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Social media-based analysis of cultural ecosystem services and heritage tourism in a coastal region of Mexico

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ABSTRACT

Understanding spatial patterns of visitation and benefits accrued to different types of natural and cultural heritage tourists may have important implications for the sustainable management of their destinations. We investigate cultural services accrued to local, domestic and international visitors to the Usumacinta floodplain, a coastal region with one of the highest biological and cultural diversities in Mexico. We combine analysis of social media photographs and high-resolution land cover mapping to identify different cultural services and their association with specific ecosystem and land cover types. Hotspots for international tourists are spatially restricted to well-known and accessible sites. Locals are 2.2–2.5 times more likely than international visitors to be associated with aesthetic appreciation and birdwatching. Locals upload more photographs of coastal lagoons, mangroves, beach and sea. Results are analyzed in light of land cover changes in the region and provide valuable information to decision makers for improved tourism management and conservation strategies.

1. Introduction

Tourism, recreation and other direct cultural interactions with the natural environment and built historical patrimony may play an important role in the conservation and sustainable management of natural ecosystems and cultural heritage sites as well as contribute to the development of local and regional communities. Ecotourism (or nature-based tourism) and cultural heritage tourism – which is understood here as an "activity by tourists in a space where historic artefacts are presented" (Poria, Butler, & Airey, 2004) – may promote win-win scenarios, in which tourists benefit from an enjoyable experience of nature and local culture, there are economic benefits for tour operators, and parts of the funds raised are reinvested in environmental conservation and improving livelihoods within local communities (Ardoin, Wheaton, Bowers, Hunt, & Durham, 2015; Stronza & Durham, 2008). While the debate on the extent to which such benefits are actually realized (Higham, 2007; Torre & Scarborough, 2017) and what constitutes sustainable tourism (Asmelash & Kumar, 2019) are still ongoing, the growth of the (eco)tourism industry in many parts of the world makes this an important area of research especially where destination sites are ecologically and/or culturally fragile (Balmford et al., 2015).

In this context, local, domestic and international visitors often differ in their cultural preferences as well as the spatial and temporal distribution of their visitation patterns. Visits by tourists tend to be more spatially concentrated than those by residents (Garcia-Palomares, Gutierrez, & Minguez, 2015; Munoz, Hausner, Brown, Runge, & Fauchald, 2019) and focus on hotspots that are more easily accessible and better equipped with infrastructure (Heagney, Rose, Ardeshiri, & Kovac, 2017; Su, Wan, Hu, & Cai, 2016). Domestic visitors may hold different attitudes toward wilderness areas compared to international visitors, whereby the expectations of the latter are often informed by the marketing strategies of tour operators (Higham, Kearsley, & Kliskey, 2001) or, in recent years, social media activity (see for instance Simmonds et al., 2018). Place-based values within natural areas that are mapped by local residents in the context of participatory GIS studies tend to differ in their spatial distribution from those produced by domestic and international visitors and, even where they overlap, locals and tourists may associate different benefits for the same areas (Munoz et al., 2019; Munro, Kobryn, Palmer, Bayley, & Moore, 2017). In urban contexts, downtown areas tend to be the most popular destinations for tourists, whereas cultural and recreational destinations are more attractive for locals (Li, Zhou, & Wang, 2018). Such differences are consistent with the

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relational dimension of cultural ecosystem services, whereby values do not simply reflect individual preferences but need to be understood in the context of the culture that informs them and, in the case of experiences shared with a broader social network (such as social media content), by social norms through the expected peer reaction (Calcagni, Maia, Connolly, & Langemeyer, 2019).

Understanding such differences may have important management, planning and decision-making implications. This is true in particular for areas that include multiple attractions, such as sites of natural and cultural interest, and are exposed to anthropogenic pressures that may differentially affect segments of the visitors' population. Characterizing the similarities and dissimilarities in the way different types of visitors interact with them may, for instance, help avoiding conflicts in areas where increased international tourism threatens the enjoyment of cultural benefits held by local residents (Li et al., 2018; Wray, Espiner, & Perkins, 2010), as exemplified in the rising anti-tourism sentiment that has recently been experienced in various popular tourist destinations (Clancy, 2017; Coldwell, 2017; Mihalic, 2018). Moreover, ecosystems such as wetlands, which are often perceived as having low economic value (Ghermandi, van den Bergh, Brander, de Groot, & Nunes, 2010) and are thus at risk of conversion to different land uses such as urban or agricultural, may be associated with important cultural values for the local population but not for non-native visitors. Finally, such information can be used to optimize the location of infrastructure and services provided to the visitors, as well as provide business opportunities for meeting their specific demands and developing currently touristically unexploited areas (Garcia-Palomares et al., 2015).

Recent developments in online social networking sites and portable GPS devices offer opportunities to improve our understanding of how ecosystems and cultural heritage sites are engaged with or enjoyed by visitors, at a fine scale (Liu et al., 2015). Traditionally, such information has been collected through surveys, interviews (e.g., on-site, phone- or internet-based) or focus groups with destination tourism stakeholders (Vu, Li, Law, & Ye, 2015). These approaches, however, involve time-consuming processes, are resource-intensive and often impractical at large scales. Social media users produce and publicly share online a large volume of georeferenced data (e.g., geotagged photographs), which is well suited to be collected and analyzed at large scales, low costs and in near-real time (Ghermandi & Sinclair, 2019). A primary focus of environmental research focusing on social media data is the spatial and temporal characterization of cultural ecosystem services, more specifically of non-extractive recreational activities (e.g., hiking, walking, birdwatching, boating) and assessment of aesthetic benefits over large scales. Among the applications, one may count the evaluation of factors contributing to eco-tourist satisfaction and tourism sites attractiveness (Tenkanen et al., 2017; Hausmann et al., 2017; Giglio, Bertacchini, Bilotta, & Pantano, 2019), the extraction of points of interest or hot spots of cultural value (Figueroa-Alfaro & Tang, 2017; Ghermandi, 2016; Lee, Cai, & Lee, 2014; Levin, Kark, & Crandall, 2015; Mancini, Coghill, & Lusseau, 2018), and the mapping of aesthetic appreciation of landscapes and scenic areas (van Zanten et al., 2016; Langemeyer, Calcagni, & Baro, 2018; Van Berkel et al., 2018). The investigation of online photographs from the photo-sharing website Flickr (http://www.flickr.com) is second only to the analysis of text messages from Twitter (http://www.twitter.com) among the applications of social media in environmental research that were identified in a recent systematic review (Ghermandi & Sinclair, 2019). Geotagged photo counts generally show a good correlation with observed spatial and temporal patterns of visitation (Preis, Botta, & Moat, 2019; Sinclair, Ghermandi, & Sheela, 2018; Tenkanen et al., 2017; Wood, Guerry, Silver, & Lacayo, 2013) and enable to convey policy-relevant information through effective visualization and analysis in maps. While several studies have investigated how online photographs can be used to identify specific cultural services (e.g., Donaire, Camprubi, & Gali, 2014) or the spatial distribution of visitors based on their origin (e.g., Garcia-Palomares et al., 2015), research on how specific cultural services are accrued to different users, including their spatial dimension and their association to different types of land covers, is largely missing.

A range of techniques for distinguishing between photographs uploaded by local residents, domestic tourists and international tourists have been used in the literature. The analysis of the information provided by Flickr users in their profiles, may be used to determine their hometown or current location, but only about 40–48% of the users provide this information (Da Rugna, Chareyron, & Branchet, 2012; Tenerelli, Pueffel, & Luque, 2017; Vu, Li, Law, & Ye, 2015). The username and/or the photographer's attitude towards the camera (e.g., whether he/she conforms to the convention of standing and smiling in front of the camera) may also provide useful indications concerning the user's provenance or whether he/she is a tourist (Angradi, Launspach, & Debbout, 2018; Donaire et al., 2014). Some studies propose to use time-based approaches such as a minimum time interval between photographs (Li, Goodchild, & Xu, 2013) or user activity restricted to a narrow timeframe over prolonged periods of time (Straumann, Coltekin, & Andrienko, 2014) to distinguish between local residents and tourists. Rules based on activity time span were used for instance by Koerbitz, Oender, and Hubmann-Haidvogel (2013) and Garcia-Palomares et al. (2015). Da Rugna et al. (2012) propose a combination of learning algorithms and expert-defined rules relying on time-based criteria to identify the country of origin of Flickr users. Bojic, Massaro, Belyi, Sobolevsky, and Ratti (2015) propose five methods to infer the home location of Flickr and Twitter users, which rely on determining the place where the user took the maximal number of photos, spent the maximal number of user days (i.e., days in which at least one photo was taken), the time span between the first and last photograph is maximal, the user took the maximal number of photos or was most active during night hours. Ghermandi (2018) and Sinclair et al. (2018) explored several of the techniques proposed by Bojic et al. (2015) and Li et al. (2013), concluding that the most accurate results are provided by the rule that infers home location from the location with most active user days.

The three main approaches that have been explored in the literature to associate online photographs with the specific type(s) of cultural services they reflect rely on the analysis of: (1) the content of the photographs; (2) the text associated with photographs' titles and tags; and (3) a combination of the two. The most common approach consists in manually analyzing the actual content of individual photos in order to classify them into categories (e.g., "Nature", "Heritage", "Culture" and "Tourist services") based on the presence or absence of specific elements in the photos, such as views of flora and fauna, historical buildings, or tourist infrastructure and facilities (Donaire et al., 2014; Heikinheimo et al., 2017; Martinez-Pastur, Peri, Lencinas, Garcia-Llorente, & Martin-Lopez, 2016; Tieskens, Van Zanten, Schulp, & Verburg, 2018). Some authors rely on categories that do not reflect common classifications of cultural ecosystem services to avoid investigator biases related to the perceived subjective nature of such classifications (Oteros-Rozas, Martin-Lopez, Fagerholm, Bieling, & Plieninger, 2018; Van Berkel et al., 2018). More nuanced, but potentially more open to subjective interpretations, versions of this approach involve trying to account for the intent of the photographer when taking the photograph (Angradi, Launspach, & Debbout, 2018) or focusing on the main subject of the photograph only (Bandara & Bandara, 2019; Casalegno, Inger, DeSilvey, & Gaston, 2013; Hausmann et al., 2017; Richards & Friess, 2015). A different approach relies on the investigation of the text associated with the titles and tags of the photographs. The presence of keywords may be used to identify specific types of cultural ecosystem services (Mancini et al., 2018; Spalding et al., 2017; van Zanten et al., 2016) or identify and eliminate irrelevant photographs (Mancini et al., 2018). Lists of keywords may be defined *a priori* by the investigators (van Zanten et al., 2016) or built bottom-up from the analysis of (a sample of) the entire corpus of keywords in the set of photographs under investigation (Dunkel, 2015; Mancini et al., 2018). A third approach consists in relying on machine learning algorithms to automatically tag photos based on the content of the image and subsequently use such tags to classify the photographs into categories of cultural ecosystem services (Lee, Seo, Koellner, & Lautenbach, 2019; Richards & Tuncer, 2018).

In this study we develop and apply innovative techniques to investigate cultural ecosystem services and historical heritage tourism and recreation activities experienced by local, domestic and international visitors to the region of the Usumacinta floodplain, a 25,000 km^2 coastal region with 7,000 km^2 of wetland extent and one of the highest biological and cultural diversities in Mexico. The emphasis is on the characterization of the different ways in which the three categories of users experience an individual site or ecosystem type, both in terms of the spatial distribution as well as the different types of benefits accrued through the recreational experience. This objective is achieved through the analysis of 8,245 photographs uploaded by visitors to the photo-sharing website Flickr and geotagged within the Usumacinta floodplain.

The remainder of this manuscript is organized as follows. Section 2 presents the case-study area. Section 3 discusses the methodologies implemented in the present study for the retrieval of geotagged photographs' data, characterization of the visitors based on their home location, association of the photographs with specific cultural services, high-resolution land cover mapping of the floodplain, and spatial/statistical analyses. Sections 4 and 5 respectively summarize the main results of the study and discuss them in the context of the literature and for their implication for the management of the natural capital and cultural heritage sites in the case-study region.

2. Case-study area: the Usumacinta floodplain

The Usumacinta floodplain (Fig. 1) is located in the southern Gulf of Mexico and is considered to be among the richest in Mexico for natural capital and cultural heritage (Carabias, Sarukhán, de la Maza, & Galindo, 2010; Hudson et al., 2005, p. 57). Freshwater pulses with high suspended sediments, inorganic nutrients and organic materials generate extensive wetlands (e.g., mangroves and coastal lagoons), notably including Terminos Lagoon and Centla Swamps. These two natural protected areas constitute major portions of the floodplain system (Yáñez-Arancibia, Day, & Currie-Alder, 2009), support a substantial fishing activity for local communities, and maintain a high diversity of invertebrates and aquatic vertebrates that are representative of the tropical wetlands of Mesoamerica (Sanchez et al., 2012). Fisheries also include reef fish, coastal migratory pelagic fish, and large oceanic pelagics of great importance at an international level (Yañez-Arancibia & Day, 2004), which also depend on the ecological integrity of the Usumacinta floodplain system, its waters and the quality of their habitats.

Given the richness of their ecosystems together with its cultural heritage sites, such as the Mayan ruins at Palenque, this region has become a very attractive destination for tourism and recreation activities. The archaeological zone of Palenque alone received around 600,000 visitors during 2016 (http://www.estadisticas.inah.gob.mx/). Tourism is an important source of foreign currency in the region. Other

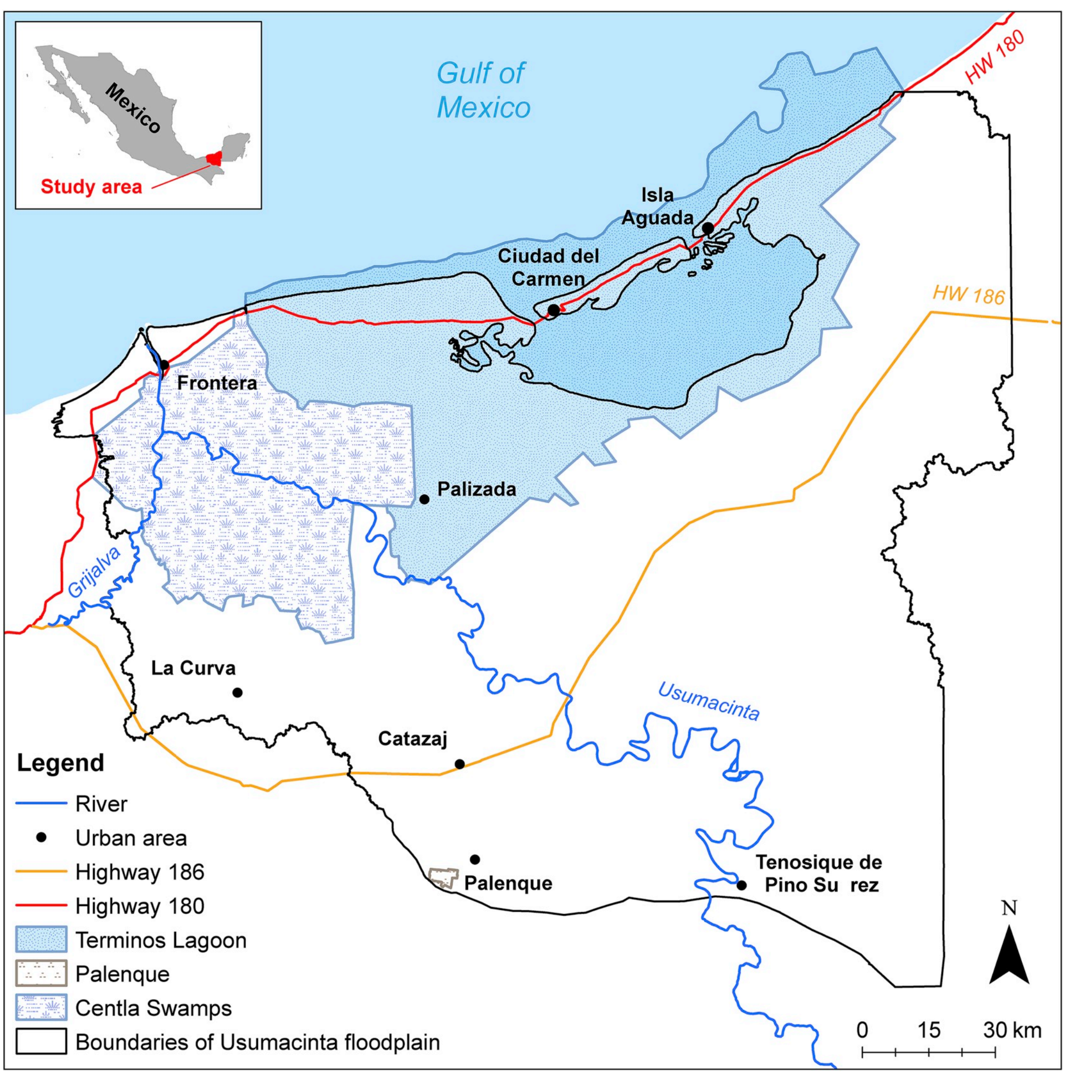

Fig. 1. Study area: the Usumacinta floodplain in Southern Mexico. The river and highway layers are derived from OpenStreetMap data.

important economic activities in the region are oil and gas production, and agriculture. These activities often lead to contamination and habitat destruction, inducing uncertainty both in economic development but also leading to conflicts of interest with environmental values (Yáñez-Arancibia, 1999).

The importance of nature-based and cultural heritage tourism and recreation both for local residents and tourists, the variety of natural ecosystems that are present (coastal lagoons, mangroves, tropical forest, sandy beaches, riverine ecosystems), as well as the threats from pollution and habitat destruction that it is currently experiencing, make the Usumacinta floodplain an ideal region in which to test the applicability of social media data analysis for the mapping and characterization of cultural services.

3. Materials and methods

3.1. Data retrieval and classification of visitors

We retrieved and analyzed the metadata of 8,245 geotagged photographs taken within the boundaries of the Usumacinta floodplain using Flickr's Application Programming Interface (API; https://www.flickr.com/services/api). Metadata, including geotags, photo titles and user-provided tags, were retrieved using the flickr.photos.search API method for a rectangular boundary box containing the study area. Photographs tagged outside of the study area were subsequently removed in ArcGIS 10.6.1. The photographs were taken between 1 January 2004 and 16 March 2017 and uploaded to Flickr by 499 individual users. The public profile of all 499 users was retrieved using the flickr.profile.getProfile and flickr.people.getInfo API methods, and subsequently investigated to determine the current home location if reported or, in the absence of such information, the hometown of the visitors. For users who do not disclose their current location or hometown in their profile, the metadata of all public photos they uploaded to Flickr were retrieved by means of the flickr.people.getPublicPhotos API method and analyzed to determine the area with the highest number of active user days, according to the procedure described in Ghermandi (2018) and Sinclair et al. (2018). Users residing within the states of Chiapas, Tabasco or Campeche were classified as local residents. A further distinction was established between domestic tourists residing in other parts of Mexico and international visitors.

3.2. Identification of cultural services

For the identification of the cultural services associated with the photos, we relied on the CICES 5.1 classification (Haines-Young & Potschin, 2018). Since the study builds on photographs that were taken by actual visitors to the area, we only considered the five classes of cultural ecosystem services that reflect direct, in-site and outdoor interactions that depend on actual presence in the environmental setting. Services reflecting "physical and experiential interactions with the natural environment" were further subdivided based on whether the interaction is with plants, birds, other wild animals, or specific elements of the landscape (e.g., waterfall, ocean, climbing). Services associated with historical sites were incorporated in the class of cultural heritage services. No distinction was made between services derived from biotic or abiotic components of the ecosystems.

In order to classify the photographs based on the class of cultural service they reflect, if any, we investigated the text associated with the titles and tags of the photos. A total of 24,517 words were extracted from the 6,317 photographs that were associated with a title and/or one or more tags. Most words were in Spanish and English, but German, French and Italian words were also found, in addition to Latin terms identifying the scientific names of various animal and plant species. The highest number of photographs was taken in 2013 (1,276 photos) followed by 2012 (1,034 photos). Fig. S2 in the Supplementary Materials shows the temporal distribution of the 6,317 photographs.

After removing duplicates, the words were investigated to identify terms associated with specific cultural services. Table S1 in the Supplementary Materials provides an overview of the cultural services identified and the keywords associated with each of the services. Photographs with multiple keywords in title or tags could be classified under multiple cultural services. The authors jointly reviewed the classification of keywords and divergences were discussed until an agreement was reached. To test the reliability of the keyword classification procedure, the content of 278 of the photos with a meaningful title and/or tags was independently assessed for whether the photograph was associated with a cultural service. The agreement between the keyword and content-based classifications was evaluated by means of Cohen's kappa coefficient (Cohen, 1960). All keyword-related analyses were performed in Microsoft Excel.

3.3. High-resolution land cover map

The land cover classification maps used in this study were produced from multi-spectral Landsat 8 OLI (path/row: 21/47; 22/47 and path/row: 21/48; 22/48) images acquired in April, May and November 2014 from the USGS Global Visualization Viewer (http://glovis.usgs.gov/). These images have eleven spectral bands and a 30-m resolution. The choice of 2014 as the year of reference for the land cover, accounts for the fact that 60% of the analyzed photographs were taken in the period 2012–2016 (see Fig. S2). A similar land cover map was produced for 2017 and used to identify changes in land cover for the relevant land cover types.

IDRISI Selva and ArcGIS 10.6.1 were used for imagery classification, GIS development and output of the final land cover maps. Prior to the image classification process, atmospheric correction was performed using the Idrisi Selva AtmosC modul and some lineal features, such as rural and urban areas, were digitized on-line in Google Earth.

The classification was performed using a supervised method with the maximum likelihood algorithm, selecting training sites previously digitized online from a color composite scene, and then, the statistical information was extracted from the selected pixels (Campbell, 1996). The validation of the output map was assessed by an error matrix and Cohen's kappa coefficient (K′) (Cohen, 1960). An error matrix was constructed using this information as reference data and compared by cross-tabulation with pixels from the classification. Coincidences between both datasets (main diagonal) were used to estimate the overall accuracy (%) and kappa coefficient (K′) to measure the correspondence between the classification and the reference data (Congalton & Green, 1999). The test points for the analysis were selected at random from the resulting thematic map and validated in the field with the assistance of a GPS.

Table 1 describes the eight classes considered in the land cover map. To these, a ninth category of "Beach and sea" was added during the analysis of the geotagged photographs to account for photographs taken in the coastal ocean water or on one of the sandy ocean beaches in the

Table 1
Classes in high-resolution land cover map.

Class	Description
Agriculture	Induced land covers: agricultural, livestock, grassland
Coastal lagoon	Subtidal estuarine wetland
Lacustrine wetland	Lacustrine continental wetland permanent and seasonal: lake, pond, other water body
Mangrove	Forested-shrub estuarine wetland: plant association formed by one or a combination of different mangrove species
Palustrine wetland	Palustrine continental wetland with more or less permanent water: swamp, marsh, tular, popal
Riverine wetland	Permanent riverine wetland: rivers, channels
Tropical forest – other land cover	Natural vegetation: tropical forests, secondary vegetation
Urban	Urban areas: villages, towns

study area. Classification of such photos was performed in ArcGIS based on images from the World Imagery base map.

3.4. Spatial and statistical analysis

For the analysis of the spatial distribution of photographs, we relied on the Hot Spot Analysis (Getis-Ord Gi*) spatial statistical tools with a grid cells size of 300 m and a radius of 5 km, as implemented in ArcGIS 10.6.1 (Ghermandi, 2016). The tool was used to identify statistically significant clustering of photographs associated to cultural services for locals, other domestic visitors, and international tourists. Hot spots were identified at the 90% confidence level or higher.

The probability of photographs from users of different origins to be associated with specific cultural services was explored through logistic regression, controlling for the fact that users who took many photographs within the region were more likely to be associated with culturally tagged photographs and relying on the Wald test to evaluate whether the overall effect of the user's place of origin was statistically significant. In addition, we analyze whether culturally tagged Flickr photos revealed different behavior by users of different origin with regard to the land-cover type in the location where the photos were taken. For each land cover type and user, we calculate the number of culturally tagged photos (without distinguishing between the individual cultural services). We control for the number of geotagged photos taken by the user within the Usumacinta floodplain by dividing by the total number of photographs taken within the region. Given that the data is skewed due to the large number of users with zero photographs, we test for statistically significant differences across local, other domestic and international visitors with the Kruskal-Wallis (KW) test on ranks, a non-parametric test that does not require the assumption of normal distribution. Under the assumption of same shape distributions, we interpret the result as indicating differences in the medians across groups. When the null hypothesis of the KW test is rejected, we use the Conover-Iman test with the Bonferroni adjustment for multiple comparisons as a *post hoc* test for pairwise comparisons across groups.

4. Results

In total, 264 of the investigated Flickr users reported their home location in their profile, corresponding to 53% of the total sample of users, a percentage that is slightly higher than what found by Da Rugna et al. (2012) and (Tenerelli, Pueffel, & Luque, 2017). Through the analysis of the entire dataset of public photos uploaded to Flickr, we could infer the home location of additional 205 users. Local residents, domestic tourists, and international tourists accounted for 19%, 30% and 51% of the sampled users, respectively. Most of the international tourists were from European (27%) and North American countries (14%).

Of the 6,317 photographs with titles and/or tags, 3,476 (55%) were found to be associated with one or more cultural services. Fig. 2 shows the results of the spatial analysis of the distribution of culturally-tagged photographs, according to the provenance of the user associated with them.

Hot spots of cultural services as derived from photographs taken by international visitors are primarily concentrated in correspondence to the archaeological sites at the Mayan ruins of Palenque, reaching in that area a substantially higher density than those of other visitors (Fig. 2B), and, to a lesser extent, the city of Ciudad del Carmen. Although the

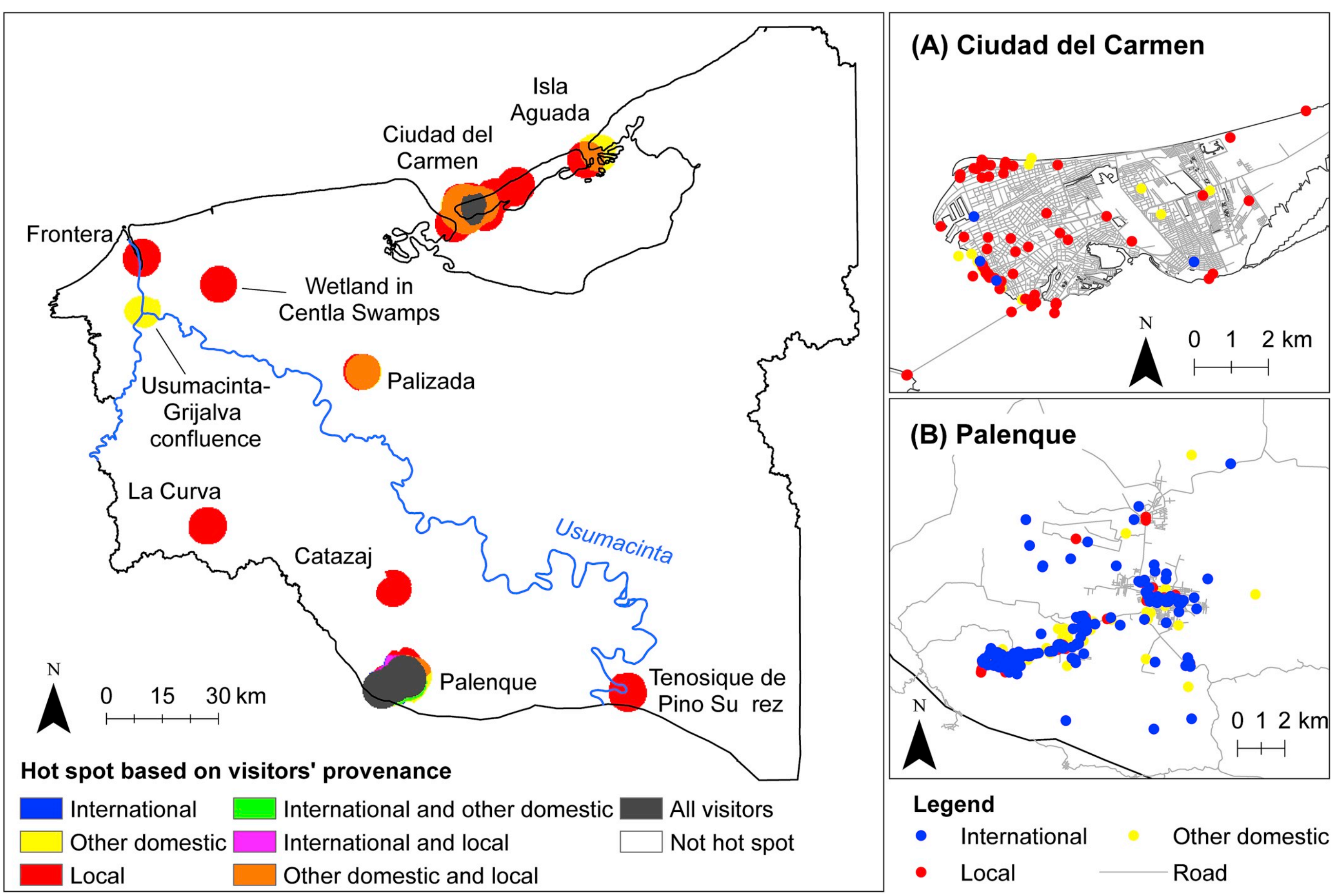

Fig. 2. Hot spots of cultural services for locals, domestic visitors and international tourists. Panels A and B show, respectively, the distribution of geotagged photographs with cultural tags in Ciudad del Carmen (A) and Palenque (B), based on visitors' provenance. The road layer is derived from OpenStreetMap data.

Palenque and Ciudad del Carmen areas appear to be of high cultural significance also for locals and other domestic visitors, the photographs associated with cultural keywords from local and domestic visitors are more widespread within the floodplain. For these visitors, additional hot spots are observed within the Terminos Lagoon protected area (e.g., Isla Aguada and Palizada). Specific wetlands within the Centla Swamps protected area and the Usumacinta-Grijalva confluence are, respectively, hot spots for local visitors and domestic tourists. Other urban areas such as Frontera, La Curva, Catazajá and Tenosique de Pino Suárez are of primary interest for locals but not for other visitors. Also within the Ciudad del Carmen hot spot, photographs by locals and, to a lesser extent, domestic visitors are more widely widespread over the broad urban context than those of international visitors (Fig. 2A). For all users there appears to be some correspondence between the location of photographs and the presence or urban areas and major roads in the region. In particular, there appears to be an alignment with the Federal Highway 180, which runs parallel to the coast, and, for international visitors only, with the Federal Highway 186 (see Fig. S1 in the Supplementary Materials). The latter observation is consistent with the fact that highway 186 is of high importance for the transit of tourists toward some the most touristic zones in Mexico located in the Yucatan Peninsula.

The analysis of the photographs' titles and tags revealed 813 individual keywords that could be associated with cultural ecosystem services and cultural heritage tourism. Comparison of such keyword-based classification with the classification of photographs based on the image content reveals a fair to good agreement between the methods. For the test subset of 278 photographs with a meaningful description in their titles or tags, we found an 87.5% overall classification agreement (Cohen's kappa = 0.54). On average, international tourists uploaded more photographs (15.3 photos per capita) than domestic tourists (7.2 photos per capita) and local residents (12.3 photos per capita). Visitors from the US and Canada were particularly active (23.0 photos per capita). The majority of photographs from international tourists (67%) were associated with at least one cultural service, compared to 46% and 50% for locals and domestic tourists, respectively. In particular, 62% of the photos from international tourists pertained to cultural heritage, with a peak of 72% for European visitors.

Table 2 shows the results of the statistical regression analysis. After controlling for the number of culturally-tagged photos taken within the Usumacinta floodplain, whose sign is as expected positive and statistically significant for all models, the logistic regression confirms that international tourists are more likely to be associated with cultural photographs among all visitors (N = 468), and in particular with cultural heritage. Interestingly, though, local visitors are more likely to be associated with birdwatching and photographs reflecting aesthetic value and mental health than any other visitor type. Domestic visitors are less likely to be associated with photographs of wild animals (other than birds) than international tourists and local residents, although the statistical significance of such finding is not confirmed by the Wald test (p = 0.130).

Table 3 builds on the results of the logistic regression to evaluate the probability of visitors to be associated with specific types of cultural services. Probabilities in Table 3 are calculated at the sample mean number of photos (12.3 photos per capita), thus controlling for the fact that international visitors take and upload more geotagged photographs than locals and domestic tourists. Overall, international visitors are more likely to be associated with at least one culturally tagged photograph, but this is largely driven by the fact that they are 1.5–2.1 times more likely than, respectively, domestic and local visitors to take and upload photographs of historical cultural heritage sites, which is consistent with the observations regarding their spatial distribution. By contrast, local inhabitants are 2.2 and 2.5 times more likely than international visitors to be associated with photographs reflecting aesthetic appreciation/mental health and birdwatching. All visitor types have a relatively high probability of being associated with elements of

Table 3
Probability of visitors being associated with a culturally-tagged photo measured at sample mean number of photos.

Cultural service	International	Other domestic	Local
Birds	7.1%	9.2%	17.8%
Other animals	15.3%	6.0%	12.8%
Plants	24.7%	17.6%	21.1%
Element of landscape	29.3%	36.5%	32.7%
Aesthetic and mental health	16.2%	18.5%	35.5%
Cultural heritage	71.8%	47.9%	33.8%

Table 2
Results of logistic regression for visitors' association with cultural services based on origin and number of geotagged photos taken in the Usumacinta Floodplain.

	Any cultural service	Physical and experiential: Observation of				Intellectual and representative	
		Birds	Other animals	Plants	Element of landscape	Aesthetic and mental health	Cultural heritage
Intercept: estimate	0.718***	−3.495***	−3.310***	−2.115***	−1.880***	−2.838***	0.467***
[95% confidence interval]	[0.363, 1.084]	[-4.332, −2.768]	[-4.082, −2.633]	[-2.619, −1.650]	[-2.331, −1.458]	[-3.450, −2.285]	[0.126, 0.815]
Photos: estimate	0.566***	0.846***	1.463***	0.919***	0.918***	1.095***	0.431**
[95% confidence interval]	[0.212, 0.934]	[0.291, 1.407]	[0.939, 2.019]	[0.522, 1.325]	[0.562, 1.282]	[0.671, 1.532]	[0.099, 0.769]
Other domestic: estimate	−0.583**	0.287	−1.032**	−0.432	0.324	0.164	−1.022***
[95% confidence interval]	[-1.035, −0.132]	[-0.631, 1.162]	[-2.149, −0.109]	[-1.067, 0.166]	[-0.178, 0.823]	[-0.509, 0.814]	[-1.460, −0.590]
Local: estimate	−0.532**	1.045**	−0.200	−0.206	0.159	1.049***	−1.608***
[95% confidence interval]	[-1.057, −0.001]	[0.201, 1.881]	[-1.123, 0.629]	[-0.905, 0.445]	[-0.440, 0.738]	[0.405, 1.692]	[-2.158, −1.083]
Degrees of freedom	468	468	468	468	468	468	468
Null deviance	587.88	248.99	282.81	425.30	524.71	398.75	648.62
Residual deviance	567.96	234.96	242.43	400.39	498.43	363.31	593.21
Residual deviance test: p-value	<0.001	0.003	<0.001	<0.001	<0.001	<0.001	<0.001
Log-likelihood	−283.98	−117.48	−121.21	−200.20	−249.21	−181.81	−296.61
AIC	575.96	242.96	250.43	408.39	506.43	371.61	601.21
Wald test: p-value	0.021	0.044	0.130	0.370	0.440	0.004	<0.001
Error rate	32.0%	7.5%	8.7%	17.1%	25.6%	14.7%	35.0%

Notes: AIC = Akaike Information Criterion; *** and ** indicate respectively 1% and 5% statistical significance levels (p-value). "International" is the omitted variable for users' origin.

landscape photography (29.3–36.5%).

Table 4 shows the average number of geotagged Flickr photographs associated with specific cultural services and land cover types, differentiating based on the provenance of the visitors. Tropical forest and agricultural land covers are among the most photographed by all visitor types, consistently with the fact that Mayan ruins are mostly associated with these two land cover types. The Kruskal-Wallis and Conover-Iman tests, however, indicate that international users take and upload a significantly larger number of culturally tagged photographs in correspondence to such land cover types than any other category. By contrast, locals are associated with a higher number of photographs in correspondence to beaches and urban areas than domestic and international tourists, although the difference for urban areas is only statistically significant in comparison with international visitors. Coastal lagoons, mangroves, palustrine and riverine wetlands are less photographed than other land cover types, but also in correspondence of such ecosystems we identify a different behavior among users, with coastal lagoons and riverine wetlands being more highly photographed by locals than by international tourists.

The association of cultural services with specific land cover types is best understood in the context of the changes in the aggregate surface for each of the land cover classes within the Usumacinta floodplain between the year of reference 2014 and 2017 (Table 5).

Over the investigated years, all wetland land cover categories have experienced a decline in extent with the most notable changes being associated with riverine wetlands (−50.1%), palustrine wetlands (−42.7%) and mangroves (−32.2%). Such changes are reflected in the coverage increase of tropical forests (+24.5%) and urban cover (+149%). Local residents, and, to a lesser extent, domestic tourists who, based on the previous results, have a high affinity with the cultural services provided by coastal lagoons and riverine wetlands, may be more substantially affected by such changes than international tourists.

Table 5
Aggregate surface per land cover class in hectares within the Usumacinta floodplain in 2014 and 2017.

Class	Surface in 2014	Surface in 2017	Percent change 2014–2017
Agriculture	1,036,607	1,040,360	+0.4%
Coastal lagoon	228,201	201,138	−11.9%
Lacustrine wetland	58,980	52,921	−10.3%
Mangrove	108,018	73,286	−32.2%
Palustrine wetland	306,298	175,588	−42.7%
Riverine wetland	52,849	26,363	−50.1%
Tropical forest – other land cover	838,456	1,043,694	+24.5%
Urban	10,781	26,841	+149%

5. Discussion and conclusions

The results of this study support the notion that monitoring and analysis of the social media activity of the visitors to sites of environmental and historical importance may lead to an improved understanding of the spatial patterns of visitation and differences in how cultural benefits are accrued to various sectors of the population. Insofar as the Usumacinta floodplain is concerned, the cultural services enjoyed by international tourists tend to be more spatially concentrated around sites of international importance, major urban centers and major roads, as well as more limited in the types of services enjoyed, with a lower appreciation of the local fauna and beauty of nature than demonstrated by local residents. Moreover, local visitors are more likely associated to cultural ecosystem services provided by coastal lagoons and mangroves than international tourists.

This has potentially important implications for the sustainable management of the local natural capital and cultural heritage sites, because it allows to identify areas where overlapping interests may result in conflicts (e.g., around the area of Palenque) as well as prioritize and tailor conservation policies to the specific and spatially differentiated demands of different sectors of the population. This is particularly important in the case-study area in light of the substantial land use changes that it has been experiencing in recent years. Improved knowledge of the different ways in which visitors can experience a specific recreational site or ecosystem can help planners to better understand their respective preferences and thus improve tourism-related decision making.

This study suggests that the analysis of the text associated with the titles and tags of geotagged photographs uploaded to social media sites may be a useful alternative or complement to more common approaches based on the analysis of the visual content of images. In spite of the limitation that not all photographs are associated with a meaningful description, the fact that titles and tags are voluntarily assigned at a later time may lead to insights into the users' mental processes, personal conceptualization and memory of the scene that are not possible through the sole analysis of the image (Dror & Harnad, 2008; Dunkel, 2015). Tags may describe elements that are not directly visible or prominently featured in the image, and provide insights into the perceived relative importance of different visual elements. We propose that future studies on geotagged photographs from social media will focus on developing techniques to systematically and conjointly tap the information that can be derived from both types of analyses.

Consistently with previous studies, our findings support the notion that visits by international tourists are more spatially concentrated than those of residents (Garcia-Palomares et al., 2015; Munoz et al., 2019) and that domestic visitors may differ from international visitors in the interest they show for wilderness-related aspects (e.g., wild animals) (Munoz et al., 2019). The relatively high percentage of culturally-tagged photographs we identified for the Usumacinta floodplain is comparable with the results of previous similar studies (Angradi et al., 2018; Van Berkel et al., 2018). Further comparison with the study by (Angradi et al. (2018)) on ecosystem benefits in the Great Lakes provides some additional insights. Similarly to (Angradi et al. (2018)) findings concerning the St. Louis River, we also observed differences in the content of photographs by local, domestic and international visitors in terms of fauna,

Table 4
Average number of culturally tagged photographs per hundred Flickr photos taken within the Usumacinta Floodplain by user origin and results of Kruskal-Wallis and Conover-Iman tests for equal distributions.

	Agriculture	Beach and sea	Coastal lagoon	Mangrove	Palustrine wetland	Riverine wetland	Tropical forest	Urban area
International (N = 88)	25.3	1.0	0.2	0.0	0.2	0.1	29.7	4.9
Local (N = 141)	8.5	10.7	1.0	0.1	0.2	1.4	11.5	10.6
Other domestic (N = 240)	13.7	4.2	1.4	0.4	0.1	1.2	20.6	9.5
Kruskal-Wallis chi-squared	26.020***	24.611***	7.767**	5.953*	1.410	5.583*	16.524***	11.960***
Conover-Iman t-test-statistics								
Local-Other domestic	−0.934	3.322***	1.403	0.102	–	0.886	−1.617	1.699
Local-International	4.402***	−5.075***	−2.732**	−1.861	–	−2.213*	3.880***	−3.392***
Other domestic-International	3.979***	−1.651	−1.394	−2.065	–	−1.457	2.469**	−1.786

Notes: ***, ** and * indicate respectively 1%, 5% and 10% statistical significance levels (p-value).

albeit in the opposite direction, i.e., with local users taking more photographs of birds than other visitors. We did not however observe differences in terms of photographs of flora. Unlike (Angradi et al. (2018)), we also found that international tourists posted more photographs depicting cultural services than local residents and domestic visitors, which appears to be consistent with the fact that the Mayan ruins at Palenque are a major international tourist attraction.

In evaluating the results of this study, one should consider that some subjective judgment is unavoidable in the development of the set of keywords and association with specific cultural services. This problem appears to be shared by the bottom-up approach presented in the study and top-down approaches based on *a priori* definitions of keywords (van Zanten et al., 2016). To limit such investigator biases, some previous studies have chosen to rely on classifications based on the presence or absence in the photographs of specific elements (e.g., tourism infrastructure, recreational equipment, elements of fauna or flora) rather than established classifications of ecosystem services (Oteros-Rozas, Martin-Lopez, Fagerholm, Bieling, & Plieninger, 2018; Van Berkel et al., 2018). An integrated text and image content analysis promises to overcome some of the limitations involved in purely text- or image-based classifications (Kruk et al., 2019). Another limitation in the interpretation of the results concerning the local population lies in the fact that domestic and international visitors are presumably more likely to upload photographs through their social networks, because unique events and situations are more likely to be shared (Ghermandi & Sinclair, 2019; Wood et al., 2013). This may bias the composition of the sample of visitors and implies that natural environments in remote locations that are not visited by tourists may be less suited for social media-based analyses (Becken, Stantic, Chen, Alaei, & Connolly, 2017). Moreover, the results of social media-based analyses may be influenced by social media trends whereby the popularity of specific destinations may promote positive feedbacks through increased visitation and increased likeliness to share photographs online. One should also acknowledge that geotagged photographs uploaded to social media likely represent a very small proportion of the total number of photographs taken by visitors (Figueroa-Alfaro & Tang, 2017). Finally, one should emphasize that although social media analysis can in principle be applied to a wider range of cultural services, in this study the analysis is limited only to the subset of cultural benefits that require physical presence and interaction with the environmental setting (Haines-Young & Potschin, 2018).

In conclusion, the present study supports the notion that the wealth of information that the users of online social networking services daily upload and make publicly available on their profile webpages represents a valuable source of information for an improved understanding of how cultural ecosystem services and benefits from cultural heritage tourism are accrued to different categories of beneficiaries and in their spatial complexity. This, in turn, may be integrated into the policy discussion and decision-making processes to yield much needed, better-informed strategies for mainstreaming the conservation and sustainable management of natural capital and cultural heritage.

Author contribution

AG and VCV conceived, performed the analyses and wrote the manuscript. THE produced the high-resolution land cover map of the study region.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.tourman.2019.104002.

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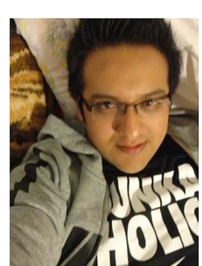

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