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Combining social media photographs and species distribution models to map cultural ecosystem services: The case of a Natural Park in Portugal

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A R T I C L E I N F O

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A B S T R A C T

Developing spatially explicit models of Ecosystem Services (ES) distribution and diversity across the territory has been increasingly attracting the interest of researchers and policy-makers due to its potential to operacionalize and mainstream the ES concept into existing planning and policy tools.

In this paper we explore the use of social media photographs to model the spatial distribution of people preferences for cultural ecosystem services (CES), map their hotspots, identify the determinant variables as well as the spatial correlation between CES. This research was applied in the Sudoeste Alentejano and Costa Vicentina Natural Park (PNSACV) located in Southwestern Alentejo, Portugal.

A collection of 1378 geo-tagged digital images taken inside the Park and posted in the Flickr web platform between 2004 and 2015 were analyzed and classified according to a tailored list of CES. To model CES spatial distribution it was used a species distribution model – Maxent – adapted to combine the observation of CES occurrence with biophysical and infrastructural variables.

This method allowed us to identify and map the social preferences for CES in this area. The distance to the ocean and distance to touristic and cultural infrastructure were the most determinant variables to explain CES distribution in PNSACV. Another relevant result of this study was the identification of pairs of CES (such as Recreation & Aesthetics services) with a significant spatial overlap.

Using social media data can be an expedite and cost-effective way to identify and map CES, although this approach embodies some challenges and biases that need to be considered. The use of species distribution models, such as Maxent, can be particularly valuable to support the design of future scenarios and assist decision-making on land use planning.

1. Introduction

The concept of Ecosystem Services (ES), understood as "the benefits people obtain from ecosystems" (Millennium Ecosystem Assessment, 2005), has been increasingly attracting the interest of scientific literature and policy-making (García-Nieto et al., 2013; Palomo et al., 2013). The concept of ES may potentially respond to the demand for a more integrated approach to ecosystems management and for a balance between human needs and nature conservation, as it stands in the interaction of ecological and social spheres. However, the implementation of the ES concept faces problems due to data deficiencies (Burkhard et al., 2009; Dick et al., 2014) and lack of appropriate methodologies.

The development of spatial models to measure and value the distribution and diversity of ES across the territory is becoming a more common approach, showing great potential as a support tool for landscape management and environmental decision-making (Burkhard et al., 2012; Martínez-Harms and Balvanera, 2012; García-Nieto et al., 2013; Palomo et al., 2013). ES mapping has been able to provide spatial identification of ES hotspots, spatial trade-offs and synergies between ES (Martínez-Harms and Balvanera, 2012). To mainstream these assessments it is necessary to find cost-effective techniques for mapping and analysing the spatial distribution of ES (Anderson et al., 2009; Egoh et al., 2009). Such efforts typically focus on provisioning and regulating services, with fewer options available for assessing Cultural Ecosystem

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Services (CES) (Crossman et al., 2013).

CES are recognized as a main pillar in existing conceptual frameworks for ES classification. Definitions and classifications vary across different frameworks. In the Common International Classification of Ecosystem Services (CICES), CES are defined as non-material ecosystem outputs that have symbolic, cultural or intellectual significance (Haines-Young and Potschin, 2012). They include both the direct benefits people obtain from ecosystems, such as recreation or aesthetic experience, as well as other benefits resulting from the interaction of natural and human/cultural capital, such as cultural heritage (Hernández-Morcillo et al., 2013). More recently the understanding of CES has evolved in a way that explicitly acknowledges the importance of the relationships between people and places, landscapes and species, and recognises CES as a co-produced and co-created outcome of people's interaction with ecosystems (Fish et al., 2016; Chan et al., 2011).

Assessing all types of CES is particularly challenging due to their intangible and subjective nature (Daniel et al., 2012; Kirchhoff, 2012). Several authors have tested different methods, most of them based on monetary valuation and socio-cultural preferences assessments through interviews (Klain et al., 2014), face-to-face surveys (Iniesta-Arandia et al., 2014; Oteros-Rozas et al., 2014), participatory mapping (Plieninger et al., 2013) and focus groups (Norton et al., 2012). Most of these studies have been performed at local scale; therefore, the spatial distribution patterns of CES at wider spatial scales (e.g. regional) remain understudied.

New methodological approaches are needed to assess the social importance of CES beyond monetary metrics. A trending approach, following the exponential development of social networks, is to use crowd sourced geospatial data, namely photographs (Richards and Friess, 2015). The volume and spatial distribution of geo-tagged photographs uploaded to online social media global platforms, like Instagram, Panoramio or Flickr, can provide a fertile source of data for new mapping methodologies (Cao and O'Halloran, 2014; Hollenstein and Purves, 2010; Li et al., 2013; Sun et al., 2013). The main advantages of using geo-tagged photographs as a proxy for people's preferences are i) using observed preferences (Hollenstein and Purves, 2010) and ii) having precise information on the real provision of the service provided by the exact location where the photos were taken (Bagstad et al., 2014).

The analysis of photoseries from social platforms has already been shown to be a suitable proxy to assess and map CES in diverse contexts (Martínez Pastur et al., 2016; Keeler et al., 2015; Willemen et al., 2015). Tenerelli et al (2016) designed and implemented a protocol for photoseries analysis of CES, which was used in this research to retrieve, organize and classify the photos. Beyond the mapping of social preferences for CES it is also important to identify the landscape settings and variables that explain CES distribution as well as the correlation between CES in the same area (Tenerelli et al., 2016; Oteros-Rozas et al., 2016; van Zanten et al., 2016). For that purpose, it is necessary to use complex methodological approaches. A maximum entropy (Maxent) technique commonly used to model species distributions using presence-only data (Elith et al., 2011) will be used to model each type of CES. Species distribution models are numerical tools that combine observations of species occurrence or abundance with environmental estimates. In the scope of CES assessments, Maxent is used combining the observation of CES occurrence (photographs) with biophysical and infrastructural variables. An application – SolVES (Sherrouse et al., 2011) which now integrates Maxent, has already been developed (https://solves.cr.usgs.gov/) to quantify the perceived social values of ES based on responses to public preference surveys.

The aim of this article is to explore the use of social media photographs to model the spatial distribution of people preferences for cultural ecosystem services in a coastal region, using as study area the Southwestern Alentejo coast, Portugal. This research intends to map, at the regional scale, a wide range of CES, namely cultural heritage and spiritual services, that are commonly absent in CES mapping research. The ultimate goal of this research is to promote the integration of CES into decision making and regional planning by identifying their hotspots, the determinant variables as well as the spatial correlation between CES.

In the following sections we first present the methodological design, followed by a description of the case study area, data collection strategy and identification of explanatory variables. The adopted model is briefly described before presenting the results of this research. The final sections include a critical discussion of the results and a reflexion on the suitability of these methods to identify and map social preferences of CES, and some concluding remarks.

2. Methods

This research uses social media photos instead of species occurrences in a framework of species distribution modelling for understanding the spatial distribution of people preferences for CES. To combine the observation of CES occurrence (spatially referenced and validated photographs) with biophysical and infrastructural layers (variables), this methodology followed a three-step process: (1) database preparation and variable selection, (2) modeling, and (3) interpretation and discussion of the model results.

At first, a spatially geo-referenced database of social media photographs was created, validated and classified according to a list of CES, tailored for the research area. The second step was to investigate and model the spatial distribution of each CES, using Maxent. This model worked with a set of socio-biophysical factors, together with a set of sample locations where CES photographs had been observed. The model outputs, such as CES maps, provided the material for the analysis of spatial CES provision in the research area, including spatial correlations among CES and relationships between environmental/infrastructural factors and cultural use.

2.1. Research area

Located in the Southwestern corner of Portugal, the Sudoeste Alentejano and Costa Vicentina Natural Park (PNSACV) covers a coastal strip composed of 60567 ha of land and 28858 ha of marine waters (see Fig. 1). This coastline with elevated cliffs, deep ravines, small beaches, temporary watercourses, estuaries and marshes, hosts a large diversity of habitats. This protected area, created in 1995, represents one of the few remaining well-preserved coastlines in Western Europe. This area faces several pressures, such as the spread of invasive species (e.g. acacia and hottentot-fig) and growing polluting activities, namely large areas of irrigated agriculture located within the Natural Park and some industries in its vicinity, contributing to the degradation of some habitats.

In a region with low population density, but with strong traditions and cultural identity namely linked to fisheries, recreational tourism has been a key driver for human pressure in some parts of the park. During high seasons (summer and hiking seasons) the number of visitors is massive, overcoming the number of local inhabitants. The restrictions imposed by the Park regulations and the advent of the economic crisis; seem to be slowing down the development of massive tourism infrastructure towards the promotion of an "all season" nature-based model. To enforce and develop this strategy, both regional/local authorities and companies are interested in learning about visitors' preferences to increase the diversity of touristic attractions by promoting other natural and cultural values beyond recreation.

2.2. Database retrieval and interpretation

The key elements for this research are social media geo-tagged photographs. These free-access resources provide a large amount of spatially explicit information that allows inferring visitors' preferences for cultural values through content analysis. For the process of

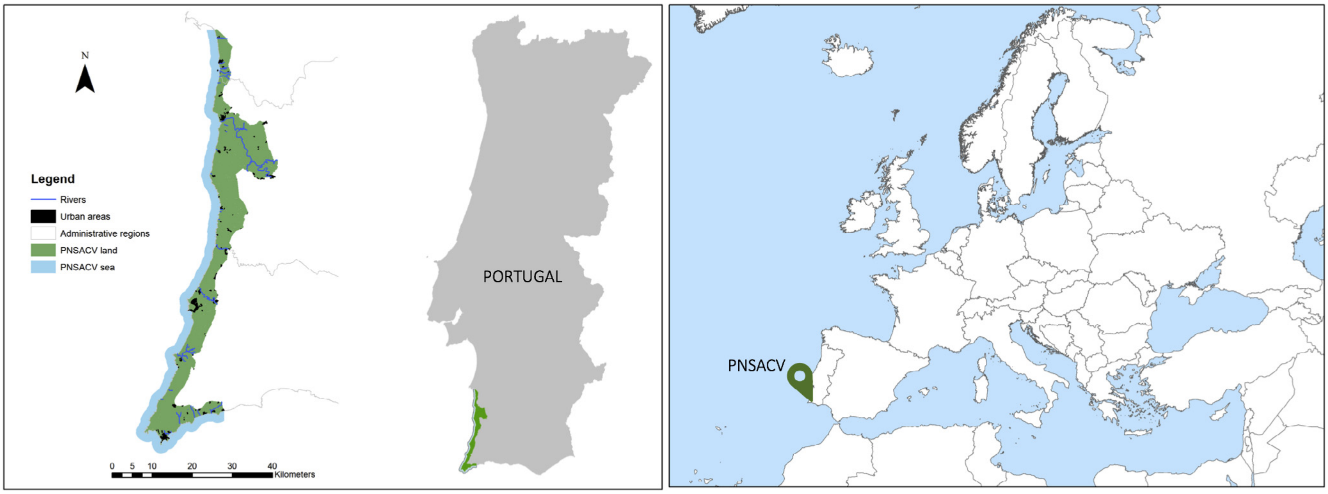

Fig. 1. Location of the study area.

retrieving and organizing social-media photographs we used the protocol developed by Tenerelli et al (2016), will small changes for the classification process which will be detailed in the following paragraphs.

Nowadays there are several online free platforms to collect this type of data (e.g. Instagram, Panoramio, Flickr). Flickr is a major image-sharing website, with 92 million monthly active users (in 2016) and an average number of a million photographs uploaded daily worldwide, according to Yahoo reports. Flickr was accessed through the publicly available Flickr Application Programming Interface (API) that uses standard Hypertext Transfer Protocol (HTTP) methods to retrieve and manipulate data (Tenerelli et al., 2016). This method allows selecting all the geo-tagged public photographs uploaded on the Flickr social network within a rectangular box around the case study area, defined using real coordinates. It is then possible to download the photos and organize them directly in an Excel spreadsheet.

It was not possible to assess how many Flickr users are based in, or have visited the park, but this platform is likely to have a reasonable market share when compared to its most similar competitors, such as Panoramio. According to recent data, Instagram appears to be used in a much higher scale in Portugal, but this platform is not suitable for this research as the API forbids automated processing of data without permission from users (Instagram, 2016).

Using the Flickr API we were able to extract 2308 photos taken between 2012 and 2015 inside the Natural Park area. The following step was to validate their geographic location and exclude the photos that did not fit the scope of this research. The geographic accuracy of photos geo-tagging can vary among the different GPS devices used. Zandbergen and Barbeau (2011) argue that most mobile phones are accurate to at least 10 m and are sensitive to natural variables such as weather conditions. Zielstra and Hochmair (2013) analyzed the 2D positional accuracy of Flickr photos and concluded that the average distance error for all scene types from Flickr in Europe was 58.5 m. This issue is particularly relevant in coastal areas where we can expect to have photos in boundary areas between land and water (e.g. cliffs, beaches). To confirm the spatial location of the photos retrieved, a set of methods was used, such as GIS data (e.g. land use and land cover maps) and virtual maps (e.g. Google Earth, street view).

Photos wrongly located (e.g. located in ocean) were excluded from the analysis. Also excluded were photos depicting people (e.g. selfies) or pets as main subject into the foreground; indoor, parking areas, private gardens; moving vehicles into the foreground; objects, signs and logos not related to the landscape; duplicate photos; or bad quality photos where the subject could not be identified (Tenerelli et al., 2016). After cleaning up the database, 1378 photos from 172 different photographers were retained for analysis.

Each photography was then classified accordingly to a list of different CES. This research followed the Common International Classification of Ecosystem Services (Haines-Young and Potschin, 2013) to define and classify the different CES. Based on this CICES classification, a tailored list was then developed to include relevant CES in the case study area (see Table 1). A set of six CES were used for the classification: Recreation; Aesthetic landscape; Scientific and educational; Cultural heritage and identity; Spiritual and religious; and Inspiration. A clear definition and a comprehensive list of examples for each service was developed in order to increase classification reliability between the two researchers conducting this task. As a pre-test, both researchers classified the same random sample of 100 photos. Differences in classification were found in approximately 4% of the photos, typically on classifying "Cultural heritage and identity" and "Inspiration" ecosystem services. The definitions and examples were then readjusted to address these difficulties, into the final version shown on Table 1.

2.3. Explanatory variables

Existing literature and expert's opinions were used to identify the socio-biophysical characteristics with potential to determine CES provision and spatial distribution. A set of eight variables were selected, including four bio-physical components: (1) distance to the ocean; (2) distance to water bodies; (3) distance to geological sites; (4) protection status; and four infrastructural factors: (5) distance to roads; (6) distance to hiking trails; (7) distance to urban areas; and (8) distance to touristic and cultural infrastructure. All the data used came from open sources. Most variables are proximity indices, calculated as Euclidian distances, assuming that attractiveness of a biophysical component or infrastructure (e.g. ocean or roads) decreases with increasing distance. All the variables are continuous, except the protection status, which is a discrete variable.

2.4. Species distribution model (Maxent)

Maxent (Steven J. Phillips, Miroslav Dudík, Robert E. Schapire. Maxent software for modeling species niches and distributions. Available from URL: http://biodiversityinformatics.amnh.org/open_source/maxent/) is one of the most popular tools to model the spatial distribution of species, with over 1000 published applications since 2006. Maxent uses point data occurrences and a set of variables considered relevant for species distribution to assign a suitability value (probability of occurrence, under certain assumptions on presence-absence data) for each spot in the study area. The accuracy of Maxent's

Table 1
List of Cultural Ecosystem Services.

Type of CES	CES	Definition	Examples for classification
Physical Benefit people obtain through physical interaction with ecosystems and their biotic and abiotic elements.	Recreation	Opportunities provided by ecosystems (their biotic and abiotic elements) for recreational activities.	Photos showing people engaged in recreational activities (e.g. hiking, swimming, surfing) or photos without people but showing the recreational equipment.
Experiential Benefit people obtain from landscapes, ecosystems and their biotic and abiotic elements from aesthetic experiences.	Aesthetics	Enjoyment provided by the aesthetic features of natural and semi-natural landscapes, ecosystems and their biotic and abiotic elements.	Photos showing landscapes
Intellectual Benefit people obtain from ecosystems and their biotic and abiotic elements through cognitive development and cultural identification.	Scientific and educational	Use of ecosystems and their biotic and abiotic elements for research or educational activities.	Photos showing people doing research or educational activities (e.g. school trips), or photos without people but showing the equipment used.
	Cultural heritage and identity	Value of landscapes, ecosystems, species or sites for local heritage and culture (including tangible and intangible heritage).	Photos showing tangible (e.g. buildings, cultural landscapes, relevant species to local culture) or intangible heritage (e.g. traditional practices, folklore).
Inspirational Spiritual and inspirational stimulus that people obtain from landscapes, ecosystems and their biotic and abiotic elements.	Spiritual and religious	Use of landscapes, ecosystems and their elements for religious or spiritual purposes.	Photos showing churches, hermitages, people meditating or religious ceremonies in natural or semi-natural settings.
	Inspiration	Use of landscapes, ecosystems and their elements in arts, architecture, advertising, local symbols, folklore, etc.	Photos showing the use or influence of nature in arts (e.g. painting, music, drama), local symbols, adds, etc. Also include here any photo that has been manipulated with an artistic purpose (e.g. increased contrast, black and white).

outcome relies on some assumptions regarding data collection, namely that observed presences result from random or representative sampling through the study area. However, sampling is often biased towards accessible locations. To overcome this issue the "target group approach" is suggested (Yackulic et al., 2013; Guillera-Arroita et al., 2015; Phillips et al., 2009). This approach consists of using as background (set of sites selected from the study area needed for calibration of Maxent) a "set of occurrence data for an entire target group of species that may be capture or observed using the same methods" (Phillips and Dudík, 2008). When presence data are based on photos, as a proxy for CES, sampling bias towards accessible areas and aesthetic values is expectable. For every CES, we ran Maxent with the locations of photos classified as belonging to that specific CES, using the eight predictors above identified. To account for sampling bias, we proceed as suggested above selecting as background the 1061 locations where at least a photo was taken, plus 7000 locations randomly selected from the study area. Data regarding the values of variables in the study area were converted to grid (raster) formats (at a resolution of $60\,m^2$/pixel), giving a total of $N = 172497$ cells. Maxent produced, for each CES s, a vector $p_s(i)$ giving the suitability of cell i (with respect to CES s), for $i = 1,\ldots,N$. The suitability for each CES was mapped for the study area.

Maxent uses a measure of goodness of fit (gain) that quantifies how closely the model is concentrated around occurrences. The uniform distribution has zero gain. Gain allows evaluating the importance of each predictor on the goodness of fit. We used this feature (using the Jackknife option) to assess the importance of each variable in modeling each CES. More specifically, the jackknife approach runs the models and provides the corresponding gains: i) with all variables ($gain_{all}$); ii) excluding each variable i at a time ($gain_{[-i]}$); and iii) with only variable i at a time ($gain_i$). For the assessment of the importance of each variable we devised the following performance measures: gain (%) which is the ratio between the gain of the model with only one variable and the gain with all the variables, i.e., $gain_i/gain_{all}$; and decrease in gain (%) which is $(gain_{all} - gain_{[-i]})/gain_{all}$. We also quantified the correlation between every pair of CES (s,s') by computing the Pearson correlation coefficient between pairs of vectors p_s and $p_{s'}$.

3. Results

3.1. Photoseries interpretation

The analysis of the photoseries database created by retrieving geotagged public photographs from Flickr provided some valuable information on CES provision and their spatial distribution in the research area. According to this database, aesthetic values were the most appreciated CES, followed by recreation and cultural heritage (see Fig. 2).

These photographs allowed as well identifying land use covers where these CES occur. Using the Portuguese land use cover categories, we can see that sea and bare rocks are the two main land covers where CES are appreciated. Beaches and dunes are also very present in this database, which is consistent with the strong preference for the natural park's coastline. Agricultural areas are among the land uses with lower occurrence of CES, despite covering a significant part of this region, particularly permanently irrigated lands (see Fig. 2). On the contrary, the bare rocks land cover has a low coverage, but it concentrates a high number of CES.

The geographical coordinates associated to each photo, allowed us to produce, using ArcGIS software, maps of CES distribution, density or diversity. Fig. 3 shows two examples of quick GIS outputs using this database. An analysis by ES makes possible to map their distribution on the study area (i.e. see all the points/photos where the same service was identified), and a density scale provides a map of hotspots for that ES. As shown on the map for recreation (on the left of Fig. 3), the red areas reveal a high concentration of points/photos appreciating this ES. This provides a clear image of the spatial presence of each CES. A second approach was to identify areas with bundles of ES, as some of these may overlap. The map of CES diversity, shown on the right on Fig. 3, identifies areas of the park where there is a high density of bundles of 3 or more CES. The southwest area of the park seems to provide more areas where different CES are valued simultaneously. Once again, almost all spots with higher CES diversity are located on the coastline.

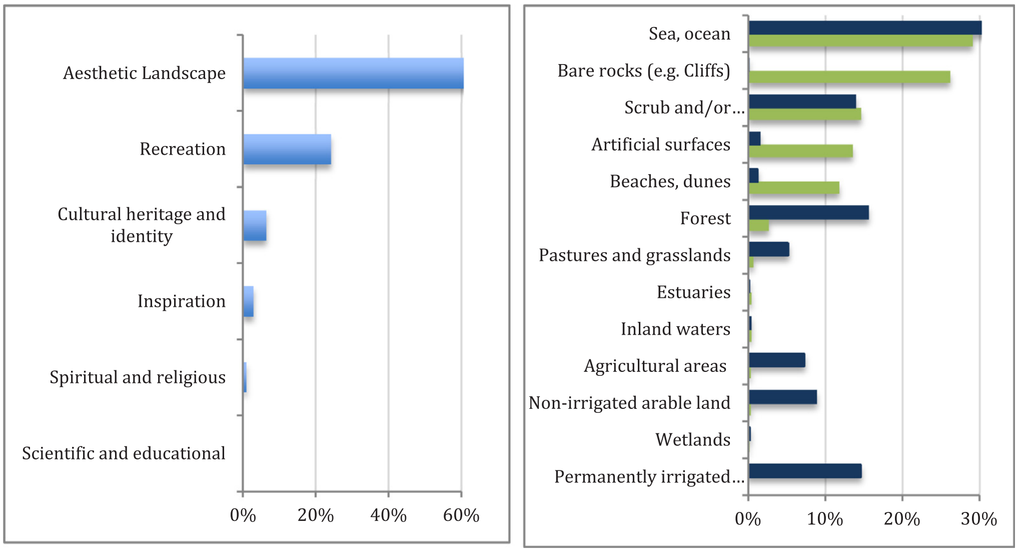

Fig. 2. CES identified in the study area (on the left); on the right the proportion of land cover types in the park (blue) vs. land cover identified on the analyzed photographs (green). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

3.2. Mapping CES using Maxent

Applying a species distribution model – Maxent – to CES assessment provided a geographic projection of the suitability of the study area for each CES analyzed. Each CES was modelled separately, resulting on the maps shown in Fig. 4. Additionally, a map "for all CES", i.e, using as occurrences photos of any CES, is displayed. For each CES, and "for all CES" a map of suitability is shown on the left side, and on the right side the geographic location of occurrences (photos taken) is represented. In each map the blue, green, yellow and red cells correspond to suitability values in intervals [min, 1st quartile], [1st quartile, median], [median, 3rd] and [3rd max], respectively. Thus, the area with each colour is 25% of the total area of the map. In general, the most suitable areas (in red) occur in sea-land interface, such as beaches or cliffs. This is not evident for spiritual CES, and certainly not true for cultural heritage CES. The blue areas (less suitable) occur mostly on agricultural lands and mountains. These maps show that aesthetics landscape and recreational services are valued/identified in almost all highly suitable areas, whereas other CES have low occurrences compared to the potential areas for its occurrence.

Figs. 5 and 6 depict the distribution of each variable in all the study area, and in sites within the study area where photos were taken, respectively. The histograms on Figs. 5 and 6 reveal that the photos distribute unevenly (non-uniformly) across the range of each variable. It is possible to identify a strong occurrence of photos close to ocean, touristic and cultural infrastructures, roads and hiking trails.

The histograms reveal that photos are also mostly located in areas with a protection status Partial II type (protection status 4) that corresponds to areas containing natural and landscape values of high or very high relevance and with moderate ecological sensitivity. The

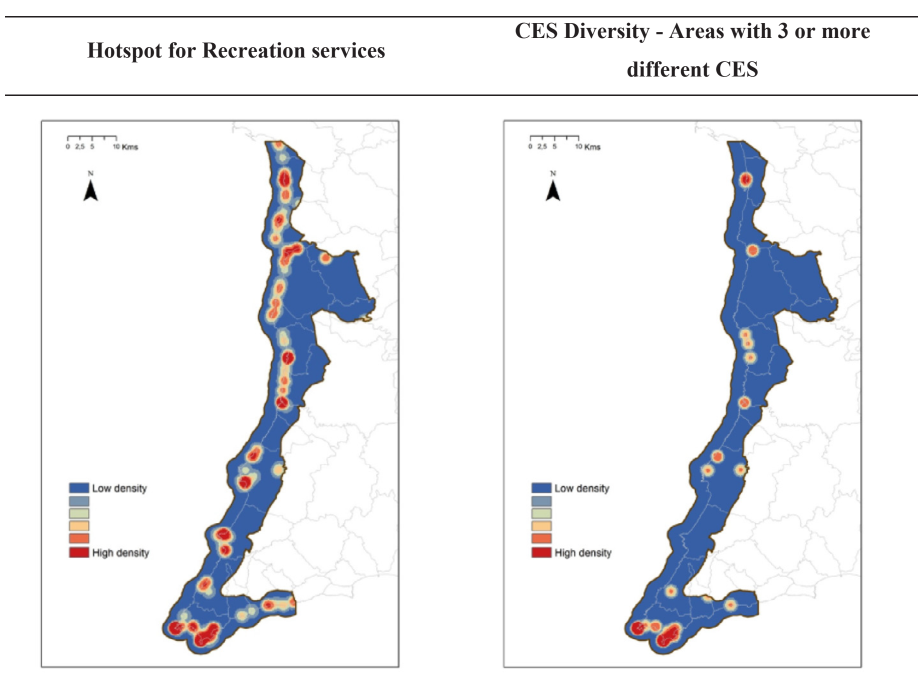

Fig. 3. Maps of CES hotspots (on the left) and CES diversity (on the right).

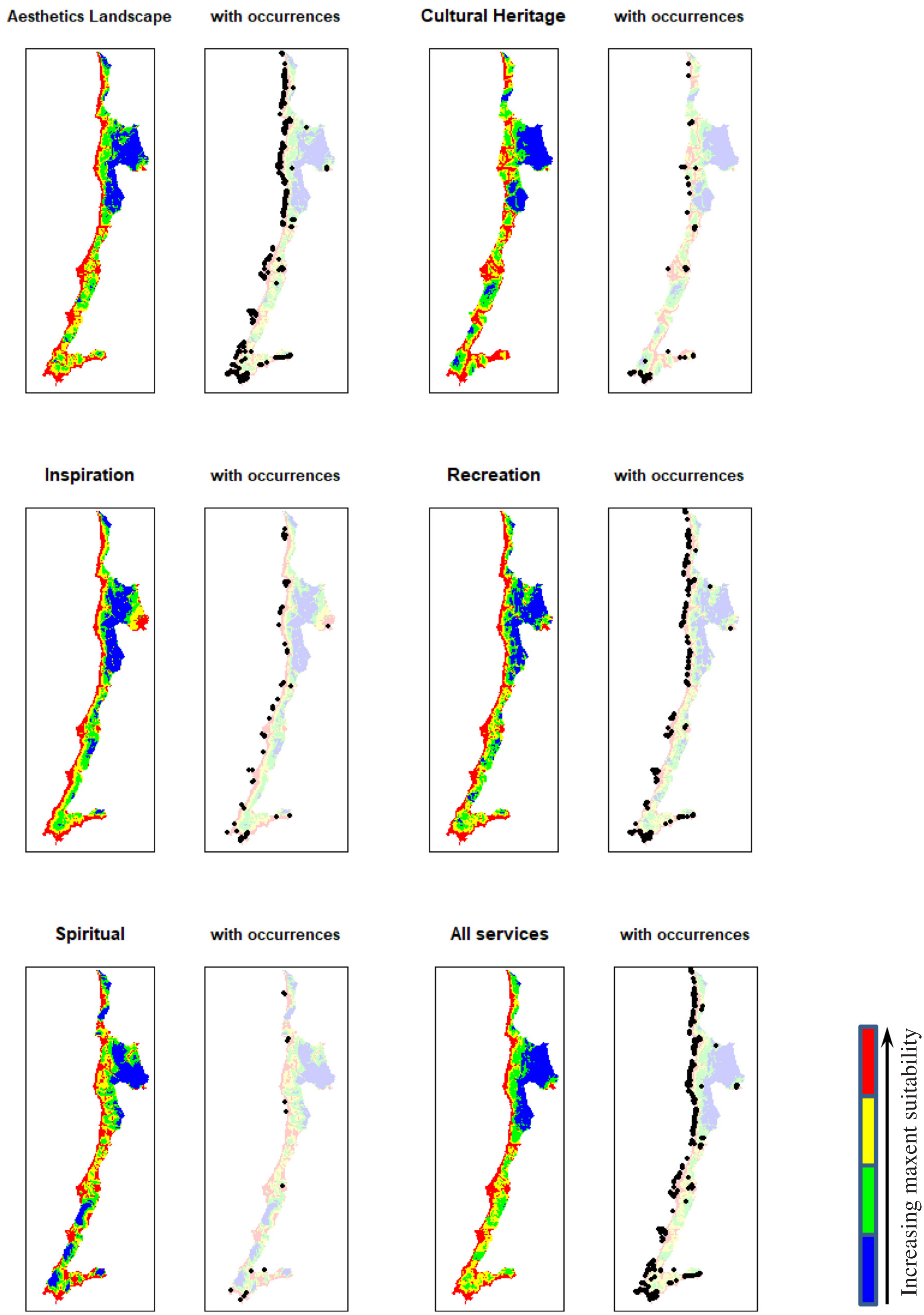

Fig. 4. Maps of CES suitability (on the left), and geographic location of occurrences (photos taken) (on the right).

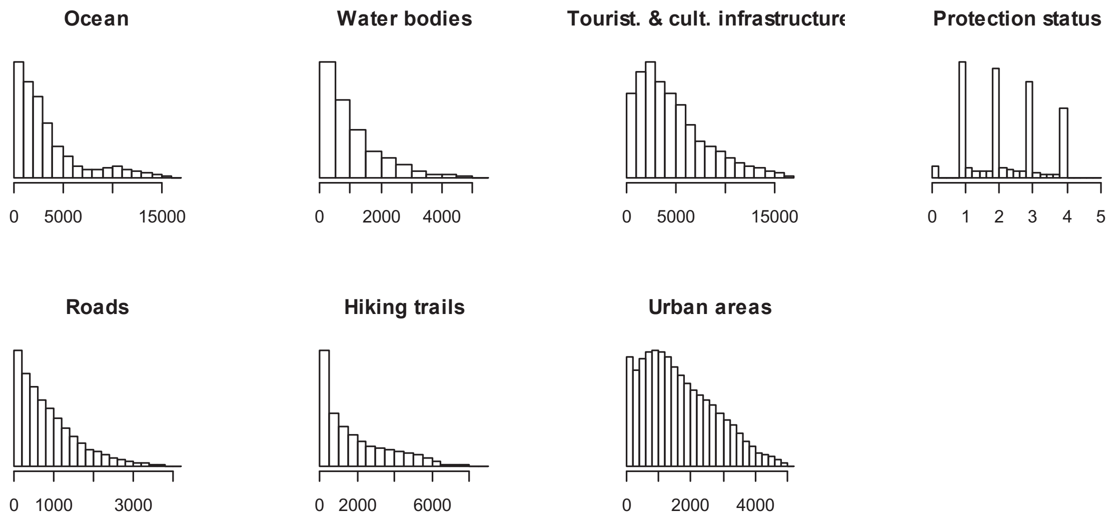

Fig. 5. Frequency distribution of each variable in the study area.

objectives of these Partial II type areas are to create transition areas or impact mitigation, necessary for the protection of core areas; to value traditional activities, especially fishing, compatible with the conservation of natural values and landscapes, but also to promote a sustainable use of resources, ensuring the local socio-economy.

3.3. Determinant variables for CES provision

Table 2 shows the importance of each variable in the modelling of each CES using Maxent (see Section 2.4). Variables with high values of gain (%) with only that variable and high decrease in gain (%) without the variable, are the most relevant to the CES model. The variable distance to "Ocean" is the one with the largest gains and can serve as better individual estimate for Aesthetic landscape, Inspiration and Recreational Services distribution; while "Touristic and cultural infrastructure" shares with "Roads" the largest gains for Cultural Heritage and with "Urban areas" the largest importance for Spiritual Services. By contrast, the variable distance to "Water bodies" achieves very little gain and seems therefore not useful on its own for estimating CES distribution. Overall, the highest gains were attained by the variables "Ocean" or "Touristic and cultural infrastructure", which therefore appear to have the most useful information for CES modelling.

The spatial overlap between CES in the study area is shown in Table 3. Using a Pearson r coefficient of correlation, it was possible to identify high correlation between Recreation & Aesthetics landscape; and Recreation & Inspiration. A little bit lower but still highly correlated are Aesthetics landscape & Inspiration; and Cultural Heritage & Spiritual. This analysis alongside with the CES diversity map (Fig. 4) highlight the fact that CES do not occur alone and people tend to perceive and value them combined.

4. Discussion

This research allowed us to identify and map the social preferences for a set of CES in PNSACV, providing a regional assessment of values often overlooked, which are in some cases intangible or difficult to measure, such as inspirational or spiritual services. CES are among the most important values people associate with Nature, it is therefore critical to understand them and acknowledge their diversity. Typically, CES assessments refer to recreational and aesthetic values that provide direct benefits to local communities and create opportunities for tourism, which is clear in this area. Being a coastal natural park, those values are strongly related with the ocean, cliffs and beaches. These areas provide a wide range of recreational opportunities alongside stunning sceneries and geological formations that are very appealing to local communities and visitors. This is increasing the pressure on the

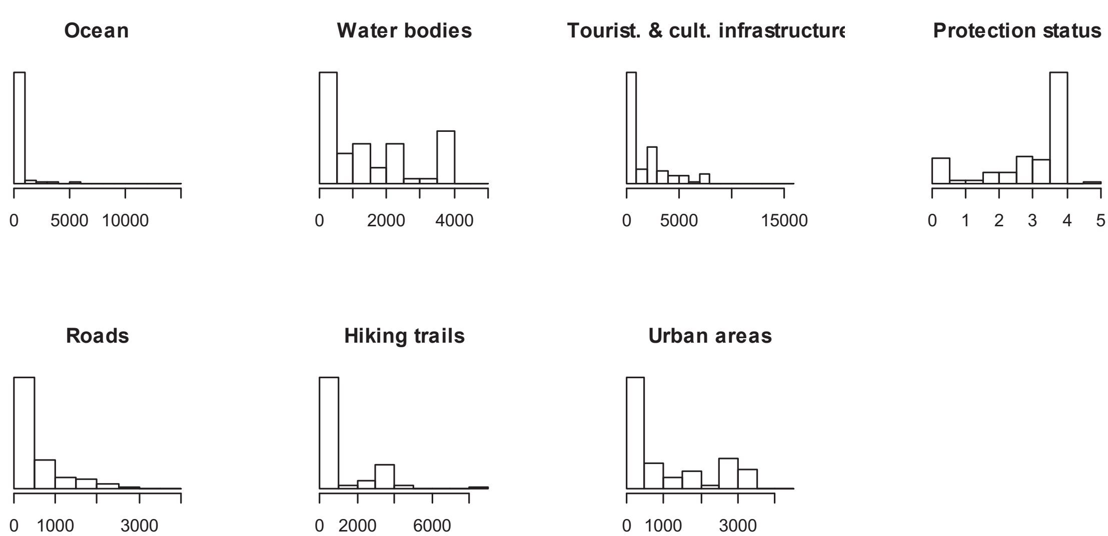

Fig. 6. Frequency distribution of each variable in the cells where some photo has been taken.

Table 2
Capacity of the variables to explain CES spatial distribution in the study area.

	Aesthetic Landscape		Cultural Heritage		Inspiration		Recreation		Spiritual	
	gain (%) only with	decrease in gain (%) without	gain (%) only with	decrease in gain (%) without	gain (%) only with	decrease in gain (%) without	gain (%) only with	decrease in gain (%) without	gain (%) only with	decrease in gain (%) without
Water bodies	1.9%	28.8%	5.8%	40.4%	1.3%	44.5%	2.5%	36.4%	2.0%	39.8%
Roads	5.7%	30.0%	18.5%	44.3%	4.3%	44.9%	4.7%	36.6%	12.2%	44.3%
Geological sites	24.3%	28.9%	10.4%	40.2%	13.8%	43.9%	19.8%	36.2%	3.5%	39.6%
Ocean	62.0%	41.1%	22.4%	40.4%	41.0%	61.5%	52.0%	49.5%	14.5%	42.2%
Touristic and cultural infrastructure	17.8%	28.3%	39.9%	42.1%	18.8%	45.3%	15.5%	35.9%	36.4%	48.3%
Hiking trails	24.2%	27.4%	14.6%	39.6%	5.7%	44.8%	16.1%	36.3%	4.9%	39.8%
Urban areas	14.7%	28.9%	29.3%	42.7%	20.5%	46.3%	20.6%	38.0%	37.9%	47.7%
Protection status	28.8%	26.5%	12.9%	40.0%	15.6%	46.1%	19.5%	36.5%	18.9%	39.4%

Table 3
Correlation between CES.

	Aesthetic Landscape	Cultural Heritage	Inspiration	Recreation	Spiritual
Aesthetic Landscape	1	0.5313	0.8764	0.9606	0.6313
Cultural Heritage		1	0.5005	0.5081	0.7648
Inspiration			1	0.8858	0.6813
Recreation				1	0.6238
Spiritual					1

Park's shore but also absorbing most of the economic and political attention. Our results confirm this essential role of the distance to ocean in the preferences for the studied CES, as most suitable areas and actual occurrences of all CES were concentrated along the coastline, in a very narrow 1 km wide corridor. Even for those CES where other variables are more relevant, the proximity to ocean always plays a significant role. This can be explained by the strong cultural identity of fishermen communities and the historical/cultural infrastructure built near the ocean linked to maritime activities, such as small old ports or lighthouses. The distance to water bodies was not a relevant variable to explain CES distribution in our case study; only Mira's estuary shows high occurrences of all different types of CES, as this estuary is an ecological and cultural hotspot of the region. The remaining water bodies are mostly small seasonal creeks with low recreational potential.

This assessment intended to go beyond recreational and aesthetic values by including other non-material benefits, namely inspiration, cultural identity and spiritual experience related to the natural environment. According to our database, these CES occur in the region, although less than recreational and aesthetic ones, but the Maxent maps show several suitable areas with no occurrences, showing a hidden potential that people are not valuing or appreciating.

The suitability maps for inspirational or cultural heritage services also show more inland areas with high suitability than the maps for recreation, which can be an opportunity to foster CES in inland areas that are being disregarded and progressively disappearing, such as local traditions or historical sites. Valuing recreational and aesthetics services in shore areas also tends to be seasonal; in our database more than 60% of the occurrences (photos) for those CES refer to the period between May and August. Promoting other CES can also provide opportunities for locals and visitors to appreciate the region in other periods of the year, rather than the high peaks in the summer.

The "protection status" variable was introduced to assess the correlation between the appreciation of CES and nature conservation priorities established on the park's management plan. Having low capacity to explain CES distribution also means that occurrences do not match the areas with high conservation status where human presence and some recreational activities are restricted or limited. This is a positive observation that the enjoyment of CES is not occurring in the park's most sensitive areas.

The results of both photoseries interpretation and Maxent modelling show a clear spatial overlap of different CES, namely between recreational, aesthetics and inspirational values. There is a positive synergy between them thus enhancing the appreciation of each CES individually. CES are interconnected with each other and are often connected to other types of ES such as provisioning (e.g. fisheries and cultural identity) and regulating services (e.g. recreation and erosion control). The different ES within these bundles often interact leading to synergies and trade-offs (Turkelboom et al., 2015; Maes et al., 2012). Different sets of social–ecological interactions produce these complex bundles; acknowledging them creates an opportunity for managers and policy makers to design and implement policies targeting these synergies and trade-offs instead of individual ES (Rodriguez et al., 2006; Ament et al., 2016).

The obtained results show that a relatively small sample of spatially explicit photographs freely downloaded from social media platforms, can provide valuable information about the CES provided by a site. These databases can become an important tool in assessing CES, a key category of ecosystem services that is generally poorly addressed, or it is done with a strong bias towards recreation. However, the use of this method embodies several challenges as highlighted below.

When using photos as a proxy for CES there is an inevitable bias towards aesthetic values. Ultimately, photographs tend to express pleasant and beautiful features (Yoshimura and Hiura, 2017). This method also entails an inherent bias related with the interpretation of photos by different researchers and with the capacity to photograph certain cultural services (e.g. photographing traditions can be challenging). Researchers' interpretations will always be subjective, despite major efforts to create protocols, common definitions and cross-validation (Richards and Friess, 2015).

Representativeness can also be a challenge; the photo-sharing community will most probably not be representative of the population (Tenerelli et al., 2016; Guerrero et al., 2016). People without access to technology will not be able to share their preferences towards CES. Education and income levels, age and user's capacity to geo-tag photos can be important factors to analyse. Nationality can also be relevant, as the cultural values identified by local communities or national citizens can vary significantly from the ones valued by foreign visitors. This is particularly relevant in our research site, as most photos in our database are from foreign visitors. Coming from different cultural, social and economic backgrounds, their preferences regarding CES might not reflect those of local communities.

This type of analysis relies on the availability of data for a specific area. However, as long as the variables are adequate predictors, the use of species distribution models, such as Maxent, may help finding areas with high suitability for a CES, even in remote regions where occurrences (photos) may lack. In our research area, there are some spots with a particularly high number of photos. Working at the regional scale may not be the best way to address these very popular sites, it could have been useful to decouple them and perform a finer analysis (Richards and Friess, 2015).

Executing these methods implies different levels of knowledge and effort. There is some time investment in classifying photographs, but this is small when compared to the time and effort required to apply other methods commonly employed to assess CES, such as interviews or surveys (Milcu et al., 2013; Hernández-Morcillo et al., 2013). Running Maxent requires some statistical knowledge to setup the model and to analyse the different outputs.

Beyond academic contributions, this research provides a tool with the potential to inform regional stakeholders and decision makers regarding land use planning and ecosystem management strategies. For decision-making, using these layers of information on CES allows to identify priority areas for intervention but also to reckon in the process of policy and decision-making the actual provision of intangible benefits related to CES. The Park's management plan is to be revised in 2019, and the Park managers have shown particular interest to incorporate the ecosystem services approach into it. A key entry point will be to include recreation and aesthetic ecosystem services maps into the design of the Park's Nature Sports Chart. All CES maps might also be added to the Plan's biophysical characterization in order to widen the scope of the Plan and enable a more integrated analysis of all relevant values. The aesthetic service will be particularly relevant for the Plan because landscape is recognized as a key value of this Park. In fact, the current Natural Park was originally created in 1988 as a Protected Landscape Area, designated as "Área de Paisagem Protegida do Sudoeste Alentejano e Costa Vicentina (APPSACV)".

These maps can also assist policy makers and other stakeholders to design more balanced strategies to promote CES in different locations. A regional overview of CES occurrences and suitability, highlights not only the crowded areas but also potential areas to promote and value other CES, such as traditions or cultural heritage. Tourism operators can benefit from this information to diversify their offer and to provide other locations with values still unknown or less explored in the region. These maps were provided to a regional non-profit association (Associação Rota Vicentina) that promotes and manages the cycling and walking trails of the region. CES maps were then used alongside other technical variables and inputs to support the design of new routes, to be implemented in 2018. The coastal trails are currently the main target of visitors of the region, but they are becoming crowded and reaching their carrying capacity. For that reason, finding new values in inland, less pressured, areas is a priority for this region. The network of new trails translates this concern by increasing the number of inland trails. The maps of spiritual and cultural heritage services were particularly useful to support the outline of these new trails routes by pointing inland hotspots with high value that were used as anchor points for the routes

5. Concluding remarks

This research contributes to the current literature on mapping cultural ecosystem services, by exploring the use of social media photographs to model their spatial distribution. This research confirms the potential of crowd sourced geospatial data analysis as a cost-effective method for researchers, managers or decision-makers to do regional scale assessments. The potential use of new free access data sources is enormous, both as raw data to feed other tools as for direct interpretation and content analysis. The accessibility to Internet, mobile devices and the growing number of platforms for interaction and data sharing will contribute to a wider use of such methodologies. It also demonstrates that tools from other knowledge fields can be valuable to ecosystem services assessments. Maxent, a species modeling software used social media photographs alongside regional biophysical and infrastructural information to create CES maps and assess the key features that explain their distribution across landscapes.

In the case of PNSACV recreational and aesthetics landscape values are highly valued, mainly in shore areas; ocean, cliffs and beaches seem to be the preferred environments to appreciate these ES. Other CES are less explored but Maxent revealed several areas, particularly inland, with high potential for their appreciation. Nourishing this diversity of ES is important to promote regional cultural values and distribute their demand in the territory (inland vs. shore) and along the year, overcoming the strong effect of seasonality in this region. The different CES identified in the Park are not spatially exclusive, as in some areas it was possible to find overlaps, creating synergies. Acknowledging this is important for stakeholders and decision makers to fully understand the dynamics and interdependencies of their actions.

These results can inform the design of plausible future scenarios of CES provision or to assist decision-making on land use planning, tourism or protected areas management. Still, this approach embodies some challenges that need to be considered, such as an over-representation of aesthetic values, a classification bias from the analysts classifying the photos and the issue of representativeness, as the photo-sharing community may not be representative of the visitors or the local communities' preferences.

Future research can focus on a proper protocol to address the comments and hashtags that people attach to the photographs in order to investigate the motivations and arguments why people value certain CES or certain landscape traits. It would be also relevant to distinguish and compare CES preferences of foreigners vs. locals/nationals. The permanent flow of geo-tagged photo sharing provides the potential for future research on medium and long-term monitoring of CES provision and social preferences trends. The complexity to assess the different CES may also require the complementary use of other data sources (e.g. video) and techniques (e.g. transcriptions) to capture the full extent of services, namely cultural heritage or inspirational services. The potential spatial synergies and trade-offs of CES with other types of ecosystem services in this area can provide relevant inputs to inform stakeholders and decision-makers.

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