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Digital conservation in biosphere reserves: Earth observations, social media, and nature's cultural contributions to people

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Abstract

In the "digital conservation" age, big data from Earth observations and from social media have been increasingly used to tackle conservation challenges. Here, we combined information from those two digital sources in a multimodel inference framework to identify, map, and predict the potential for nature's cultural contributions to people in two contrasting UNESCO biosphere reserves: Doñana and Sierra Nevada (Spain). The content analysis of Flickr pictures revealed different cultural contributions, according to the natural and cultural values of the two reserves. Those contributions relied upon landscape variables computed from Earth observation data: the variety of colors and vegetation functioning that characterize Doñana landscapes, and the leisure facilities, accessibility features, and heterogeneous landscapes that shape Sierra Nevada. Our findings suggest that social media and Earth observations can aid in the cost-efficient monitoring of nature's contributions to people, which underlie many Sustainable Development Goals and conservation targets in protected areas worldwide.

KEYWORDS

big data, crowdsourced photos, cultural values, Doñana, ecosystem services, multimodel inference, protected areas, participatory sensing, remote sensing, Sierra Nevada

1 | INTRODUCTION

The Anthropocene is characterized by fast environmental changes, calling for new approaches to conservation planning and management (Palomo, Montes, et al., 2014). Conservation mechanisms, such as the establishment and management of protected areas, have been reshaped to accommodate social–ecological perspectives on biodiversity

(García-Llorente et al., 2018). The UNESCO's network of biosphere reserves is an emblematic effort in this regard, aiming to reconcile nature conservation with the achievement of a good quality of life (Van Cuong, Dart, & Hockings, 2017), namely, through ecotourism and recreation (Reed, 2016). Nature-based recreational experiences may, however, hold unintended consequences for ecosystems and biodiversity (Van Cuong et al., 2017). Understanding how such nature's contributions to people (Díaz et al., 2018) are shaped inside biosphere reserves is thus key to promote conservation policy, management, and communication (Turnhout, Waterton, Neves, & Buizer, 2013).

Nature-based experiences and preferences have traditionally been analyzed from revealed and stated preference methods (e.g., social surveys), which are often costly and lack adequate spatial and temporal coverage (Di Minin, Tenkanen, & Toivonen, 2015). To overcome these limitations, digital technology and public data from large audiences have been increasingly used by conservationists to support the surveillance and management of nature's contributions to people at several scales (Richards & Friess, 2015). Under this "digital conservation" paradigm (Arts, van der Wal, & Adams, 2015; van der Wal & Arts, 2015), the use of social media data have received particular attention (Sherren, Smit, Holmlund, Parkins, & Chen, 2017). Examples include the content analysis of georeferenced photos from social media platforms (e.g., Flickr and Instagram) to infer on aspects of nature appreciation (Oteros-Rozas, Martín-López, Fagerholm, Bieling, & Plieninger, 2018), monitor visitors' movements (Tenkanen et al., 2017), or identify visitors' preferences in protected areas (Hausmann et al., 2018).

Earth observation technology, including Geographic Information Systems (GIS) and multisource remote sensing, has also emerged as a powerful tool to describe nature-based experiences and preferences. Examples include the identification of nighttime lights to identify hiking trails from satellite imagery (Braun, Damm, Hein, Petchey, & Schaepman, 2018) or viewshed analysis to model landscape aesthetics (Swetnam, Harrison-Curran, & Smith, 2016). Combining georeferenced photos from social media with Earth observations provides opportunities to advance our understanding of nature's cultural contributions to people. For instance, grounded on a set of GIS variables and Flickr photoseries, Tenerelli, Demšar, and Luque (2016) revealed social preferences for several cultural ecosystem services; Van Berkel et al. (2018) assessed landscape quality underlying cultural recreation using Panoramio photos and high-resolution Light Detection And Ranging (LiDAR); and Vaz et al. (2019) used a combination of satellite imagery and Flickr photographs to infer on recreational and aesthetic preferences associated to trees.

Despite the potential of Earth observations and social media for addressing conservation challenges, their combined application is still in its infancy. This study combines freely available data from those two digital sources to assess nature's cultural contributions to people in biosphere reserves. We aim to (a) identify which nature's cultural contributions prevail in the biosphere reserves; (b) understand if and how those contributions relate with biophysical and landscape features evaluated through GIS and satellite Earth observations; and (c) predict the potential for nature's cultural contributions in a spatially explicit way. We use two contrasting biosphere reserves in Spain, Doñana (coastal wetland), and Sierra Nevada (mountain) as test areas to infer on the whole-reserve potential of different nature's cultural contributions, based on social media photographs and a multimodel inference framework fed with different sets of Earth observation predictors.

2 | METHODS

2.1 | Methodological framework

Our methodological framework included three main steps (Figure 1a–c). First (a), we compiled a georeferenced dataset of in-field photographs from the social media platform Flickr. We analyzed the content of the dataset through manual classification of the main type of nature's cultural contributions displayed in each photograph. Second (b), we compiled a set of spatially explicit variables (related to environmental context, landscape biophysical properties, points of leisure interest, and landscape visual-sensory attributes) potentially explaining those cultural contributions. Finally (c), we applied a multimodel inference to evaluate the explanatory power of our variables regarding the several nature's cultural contributions to people (inferred from the social media content).

2.2 | Test areas

Our approach was tested in two contrasting UNESCO biospheres reserves included in the biodiversity hotspot of the Mediterranean region, Doñana and Sierra Nevada, at southern Spain (Figure 1). Doñana (ca. 2,687 km^2) is a Ramsar wetland, spreading over a 26-km coastal system. Its dynamic hydrological cycle results in a high diversity of habitats and species, including several endemic and threatened *taxa* (e.g., marbled teal, imperial eagle, and Iberian lynx). Key socioeconomic activities comprise agriculture, ecotourism, and beach recreation. Sierra Nevada (ca. 1,722 km^2) spreads over a mountainous region (elevation between 860 and 3,482 m), presenting several species listed in the European Union Habitats and Birds directives. Its socioeconomy relies mostly on rural tourism and sports. Both areas hold several protection regimes (Natural and National Parks, Natura 2000 Special Protection Area and Special Area of Conservation, Biosphere Reserve) and are part of the European Long-Term Ecosystem Research Infrastructure.
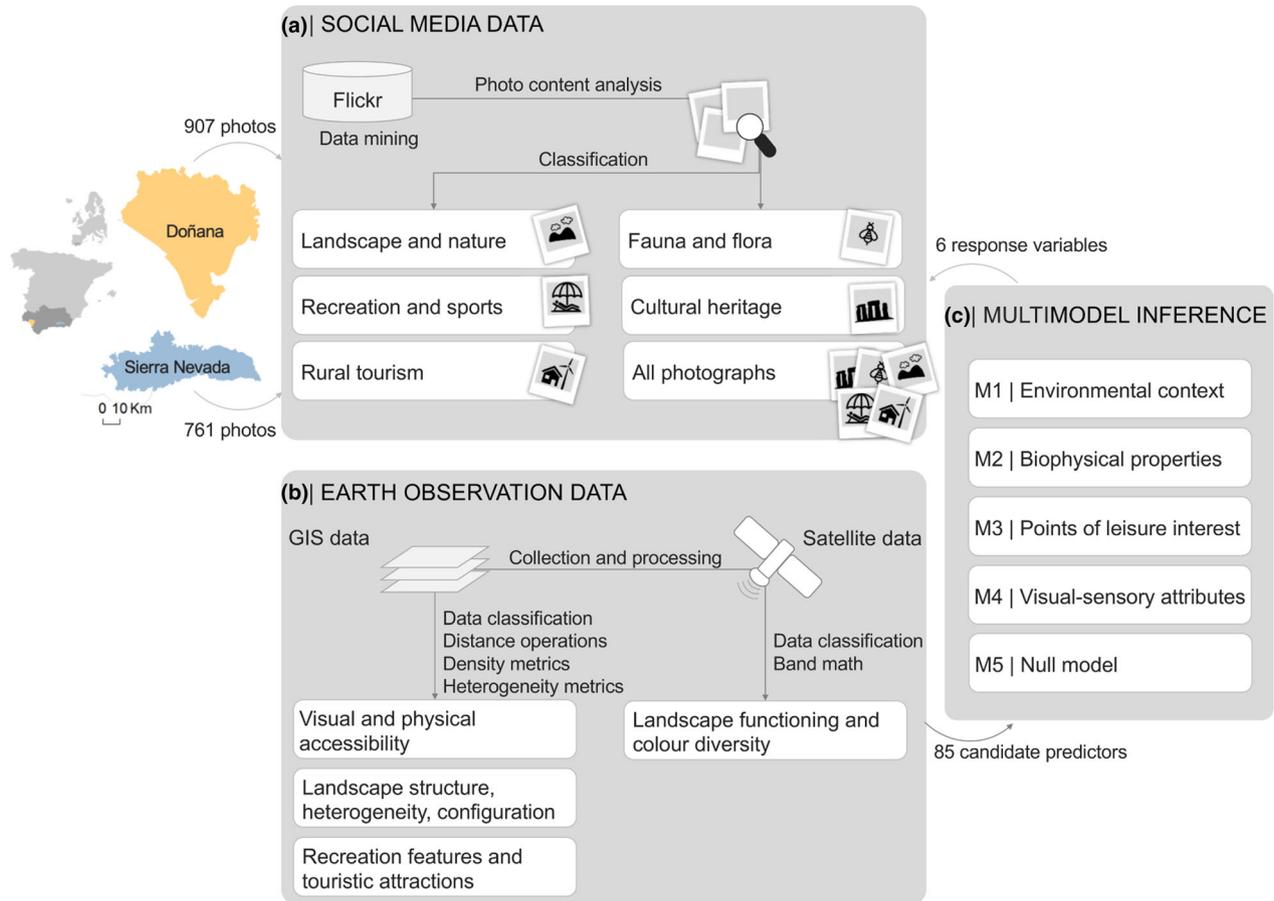
FIGURE 1 Methodological framework adopted to evaluate nature's cultural contributions to people in Doñana and Sierra Nevada: (a) content analysis of social media photographs, as proxies for cultural contributions; (b) Earth observation predictors, from satellite and Geographic Information Systems (GIS) data; (c) multimodel inference, assessing the explanatory power of different groups of predictors on those contributions

TABLE 1 Categories used in the content analysis of Flickr photographs

Category	Description
Landscape and nature	The photograph is focused on wide views of nature (e.g., land/seascape with visible horizons)
Flora and fauna	Fauna and/or flora are the main topic of the photograph (e.g., close-up shots of species)
Recreation and sports	Human activities related to sports and recreation prevail in the photograph (e.g., beach or ski activities)
Cultural heritage	The photograph is dominated by cultural elements and religious places (e.g., monuments and churches)
Rural tourism	Elements associated to rural tourism are the main topic (e.g., lodges and rural infrastructures)

2.3 | Social media data

Nature's cultural contributions to people were evaluated through the screening of social media photographs from Flickr (Gosal, Geijzendorffer, Václavík, Poulin, & Ziv, 2019; Richards & Friess, 2015). We collected georeferenced photographs up to 2018 using the Application Programming Interface together with Python collection tools. Pictures were obtained through a stratified sampling strategy that captured the diversity of prevailing land-use regimes in each reserve. We classified each individual photograph manually in one of five categories (following Hausmann et al., 2018;

Vaz et al., 2019; see Table 1). Photographs with irrelevant subjects (e.g., advertisements) were excluded. The final set included 907 and 761 photographs for Doñana and Sierra Nevada, respectively. Appendix 1 in the Supporting Information shows details on sampling procedure, data mining, and classification.

2.4 | Earth observation data

We computed 85 candidate predictors for modeling nature's cultural contributions, derived from the most updated satellite

TABLE 2 Predictors considered in each competing model (see Table S1 for details)

Groups of predictors	Predictors (related to…)	Input data
**Model 1	Environmental context**		
Visual accessibility	Viewshed dimension	Digital elevation model (20 m² resolution)
Physical accessibility	Elevation; slope	
	Distance to/density of trails and rivers	Local trails and hydrographic networks
**Model 2	Landscape biophysical properties**		
Landscape structure and configuration	Shape; isolation and proximity; contagion and interspersion; area and density	Land cover map 2018 (1:10,000 resolution)
Landscape heterogeneity	Patch richness, evenness, and diversity	
**Model 3	Points of leisure interest**		
Recreation features	Density and distance to beaches, ski resorts, and lakes	Local distribution map
Tourist attractions	Density and distance to public facilities, villages, and protected sites	
**Model 4	Landscape visual-sensory attributes**		
Landscape functioning	Normalized Difference Vegetation Index (NDVI); Ecosystem Services Provision Index (ESPI)	Sentinel-2 MSI L1C images (10 m; 2015–2018)
Color diversity	Reflectance for red (R), green (G), and blue (B) bands; diversity of RGB clusters per meteorological season	

and GIS data available (Table 2). GIS data included information on: (a) environmental context (visual and physical accessibility), (b) biophysical properties (landscape structure, configuration, and heterogeneity), and (c) points of leisure interest (recreation and touristic features). Satellite data (Sentinel-2a/b L1C images) were used to obtain predictors expressing (d) visual-sensory attributes, namely, landscape functioning and color diversity, with the latter being computed separately for each season of the year (Vaz et al., 2019). Seasonal variations in landscape functioning were calculated from time-series data (2015–2018) based on the Normalized Difference Vegetation Index (NDVI; Tucker, 1979) and the Ecosystem Services Provision Index (ESPI), which provide information on the spatial and temporal changes in the supply of ecosystem services (Paruelo et al., 2016). Spatial autocorrelation tests with increasing moving-window sizes were used to determine the suitable cell size for subsequent analyses (Vicente et al., 2014). A regular grid of $1,000 \times 1,000$ m and 500×500 m was established for Doñana and Sierra Nevada, respectively. Appendices 2 and 3 in the Supporting Information show details on autocorrelation tests and grid size selection.

2.5 | Multimodel inference

For each grid cell, the number of photographs from each category of cultural contributions (Table 1) was used as response variables in a multimodel inference framework (Burnham & Anderson, 2002). We considered four competing models (M1–M4) to test the hypotheses that nature's cultural contributions were mostly explained by: M1—environmental context; M2—biophysical properties; M3—points of leisure interest; or M4—visual-sensory attributes. Generalized Linear Models with Poisson distributions were fitted separately for each category of cultural contributions, following Burnham and Anderson (2002) and Wisz and Guisan (2009), in R software (R Core Team, 2019). Due to our relatively small sample size, the maximum number of predictors per model was set to four. To avoid correlation and multicollinearity, only predictors with a pairwise Spearman value lower than 0.6 and Variance Inflation Factor lower than 5 were considered (Fox & Weisberg, 2018).

To overcome dependence on sample size and allow comparability among models, we calculated the Akaike Information Criterion difference (ΔAICc; Burnham & Anderson, 2002; Shono, 2000). We further considered the weight (wi) of each competing model, which represents the proportion of evidence from a competing model in relation to the total evidence from all models. We used Nagelkerke deviance D2, based on null model testing from an extra competing model (M5) as goodness-of-fit measures (Dormann et al., 2018). Finally, we weighted all competing models based on their wi and used the averaged model for predicting the areas with the highest and lowest potential for cultural contributions to people inside each biosphere reserve (Burnham & Anderson, 2002; Dormann et al., 2018). Appendix 4 in the Supporting Information shows details on model implementation.

FIGURE 2 Number of Flickr photographs from each category of nature's cultural contributions to people in Doñana and in Sierra Nevada
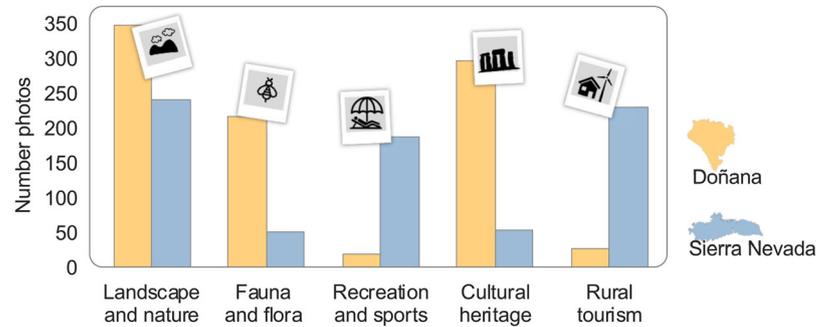
3 | RESULTS

3.1 | Nature's cultural contributions in the two reserves

"Landscape and nature" was the most frequently represented category in both Doñana (38% of all photographs) and Sierra Nevada (27%; Figure 2). "Cultural heritage" and "fauna and flora" photographs were more frequently found in Doñana (33% and 24%, respectively) than in Sierra Nevada (both with ca. 6%). Conversely, photographs associated with "rural tourism" as well as "recreation and sports" were more frequent in Sierra Nevada (25% and 21%, respectively) compared to Doñana (3% and 2%, respectively).

3.2 | Predictors of nature's cultural contributions

The most parsimonious model to explain the distribution of nature's cultural contributions in Doñana was based on land-scape visual-sensory attributes (M4; Figure 3). The distribution of "recreation and sports" and "cultural heritage" photographs was also explained (to a minor extent) by landscape biophysical properties (M2).

In Sierra Nevada, the model based on landscape visual-sensory attributes (M4) also showed high explanatory power over the various categories, being the most parsimonious model only for "fauna and flora" (Figure 3). The remaining categories were primarily explained by leisure features (M3). The environmental context also contributed to explain "landscape and nature," "cultural heritage," and "rural tourism." The distribution of the last two categories also related with landscape biophysical properties.

3.3 | Potential for nature's cultural contributions

The spatial projections of the average models for Doñana and Sierra Nevada reflect the prevailing influence of distinct
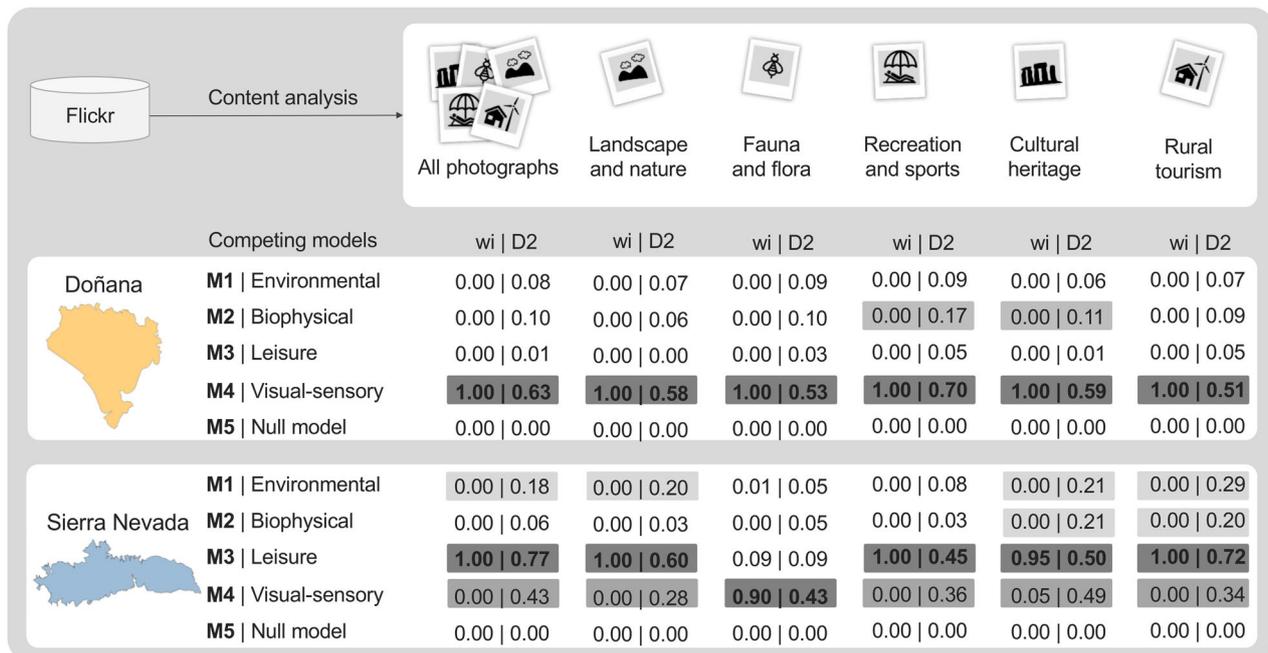

	Competing models	All photographs wi | D2	Landscape and nature wi | D2	Fauna and flora wi | D2	Recreation and sports wi | D2	Cultural heritage wi | D2	Rural tourism wi | D2
Doñana	M1 | Environmental	0.00 | 0.08	0.00 | 0.07	0.00 | 0.09	0.00 | 0.09	0.00 | 0.06	0.00 | 0.07
	M2 | Biophysical	0.00 | 0.10	0.00 | 0.06	0.00 | 0.10	0.00 | 0.17	0.00 | 0.11	0.00 | 0.09
	M3 | Leisure	0.00 | 0.01	0.00 | 0.00	0.00 | 0.03	0.00 | 0.05	0.00 | 0.01	0.00 | 0.05
	M4 | Visual-sensory	**1.00 | 0.63**	**1.00 | 0.58**	**1.00 | 0.53**	**1.00 | 0.70**	**1.00 | 0.59**	**1.00 | 0.51**
	M5 | Null model	0.00 | 0.00	0.00 | 0.00	0.00 | 0.00	0.00 | 0.00	0.00 | 0.00	0.00 | 0.00
Sierra Nevada	M1 | Environmental	0.00 | 0.18	0.00 | 0.20	0.01 | 0.05	0.00 | 0.08	0.00 | 0.21	0.00 | 0.29
	M2 | Biophysical	0.00 | 0.06	0.00 | 0.03	0.00 | 0.05	0.00 | 0.03	0.00 | 0.21	0.00 | 0.20
	M3 | Leisure	**1.00 | 0.77**	**1.00 | 0.60**	0.09 | 0.09	**1.00 | 0.45**	**0.95 | 0.50**	**1.00 | 0.72**
	M4 | Visual-sensory	0.00 | 0.43	0.00 | 0.28	**0.90 | 0.43**	0.00 | 0.36	0.05 | 0.49	0.00 | 0.34
	M5 | Null model	0.00 | 0.00	0.00 | 0.00	0.00 | 0.00	0.00 | 0.00	0.00 | 0.00	0.00 | 0.00

FIGURE 3 Multimodel inference Akaike weights (wi) and explained adjusted deviance (D2). A gray shading (D2 > 0.10) is used in the figure to highlight the first (dark gray) and second (light gray) best models for each category of cultural contributions
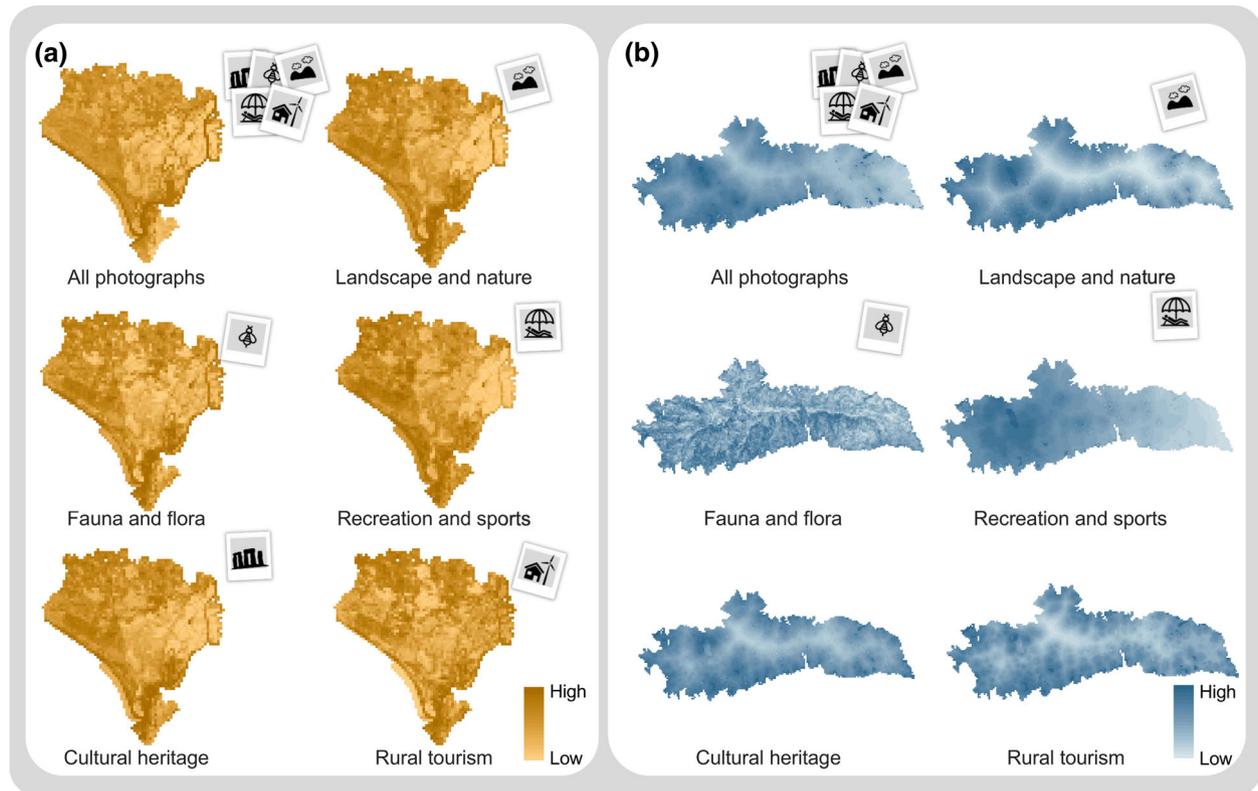
FIGURE 4 Spatial projections of average models for the categories of nature's contributions to people in Doñana (a) and Sierra Nevada (b). Darker colors on the maps indicate a higher potential for cultural contributions

predictors on nature's cultural contributions (Figure 4; see Table S2 for details). In Doñana, higher potential for nature's contributions was found in areas with higher spatial heterogeneity of vegetation functioning, higher landscape contiguity, and lower shape complexity (Figure 4a). These correspond to transition areas between natural forests and beaches (southwest part of the reserve) and to marshlands and rice fields neighboring the Guadalquivir river (eastern part; Figure 4a).

In Sierra Nevada, the heterogeneity of vegetation functioning was also an important predictor for "fauna and flora" photographs, which are potentially more common in the upper hills and mountain headwaters (south and west parts; Figure 4b). The potential distribution of the remaining categories prevailed around villages, public infrastructures (e.g., viewpoints), and ski facilities. With the exception of "recreation and sports," there was also an association with the proximity to roads and trails as well as to structurally complex landscapes (Figure 4b).

4 | DISCUSSION

This study describes an approach to assess the potential for nature's cultural contributions to people, combining information from social media and Earth observations in a multimodel inference framework. Our approach was tested in two contrasting biosphere reserves and allowed the evaluation

of nature's cultural contributions and their key predictors. The analysis of Flickr content showed contrasting numbers of photos assigned to each category of nature's cultural contributions in Doñana and Sierra Nevada (Figure 2). "Landscape and nature" prevailed in both reserves, being congruent with the natural values that typically dominate protected areas (Hausmann et al., 2018; Richards & Friess, 2015). "Cultural heritage" and "fauna and flora" were also widely represented in Doñana, whereas "rural tourism" and "recreation and sports" were more common in Sierra Nevada. These patterns also reflect the natural and cultural capital of the two reserves: Doñana includes natural wetland landscapes and a diversity of species that are attractive for many visitors (especially birdwatchers), while also holding popular cultural and religious traditions, whereas Sierra Nevada offers mountain-related activities (e.g., skiing), alongside rural villages of touristic importance (e.g., Alpujarras).

Multimodel inference revealed that nature's cultural contributions from the two biosphere reserves relate with different Earth observation predictors (Figure 3). In Doñana, those contributions were primarily explained by landscape visual-sensory attributes expressing the heterogeneity of vegetation functioning (based on NDVI and ESPI). These results converge with previous studies highlighting the importance of remotely sensed visual-sensory attributes (related to vegetation functioning) for the assessment of

ecosystem benefits (Krishnaswamy, Bawa, Ganeshaiah, & Kiran, 2009; Paruelo et al., 2016). However, despite the potentialities of considering the seasonality of color diversity in the evaluation of landscape appreciation (Vaz et al., 2019), no significant relation was found between nature's cultural contributions and predictors expressing landscape color diversity. Nevertheless, landscape biophysical attributes (i.e., shape complexity and patch contiguity) explained nature's cultural contributions oriented to "recreation and sports" (e.g., beach activities) and "cultural heritage" (e.g., monument visitation). This agrees with the previous work from Tengberg et al. (2012), Tieskensa, Van Zanten, Schulp, and Verburg (2018), or Tveit, Ode, and Fry (2006) on which landscape patterns shape the character of the landscape enrolled in the supply of recreation, aesthetic, and heritage values.

In contrast to Doñana, the different categories of nature's cultural contributions of Sierra Nevada were driven by a larger number of predictors. Due to its topographic heterogeneity and land-use diversity, Sierra Nevada is a complex territory with potential to deliver a variety of nature's contributions to people (Zamora, Pérez Luque, Bonet, Barea-Azcón, & Aspizua, 2016). The distribution of "fauna and flora" contributions was the only one primarily determined by landscape visual-sensory attributes. The remaining contributions, however, were mostly associated to the presence of recreation features (i.e., ski sites) and tourist attractions (i.e., villages), particularly in accessible areas (e.g., near trails). These results are congruent with previous studies showing a relevant role of leisure facilities and terrain accessibility in explaining nature's preferences by people in mountain landscapes (Schirpke, Timmermann, Tappeiner, & Tasser, 2016; Tenerelli et al., 2016; Vaz et al., 2019). Conversely to previous studies (Schirpke et al., 2016; Van Berkel et al., 2018), no significant relation was found with visual accessibility (i.e., viewshed dimension), suggesting other factors as most relevant for nature's enjoyment and preferences by people in the test areas.

The spatial projection of the predictive models allowed to identify and map the potential distribution of nature's cultural contributions in both biosphere reserves (Figure 4). In Doñana, this potential seems to match with transition areas between natural forests and beaches, as well as with nearby marshlands and rice fields along the river. In Sierra Nevada, nature contributions appear to be most prevalent in the neighborhood of villages, public infrastructures, and ski facilities, as well as along hiking trails and roads. An exception is found for the cultural appreciation of "fauna and flora," particularly evident in upper hills and headwaters, where most endemic species typically occur (Blanca, Cueto, Martínez-Lirola, & Molero-Mesa, 1998). The maps produced for the two reserves generally agree with those obtained for nature tourism based on the attribution of land-use scores (Palomo, Martín-López, Alcorlo, & Montes, 2014), adding detail on the potential

location of different nature's cultural contributions. Our spatial projections can inform management decisions, for example, on prioritizing land planning efforts and resources (Krishnaswamy et al., 2009). They can also be used to maximize synergies between biodiversity conservation and cultural values (Turnhout et al., 2013), identify conflicting areas between tourism and strictly protected zones (Van Cuong et al., 2017), support the monitoring of the natural and cultural capital through remote observations (Arts et al., 2015), and assist on data collection and dissemination for scientific research and evidence-based conservation (Sherren et al., 2017).

Our approach does justify some methodological considerations. First, social media users make decisions on which photos they share in social networks, not necessarily meaning that those photos express their most preferred and valued elements from nature (e.g., Malik, Dhir, & Nieminen, 2016). The process of cultural evaluation of nature differs across social–ecological contexts, individuals, and time (Di Minin et al., 2015). Future research should focus on understanding the motivations underlying people's choices and perceptions toward nature, for instance by using complementary sources of social media content (e.g., tags and platforms; Gosal et al., 2019; Oteros-Rozas et al., 2018). Second, Earth observation (satellite and GIS) data were available at different spatial scales, potentially biasing comparisons among them. However, this was likely insignificant in our study, due to the aggregation of photographs and predictors at coarser resolutions. Nevertheless, considering time series data could be a useful approach in the future to further understand seasonal variations (e.g., Summer vs. Winter) in nature-based contributions and preferences (Vaz et al., 2019). In addition, improvements could also be made by considering additional sources of predictors in the models (e.g., demography and economy; Tenerelli et al., 2016), whenever available.

Our study considered the most relevant available spatial data to assess the cultural contributions from nature and biodiversity in the biosphere reserves of Doñana and Sierra Nevada. We combined Earth observations and social media data to identify the major nature's cultural contributions in the two reserves, to understand how they relate with distinct Earth observation predictors, and to evaluate the potential for nature's cultural contributions in a spatially explicit way. The content analysis of social media photographs showed a dominance of different categories of nature's cultural contributions, in agreement with the natural and cultural capital of these biosphere reserves. Those contributions also related with different Earth observation predictors, being mostly shaped by visual-sensory attributes that characterize Doñana landscapes, and by points of leisure interest, landscape heterogeneity, and environmental accessibility that shape Sierra Nevada.

The analytical framework proposed in this study is reproducible in other (protected) areas. Inevitably, some

adjustments are required, such as different image categories (for social media content) or devising other image features from satellite data. Current advances in automated satellite processing (Fu & Rui, 2017) and social media content analysis (Gosal et al., 2019), together with increasing availability of satellite data with enhanced coverage (e.g., Guanter et al., 2015) and developments in powerful geospatial analysis platforms (e.g., Gorelick et al., 2017), will boost the assessment of nature's cultural contributions to people and the monitoring of conservation targets in wider areas.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.