in Galapagos 72% and in Easter Island 46%.

Captionbot capability of correctly describing photo content differed between CES classes, as some classes were easier to capture than others. While image content related to landscape, nature, recreational activities or social interactions was identified by the algorithm, it failed to detect CES classes related to research and education, spirituality, art or his- torical monuments/heritage.

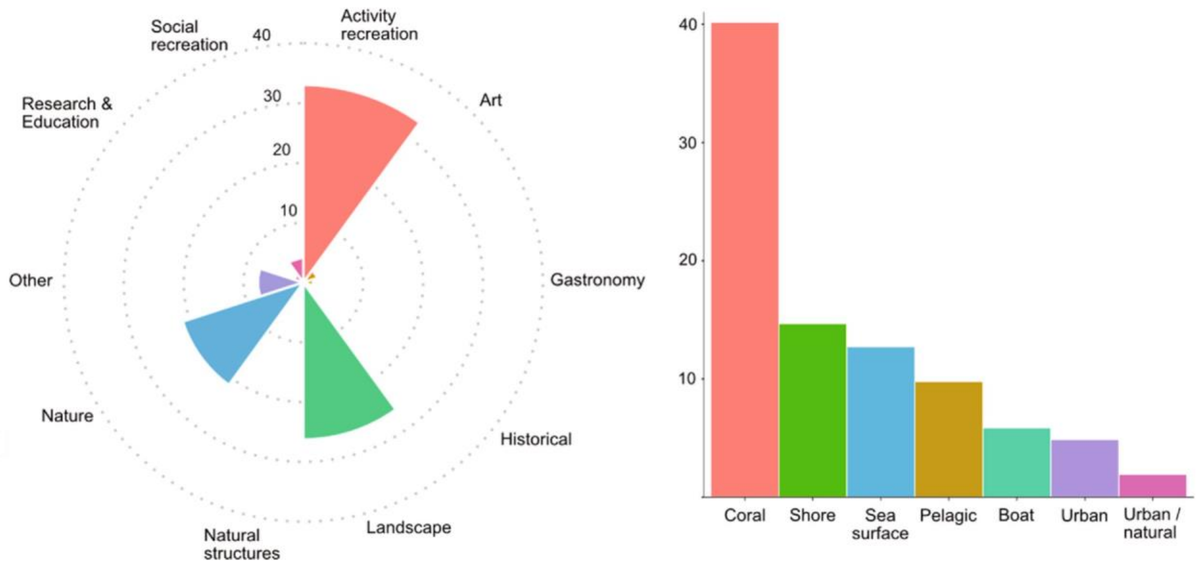

Fig. 1. Instagram manual image content analysis for Great Barrier Reef. Left: percentage of photographs depicting specific CES. Right: percentage of photographs depicting specific habitats.

3.2. Network analysis

3.2.1. Great Barrier Reef

In GBR, the Instagram graph visualization based on Eigenvector centrality indicated that concepts related to underwater activities (e.g. diving, snorkel, underwater photography hashtags), underwater life (e.g. reef, coral, fish) and travel (e.g. travel, holidays) occupied central positions within the network structure and were frequently related to the “greatbarrierreef” hashtag (i.e. the query). These hashtags had high Eigenvector values, indicating that they frequently appeared on GBR related posts and at the same time were related to concepts also ap- pearing frequently. High Eigenvector values also revealed geographical locations frequently related to popular hashtags, e.g. “whitsundays” was well connected to “nature”. Concepts related to positive and “feel- good” aspects (e.g. love, happiness, beach life, fun) were often located surrounding the core concepts on the graph’s centre although did not occupy central positions. Hashtags related to environmental awareness also featured as part of the network (e.g. global warming) but did not

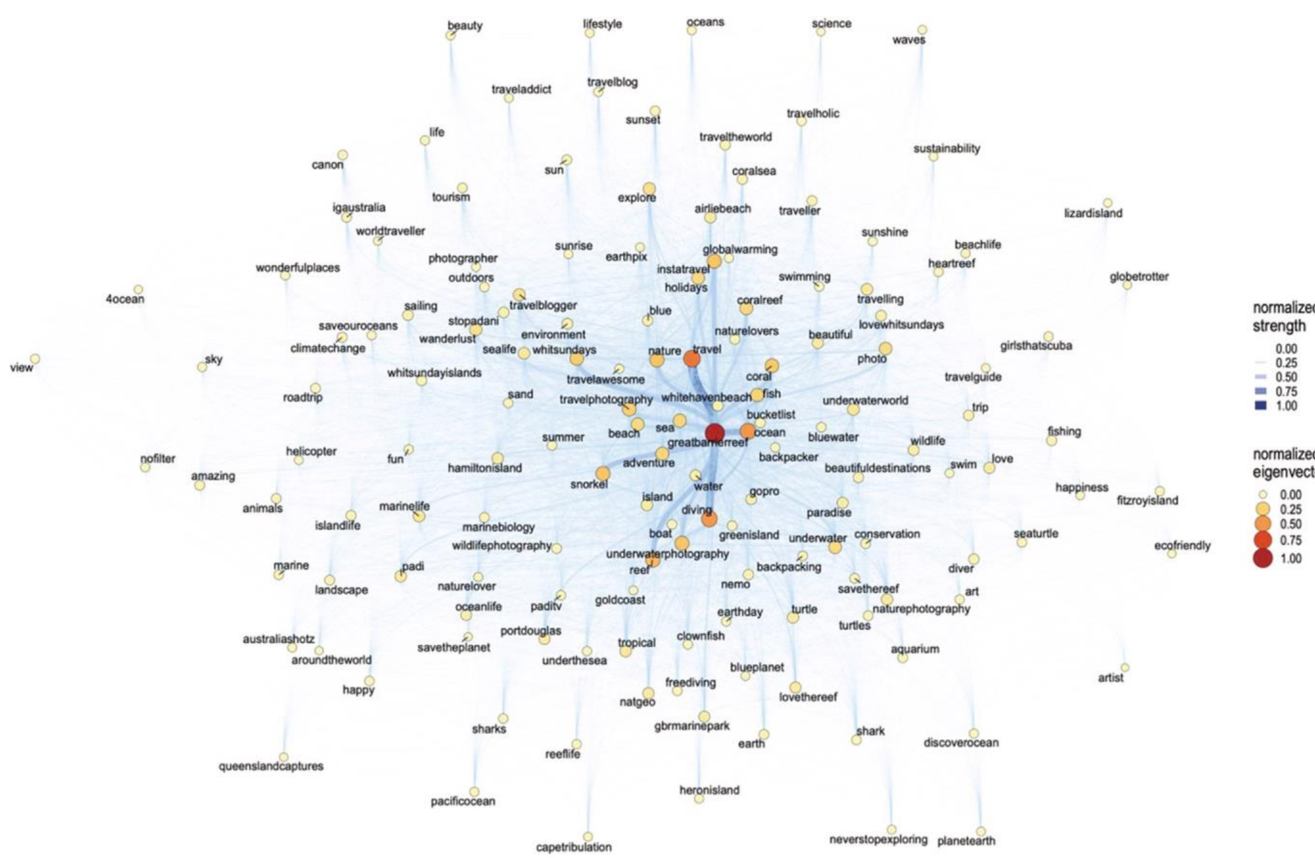

Fig. 2. Great Barrier Reef Instagram Eigenvector network.

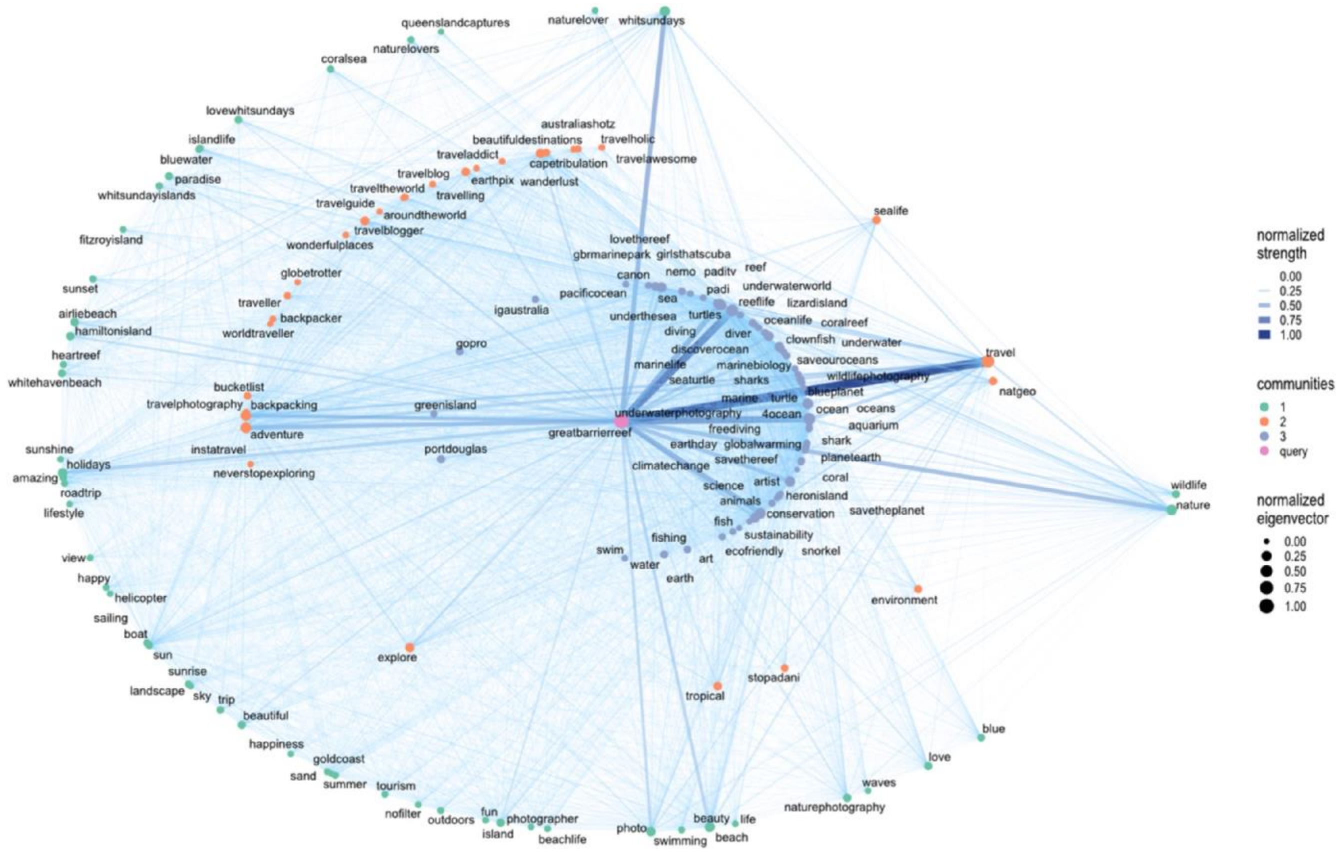

Fig. 3. Hashtags communities generated through Fast Greedy algorithm from Great Barrier Reef Instagram Eigenvector network.

occupy a central position in the structure (Fig. 2).

In GBR, the community detection algorithm grouped the different hashtags into 3 overarching themes (Fig. 3). Hashtags in the first community were mainly related to the underwater marine world (e.g. reef, ocean life, shark) and associated recreational activities (e.g., free diving, snorkel, underwater photography), as well as to concepts re- lated to environmental conservation (e.g. sustainability, conservation, earth day). This community identified key habitats and species as providers of CES, such as coral, fish, turtles or sharks.

In addition, cognitive services also featured in this community (e.g. science, marine biology) with lower eigenvector values. The second community was predominantly dominated by hashtags related to tra- velling (e.g. travel, wanderlust, travelholic) and what travelling allows, such as fulfilling life long wishes (e.g. bucket list), reaching remote places (e.g. wonderful places, around the world, beautiful destinations)or creating feelings of adventure (e.g. explore, adventure, never stop exploring). In the third community, hashtags with greater Eigenvector values were related to the provision of nature and wildlife holidays, thefeelings those experiences create (e.g. fun, happiness, love), activities enjoyed (e.g. swimming, outdoors, boat, sailing), memorable moments and places and descriptions associated to them (e.g. sunset, sunrise, beauty, amazing).

In the Eigenvector-based Twitter visualization, hashtags with greater Eigenvector values and most frequently connected to the query ("greatbarrierreef"), mainly revolved around climate change (e.g. cli- mate action, climate crisis, climate emergency) and the environment (e.g. coral, ocean, reef, nature), creating a strong environmental awareness theme (Fig. 4).

Hashtags related to underwater activities and specific underwater life were present in the network, although they were mostly located towards the periphery of the network, displaying a secondary role.

Three communities were detected in the Twitter GBR network (Fig. 5).

The community closest to the centre was dominated by marine environmental science concepts (e.g. bleaching, sea level rise, ocean warming, acidification) and marine life (e.g. shark, reef, algae). The second community followed a political discourse around climate change and action for change and sustainability (e.g. Fridays for future, climate strike, renewables, extinction rebellion). The third community rotated around holidays, travelling and memorable moments (e.g. beach, paradise, sunset), recreational activities (e.g. boat, scuba, snor- kelling) and marine life (e.g. snapper, nudibranch, starfish).

3.2.2. *Galapagos*

In Galapagos' Eigenvector-based Instagram visualization, the ver- tices with greatest Eigenvector values were related to nature and wildlife concepts in general and to specific animal groups in particular (e.g. sea lion, birds, iguana, tortoise). Travel, photography and diving were also prominent hashtags within the network. Overall, the Galapagos network was mostly dominated by wildlife related hashtags (Fig. 3, Appendix 2).

In Galapagos Instagram network, hashtags were grouped into five communities (Fig. 4, Appendix 2). The first community was dominated by hashtags related to the marine environment, underwater marine life and associated recreational activities. Hashtags in the second commu- nity revolved around travel and the desire for travelling, in a similar way as in GBR. The third community also centred on travelling but froman adventurous and laidback approach. The fourth community was dominated by wildlife and nature aspects, as well as by the love for nature and conservation values. A high number of hashtags re- presenting different animal groups were allocated to this community. The fifth community related to life and nice feelings.

In Galapagos' Eigenvector-based Twitter visualization (Fig. 5, Appendix 2), hashtags with greater Eigenvector values were similar to

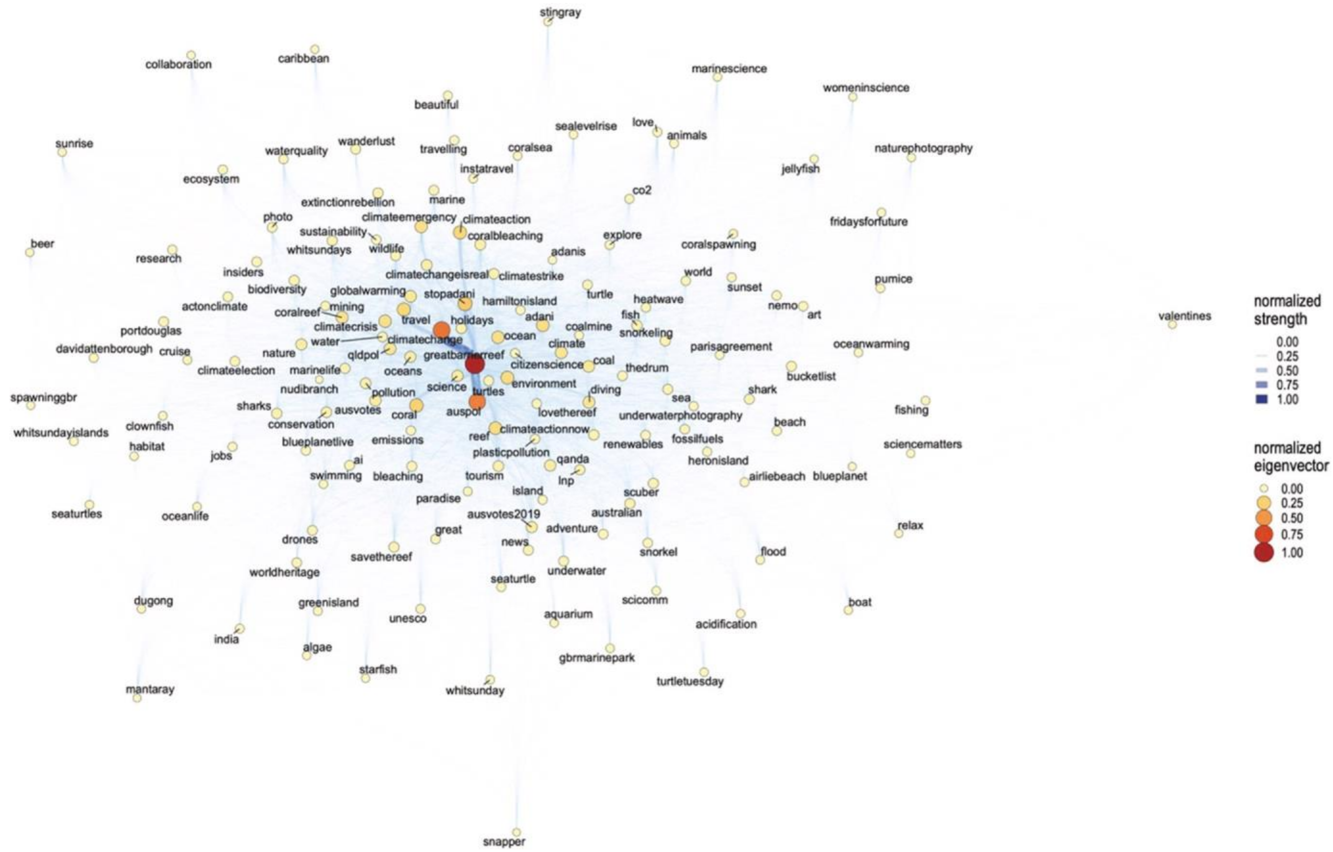

Fig. 4. Great Barrier Reef Twitter Eigenvector network.

those in Instagram. Nature, wildlife and travel concepts occupied the most central positions in the network and had greater Eigenvector va- lues. Hashtags referring to iconic animals were also centrally posi- tioned.

Hashtags were clustered into two big groups by the community detection algorithm (Fig. 6, Appendix 2). In the community closer to the centre, all hashtags had similar eigenvector values and turned around iconic wildlife groups and recreational activities. The second community revolved around travelling to locations that enable the enjoyment of wildlife and nature.

3.2.3. *Easter Island*

Instagram Easter Island's network was dominated by concepts re- lated to travelling, culture and cultural identity, which occupied centralpositions in the Eigenvector-based visualisation (Fig. 7, Appendix 2). Photography and aesthetics concepts also featured frequently althoughthey were not central.

Hashtags were grouped into four communities (Fig. 8, Appendix 2).The central community was explicitly related to underwater recrea- tional activities, in particular diving and underwater photography. The second community mostly revolved around the cultural heritage ofEaster Island as it included hashtags such as music, sculpture, archi- tecture or archaeology. The third community was dominated by travel related hashtags. The last community was more heterogeneous as it bundled concepts of cultural identity, nature and "living a good life" concepts.

In Twitter, aside from the hashtags used to build the network, the hashtag "chile" (country where the case-study is located) and "moai" (the monolithic human figures carved by the Rapanui people), the rest of the hashtags had low Eigenvector values (Fig. 9, Appendix 2). Hashtags related to travel, aesthetics, heritage and holidays were lo- cated in central positions; however, their associated Eigenvector values were low, and no particular trend was noticeable. Concepts related to aspects related to living a meaningful life were located towards the periphery of the network.

The resulting communities from Easter Island Twitter's network presented a more miscellaneous typology and were not as defined as theones in the other two case-studies (Fig. 10, Appendix 2). Hashtags weregrouped into three communities. Starting from the centre, the first community revolved mainly around historical and cultural heritage. Nodiscernible overall discourse was detected in the second community, asit bundled hashtags related to travel, photography and nature, among others. The majority of hashtags in the third cluster were in Spanish language and no obvious pattern emerged from this cluster.

4. Discussion

The focus of this study was to introduce a novel methodology for CES assessment using SM. The analysis of SM data from two different platforms and the application of different methodological approaches allowed us to establish comparisons in terms of the outputs obtained and the cost-effectiveness of the methods used.

Results indicated that the use of graph theory to analyse SM data provided a holistic perspective on CES assessment, including a range oftangible values, such as recreational activities, to intangible values re- lated to feelings and perceptions. Manual image content analysis pro- vided a thorough assessment of uses and ecosystem preferences, how- ever, more intangible aspects such as relational values were not representatively captured.

As in previous studies, we identified that manual image content analysis of SM photographs provides in-depth information on the CES classes (e.g., Oteros-Rozas et al., 2018), activities (e.g., Wood et al., 2013) and benefits (e.g., Gliozzo et al., 2016) arising from specific areas, as well as on the habitat types and species providing those

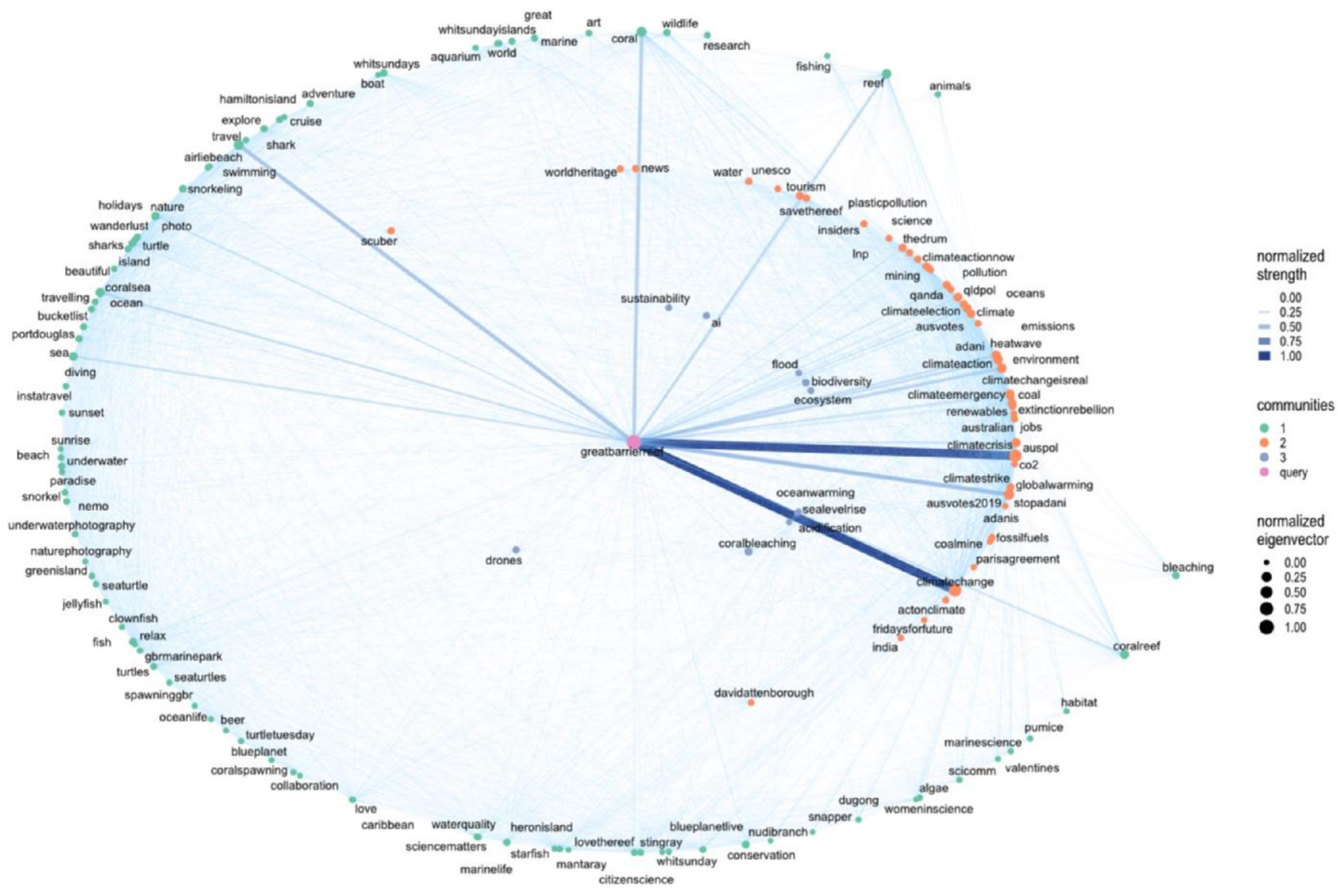

Fig. 5. Hashtags communities generated through Fast Greedy algorithm from Great Barrier Reef Twitter Eigenvector network.

benefits (e.g., Sbragaglia et al., 2019). However, the application of this manual method is extremely time consuming (approximately, 2–4 min per picture) and while it might be a suitable approach for small geo- graphical scale applications (e.g., Clemente et al., 2019; Hausmann et al., 2017; Retka et al., 2019; Schirpke et al., 2018), it is not a cost- effective methodology for large scale assessments.

In our study, the alternative to the manual identification of photo content using Captionbot with natural language outputs was considered not satisfactory, as the level of agreement between human and ma- chine-based CES classification was low. That is not to say that the ap- plication of machine learning is not suitable for CES assessments, as there is an increasing number of studies that have successfully applied it(e.g., Gosal et al., 2019; Lee et al., 2019). Several factors might have contributed to the low quality of our results. A determining factor in result quality is the choice of the automatic classification algorithm used for picture content analysis, as it will determine the finesse of the results obtained. Studies using alternative automatic image classifica- tion engines such as Clarifai (e.g. Lee et al., 2019) or Google Cloud Vision (e.g. Gosal et al., 2019; Richards and Tunçer, 2018) have showedhigher levels of accuracy in their results. Therefore, our results might had been different if we had chosen a different engine. In addition, instead of focusing on a single output in the form of natural language, the automatic assignation of multiple tags for each picture and sub- sequent analysis of the tags might have generated different results (e.g., Lee et al., 2019). Nevertheless, the greatest challenge in the use of automatic picture classification for CES assessment is that algorithms are not yet fully capable of capturing intangible aspects such as spiritual or cultural heritage values. Moreover, photographs *per se* cannot always convey elusive aspects such as feelings, social ties or cognitive values (Lee et al., 2019).

The application of GTNA revealed the most frequent concepts arising from each of the case study areas and the interactions between them. It provided information on three different fronts; (i) what the main CES stemming from the area were and how different services tended to appear together as CES bundles; (ii) on ES providers (ESP), that is, the main elements, including habitats, species or natural structures supporting CES; and (iii) finally, on the frequency of linkages between geographical hashtags and benefits hashtags, allowing the extraction of information regarding popular places where there is de- mand for particular CES. Previous SM image analysis studies have also demonstrated the capacity to identify CES bundles (Oteros-Rozas et al., 2018), ESP providers (Arbieu et al., 2018; Hausmann et al., 2017) and the spatial distribution of CES provision and demand (Clemente et al., 2019; Fischer et al., 2018; Gosal et al., 2019). However, while the analysis of photographs mostly offers a vision of “what the eye can see”, the analysis of associated text offers a perspective beyond the material or instrumental values associated to nature to move into the realm of relational values.

The concept of relational values (Chan et al., 2016) broadens the notions of intrinsic and instrumental values to include the values re- lative to the meaningfulness of relationships between people and nature (Stenseke, 2018). Along these lines, concepts related to nature-inclusive eudaimonia are also a form of relational values (Knippenberg et al., 2018). Eudaimonic values can be defined as the values associated with living a good and meaningful life (Ryan and Deci, 2001; Ryff and Singer, 2008), with nature being an integral part of it (Knippenberg et al., 2018). Here, we show how the analysis of hashtags through GTNA offers a description made by the user itself (Giannoulakis and Tsapatsoulis, 2016) that often includes relational values aspects.

Previous studies based on SM manual image analysis have already made some first steps towards capturing values pertaining to the realm of relational values, such as existence (Martínez Pastur et al., 2016), spiritual or social values (Oteros-Rozas et al., 2018). Similarly, although fewer, some studies have used automatic image content analysis and tag allocation to capture existence values (Lee et al., 2019). However, these studies have been based on proxies, such as the presence of places serving as meeting points being equal to social values (Oteros-Rozas et al., 2018), the assumption that pictures focusing on nature appre- ciation are equivalent to an existence value (Martínez Pastur et al., 2016) or the correspondence between automatically generated tags such as flora, season or growth and an existence value. However, whilst these assumptions and associations might be sound, they are inherently linked to a researcher's interpretation bias, therefore perhaps not fully or rightly capturing the meaning of the picture. Conversely, the analysis of hashtags allows to capture eudaimonic notions such as sharing ex- periences with those who are more important to us (e.g., family, friends…), positive feelings emerging from being in contact with nature (e.g., happiness, fun, love), the love for nature (e.g., nature lovers in Galapagos or love the reef in GBR), the urge to preserve nature (e.g., save our oceans, save the planet in GBR) or cultural identity aspects (e.g., tapati, chilepo in Easter Island) which are expressed by the users themselves. Other studies focusing on the analysis of SM text using natural language processing methods have extracted similar informa- tion regarding sentiments towards the environment (Becken et al., 2017) or surrounding concepts such as sustainability (Ballestar et al., 2020). Thus, we argue that the analysis of SM text in general, and the analysis of hashtags through GTNA in particular, offers a different level of nuanced comprehension of relational value aspects and sentiments when compared to the analysis of photo content. It offers a window through which we can contemplate the different relational aspects people experience when in contact with nature, minimising the po- tential distortions associated to interpreter's bias.

Our results show that it is important to consider the outputs stem- ming from different SM platforms. Although the themes emerging from Instagram and Twitter were similar, their magnitude of centrality, and therefore importance, differed within the case studies analysed. While Twitter generally reflected what users' thought, including their political and environmental views and concerns, Instagram contained informa- tion at a more emotional and relational level, as it focused on what people do and want to show. These aspects have also been captured by other studies, as Manikonda et al., (2016) describes through the ex- pression "tweeting the mind and instagramming the heart". Thus, we argue that data integration offers a more comprehensive understanding of the different values held by people on nature.

Although the potential of SM data is far-reaching, SM studies suffer from several biases and limitations. While the use of SM platforms is increasing and about half of the world's population is active on these platforms (Statista, 2020), it is very difficult to obtain user meta-data to assess the representativity and potential biases associated to SM studies. Among others, individual platforms suffer from population and content bias due to an unbalanced user composition and specific use of the platform (Ruths and Pfeffer, 2014). Moreover, the views and percep- tions of people from areas of the world where no access or censorship might preclude the use of SM platforms, cannot be captured through this media.

Another aspect to consider is the limitation associated with the translation to and choice of English as the main vehicle for this study. While the translation of the most frequent hashtags to English might have allowed us to unify and present more compact networks, it will have influenced their structure by potentially suppressing groupings in different languages and therefore masking particular aspects. In addi- tion, while the translation of all hashtags, particularly at large or global scales, is unfeasible, translating none of them would neglect the fact that communities speaking different languages might hold similar va- lues for a specific site, as hashtags in other languages would not be included in the network due to their low frequency of appearance. In opposition to this, the analysis of photo content through the automatic assignation of tags is not exposed to language limitations. Therefore, considering the strengths and limitations associated to image and text analyses, an integrative approach that combines different data types in the same analysis could offer a wider encompassing view into people's values and relations with nature (Ghermandi et al., 2020).

A third limitation identified in our study was related to the lack of post geolocation. Generally, CES assessment studies using SM data make use of geo-located photographs. This allows for the identification of spatial distribution patterns of CES demand (e.g., Clemente et al., 2019), which is relevant in terms of natural areas conservation and management. In our study, access to geolocated data was not possible due policy restrictions. However, although not as precise as the use of geo-tagged photographs, the recurrent presence of geographical or places hashtags, frequently appearing together with certain activities (e.g. diving in specific areas of GBR or hiking in Galapagos) also allows for the identification of activity hotspots. Despite these shortcomings, we consider the application of GTNA on SM data a cost-effective method due to the short time needed to process the data and its ap- plicability at multiple spatial scales, as it can be used at local to global scales through the simultaneous analysis of different locations.

5. Conclusions

SM data has emerged as a powerful source of information to in- directly assess the provision of CES. Generally, studies focus on the analysis of data stemming from single platforms. In addition, the most widely used method is based on the analysis of photo content, which offers a partial vision of the range of CES offered by nature. Partial in terms of the type of values captured and associated interpreter's bias. Here, we introduce GTNA as a novel way to analyse different sources of SM data to assess CES. We conclude that the analysis of hashtags as- sociated to SM posts using graph theory offers information, not only on the instrumental values associated to nature, but goes further and provides information on human-nature relational aspects and eu- daimonic concepts. These are aspects that photo content analysis has not yet been able to fully capture. We also highlight the importance of considering data from different SM platforms as the type of users and information offered by the different platforms convey different CES aspects. Resulting networks are a reflection of the interactions between the SM platform used and the environmental and cultural character- istics of the area under consideration. As an example, in Instagram, GBR users tend to share their coral reef diving experiences, highlighting aspects of adventure and discovery. While in Easter Island, Twitter highlights aspects related to cultural heritage preservation. Thus, the combination of the SM platform and the cultural and environmental characteristics of the area, establish a framework of content possibilities from which the users tend to highlight certain aspects. The ease of application and relative short computing processing times involved in the retrieval and analysis of the data makes the use of GTNA a cost- effective method with the potential of being applied to large geo- graphical scales.

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