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Article *in* Journal of Great Lakes Research · April 2018

DOI: 10.1016/j.jglr.2017.12.007

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Journal of Great Lakes Research xxx (2018) xxx–xxx

Contents lists available at ScienceDirect

Journal of Great Lakes Research

journal homepage: www.elsevier.com/locate/jglr

Determining preferences for ecosystem benefits in Great Lakes Areas of Concern from photographs posted to social media

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A R T I C L E   I N F O

Article history:
Received 21 June 2017
Accepted 12 December 2017
Available online xxxx

Communicated by Marc Gaden

Keywords:
Great Lakes Areas of Concern
Social media
Photo sharing
Ecosystem services and benefits
Decision making
Restoration

A B S T R A C T

Relative valuation of potentially affected ecosystem benefits can increase the legitimacy and social acceptance of ecosystem restoration projects. As an alternative or supplement to traditional methods of deriving beneficiary preference, we downloaded from social media and classified ≈21,000 photographs taken in two Great Lakes Areas of Concern (AOC), the St. Louis River and the Milwaukee Estuary.

Our motivating presumption was that the act of taking a photograph constitutes some measure of the photographer's individual preference for, or choice of, the depicted subject matter among myriad possible subject matter. Overall, 17% of photos downloaded from the photo-sharing sites Flickr, Instagram, and Panoramio depicted an ecosystem benefit of the AOC. Percent of photographs depicting a benefit and the photographs' subject matter varied between AOCs and among photo-sharing sites. Photos shared on Instagram were less user-gender biased than other photo-sharing sites and depicted active recreation (e.g., trail use) more frequently than passive recreation (e.g., landscape viewing). Local users shared more photos depicting a benefit than non-local users. The spatial distribution of photograph locations varied between photos depicting and not depicting a benefit, and identified areas within AOCs from which few photographs were shared. As a source of beneficiary preference information, we think Instagram has some advantages over the other photo-sharing sites. When combined with other information, spatially-explicit relative valuation derived from aggregate social preference can be translated into information and knowledge useful for Great Lakes restoration decision making.

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Introduction

The assessment of ecosystems services (key terms are defined in Table 1) and associated ecosystem benefits has been recognized as useful for prioritizing, designing, and comparing habitat conservation and restoration projects (reviewed by Boulton et al., 2016). Angradi et al. (2016) showed how habitat restoration scenarios for Great Lakes Areas of Concern (AOCs) could be compared based on trade-offs resulting from marginal change in the area of habitats supporting different ecosystem services. They felt that the reliability, credibility, and social acceptance of these analyses would be increased if marginal changes in the area of habitats associated with restoration could be weighted using relative valuation elicited directly from beneficiaries, an idea with strong support in the literature (e.g., Daily et al., 2009; Lin et al., 2017; Rodrigues et al., 2017, and papers cited therein). The traditional method for obtaining stated preference information from beneficiaries is via surveys, interviews, and focus groups which are time consuming and expensive (Richards and Friess, 2015; Tenerelli et al., 2016). As a possible alternative or supplement to stated preference methods we explored using sets of geotagged (attributed with geospatial metadata) photos posted to social media.

Photographs may reflect the aesthetic values, interests, sentimental attachments, and emotional state of the photographer at a particular time and place (Garrod, 2007; Guerrero et al., 2016; Stedman et al., 2004). Although we cannot know the photographer's exact motivation behind each photograph, we reasoned that the act of taking a photograph reflects the photographer's individual preference for, or choice of, the depicted subject matter among all the other possible subject matter. In aggregate for a spatially explicit set of photographs, these preferences may serve as a relative rank or weight coefficient for ecosystem services and benefits associated with a habitat restoration (Satz et al., 2013).

This approach of using the content of photographs posted to social media to quantify or map ecosystem benefits or preferences is supported by some recent studies (Hausmann et al., 2017; Heikinheimo et al., 2017; Richards and Friess, 2015; Richards and Tunçer, 2017; Tenerelli et al., 2016; Wood et al., 2013; Yoshimura and Hiura, 2017),

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https://doi.org/10.1016/j.jglr.2017.12.007
0380-1330/Published by Elsevier B.V. on behalf of International Association for Great Lakes Research.

Table 1
Explanation of key concepts used in this paper.

Beneficiary: a member of a class comprised of individuals who benefit similarly from ecosystems via active or passive consumption, use, or appreciation (after Harwell et al., 2017).
Cultural ecosystem services: the non-material benefits people obtain from ecosystems through spiritual enrichment, cognitive development, reflection, recreation, or sensory experiences (after MEA, 2005; see also Chan et al., 2012; Dickinson and Hobbs, 2017).
Ecosystem or ecological benefit: the contribution to human ***well-being*** that results from the consumption, use, or appreciation of a final ecosystem good or service (after Harwell et al., 2017). Benefits are realized when labor and capital (often in the form of human effort) are added to final ecosystem goods and services (Landers and Nahlik, 2013).
Ecosystem services: broadly, biophysical outputs of ecosystem processes from which humans derive benefits (after Harwell et al., 2017).
Final ecosystem goods and services (FEGS): components of nature directly enjoyed, consumed, or used to yield human benefits. FEGS are biophysical outputs, qualities, or features of nature that need minimal translation for relevance to human ***well-being*** (Boyd and Banzhaf, 2007).
Final ecosystem goods and services classification system (FEGS-CS): a hierarchical framework for defining and classifying final ecosystem services and associated human beneficiaries (Landers and Nahlik, 2013)
Great Lakes Area of Concern: geographic areas designated by the Parties of the Great Lakes Water Quality Agreement (Annex 1 of the 2012 Protocol) where significant impairment of beneficial uses has occurred as a result of human activities at the local level.
Intermediate ecosystem goods and services: ecological processes, functions, structures characteristics, and interactions that are essential to the existence of FEGS, but are usually not directly enjoyed, used, or consumed by human beneficiaries (Landers and Nahlik, 2013).
Relative valuation (of benefits): non-monetary comparison among preferences for ecosystem benefits based on percentages, weights, ranks or other relative scale.
Human well-being: the condition of humans and society, defined in terms of the basic material needs for a good life, freedom, choice, health, wealth, social relations, and personal security (after MEA, 2005)

but is not yet widespread (Andrew et al., 2015; Casalegno et al., 2013; Guerrero et al., 2016). We are aware of only a few applications of this approach in the Great Lakes. Allan et al. (2015, 2017) used crowdsourced birdwatching hotspots and geotagged photographs of Great Lakes beach-use to map these cultural/recreational services around the Great Lakes. Annis et al. (2017) also used crowdsourced birdwatching hotspot data to inform coastal conservation planning. Hoellein et al. (2015) used the number of photographs of Lake Michigan beaches posted to social media as a proxy measure of beach visitation rate.

Information derived from social media can support decision making at a variety of scales from regional restoration and conservation planning (see Allan et al., 2015) to local projects. Our focus here is using AOC-scale information to address AOC and restoration project scale decisions. Our objective was to explore the potential for using photographs posted to photo-sharing sites to quantify relative valuation of ecosystem benefits in Great Lakes Areas of Concern. We addressed several questions: 1) what percent of photographs taken in each of two Great Lakes AOCs and posted to three different social media photo-sharing sites (PSSs) depicted an ecosystem service or associated ecosystem benefit?; 2) does the percentage vary among PSSs or between AOCs?; 3) are there user gender or user origin (e.g., local or non-local) biases in the data that can be identified using available metadata; 4) what are the most often-depicted ecosystem benefits and do they vary across PSSs or AOCs?; 5) are there spatial patterns in what is depicted in photographs within and across AOCs?; and 6) how might relative valuation of ecosystem benefits derived from social media photographs be translated into information useful in AOC decision-making, in particular restoration project planning and design?

Methods

We downloaded photographs and metadata from PSSs for two AOCs, the St. Louis River, a tributary to western Lake Superior and a border water between Minnesota and Wisconsin, and the Milwaukee Estuary in Wisconsin, which includes rivers tributary to Lake Michigan (see Appendix A1 for area maps and boundaries). The St. Louis River (67.4 km^2) has extensive open water areas including estuarine lower reaches and a more riverine upper reach. Lake Superior proper is excluded from the AOC in this analysis. The St. Louis River AOC becomes progressively less industrial or otherwise developed in the upriver direction. The Milwaukee Estuary AOC (56.8 km^2) includes several long river reaches, and a section of Lake Michigan. The St. Louis River is adjacent to Duluth, Minnesota and Superior, Wisconsin, with a combined population of 113,509 and density of $\approx$500 people/km^2 (United States Census Bureau, 2017). Milwaukee, Wisconsin has a population of 594,738 and a density of $\approx$6000 people/km^2. We selected these AOCs for analysis to support our ongoing ecosystem services research there and because they afford a comparison between a highly developed urban AOC (Milwaukee Estuary), and a partly undeveloped AOC (St. Louis River).

We wrote scripts (Debbout, 2017) to connect to each photo-sharing site's application programming interface (API) to allow us to download geotagged photographs and videos (Instagram only) from Panoramio, Instagram and Flickr. Panoramio.com, owned by Google, Mountain View, CA, was launched October 2005 and closed November 2016. Flickr.com, owned by Yahoo!, San Francisco, CA was launched February 2004. Instagram.com, owned by Facebook, Menlo Park, CA, was launched October 2010. Ninety-four million photographs had been uploaded to Panoramio by the time it closed (Trull, 2017). As of May 2015, 10 billion images had been uploaded to Flickr; up to 25 million new images are uploaded each day (DMR, 2017) Thirty-five billion photographs have been shared on Instagram (Statistic Brain, 2017). We chose Instagram and Flickr because they were the most popular photo-sharing sites in the world when we downloaded images (eBizMBA, 2017). We included Panoramio because, although it is closed to new images, the archived data are available, and previous studies have used Panoramio data (e.g., Casalegno et al., 2013; Figueroa-Alfaro and Tang, 2017).

We downloaded all available public photographs and metadata as of August 2016 from within each AOC plus a 100 m AOC boundary buffer (Appendix A1). For the Milwaukee Estuary AOC there were >70,000 posted Flickr photographs. To reduce effort and make the sample size more equitable between AOCs, we randomly extracted 5000 Milwaukee Estuary Flickr photographs for classification. We included the boundary buffer to capture riparian and AOC-adjacent terrestrial habitats that may be relevant for restoration. We used geotags to identify photographs taken within the target area. Instagram photographs are tagged with the name of a location with generalized coordinates, rather than unique coordinates, such that there may be hundreds of photographs posted by different users at different times with the same place-name tag and coordinates. This introduces some location error into the data which is relevant when the named place is near or outside the boundary of the AOC. Of 22,059 original downloaded photographs, 3.8% were outside the target area, and 1.7% had bad hyperlinks.

We viewed every photograph and video with a working hyperlink. We did not filter out or classify photographs using image tags or titles. This metadata was missing for many images and when present rarely provided sufficient detail to classify the depicted subject matter using our classification scheme (described below). For each usable photograph, we attempted to determine the user's gender and origin (Flickr only for origin), the subject matter of the photograph, and if the photograph depicted an ecosystem service or benefit.

For each photograph we used a two-part characterization of the subject matter (i.e., level 1 subject + level 2 subject) to classify the photographs which we then linked to the Final Ecosystem Goods and Services Classification System (FEGS-CS; see Table 1). FEGS-CS has some advantages for our purpose: it provides clear rules for what is and is not an ecosystem service; it explicitly links human beneficiaries to FEGS; and it prevents double counting of benefits (Landers and Nahlik, 2013; Boulton et al., 2016). In some classified photographs, an ecosystem

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service was depicted (e.g., fauna, flora, natural scene), and in other photographs the human benefit of the service was directly depicted (e.g., sailing, trail use). In the FEGS-CS context, the distinction between FEGS and benefits is as follows: FEGS are the end products of the environment with which beneficiaries interact. The FEGS benefit is not realized without some input of labor and capital goods. For example, the sailing benefit requires at least a sailboat and the effort of operating the vessel. Hiking requires at least traveling to the trail and expending the energy to realize the sensory experiences and health benefits of the hike. In the broadest sense, the act of photographing something in nature and posting the image to social media represents a minimal input of labor and capital for every posted image. Although we attribute each classified photograph depicting natural amenities as either a FEGS or a beneficiary enjoying a FEGS (Appendix A2), we attributed all these photographs with an ecosystem benefit for the analysis. All photographs were classified, but not all photographs depicted a benefit.

Excluded from consideration as FEGS are components of the built environment, disconnected nature (e.g., trees in planters, fish in aquaria), crops, plantations, and livestock (Landers and Nahlik, 2013). Final and intermediate ecosystem services are distinguished in FEGS-CS. Although there is inherent ambiguity in classifying photographs depicting natural habitats as intermediate services or final services, we interpreted all services depicted in photographs as FEGS. For example, we attributed the benefit of "scene viewing and experiencing" to habitat photographs but they also depict, presumably unintentionally in most cases, intermediate services such as fish habitat, bird habitat, or photosynthesis.

We classified the subject matter of photographs and attributed benefits from the perspective of the photographer (i.e., the beneficiary) rather than on the content of the photograph abstracted from the photographer. We did this so that our attribution of services and benefits would be as consistent as possible with the principals and structure of the FEGS-CS and to avoid attributing an ecosystem benefit to a photograph when it was, in our opinion, unlikely that the intent of the photographer was to capture an image of or personal human interaction with nature. For example, we would not consider a photograph of a Great Lakes ore carrier (ship) to depict the valid final ecosystem service of "water of a suitable depth for shipping" (Appendix A2) because the most direct and unambiguous beneficiary of the FEGS is the owner of the ship, not the photographer who presumably values the ship as a compelling human-made object worth photographing and not as reflecting an ecosystem service. Attributing a value to shipping from the perspective of the photographer would also double count the benefit because the apparent value to the photographer would be added to the true value of the benefit to the ship's owner. On the other hand, a photograph of a recreational sailboat does reflect a valid FEGS (water of a suitable depth for recreational sailing) if it is from the perspective of recreational sailors aboard the sailboat because the photographer-sailor derives a direct recreational benefit from the service. (A photograph of a tall sailing ship not taken from aboard-ship is treated like the ore carrier because tall ships are foremost tourist attractions not normally used for leisure sailing, and the photographer is a neither a participant nor likely to be an owner of the ship.) Table 2 gives additional examples illustrating how the beneficiary perspective underlies our photograph classification approach. Nearly all of the services depicted in photographs posted to PSSs were of cultural ecosystem services or associated benefits, although this categorization is not explicit in FEGS-CS.

Some users posted multiple photographs on a single date of the same subject matter at the same location. We omitted these redundant photographs by sorting the images by user and date and viewing them sequentially. Images that depicted the same people enjoying nature in the same way at the same locations were omitted. Likewise, images depicting the same natural subjects at the same location were omitted. We only did this for photographs depicting a service or benefit to save time. Therefore, for comparisons between photographs depicting and not depicting a service or benefit, all photographs were included.

We determined the PSS user's gender and origin (e.g., local or non-local) for each photograph by the username (Panoramio) or by visiting the user's public online profile page for each PSS (Flickr only for origin). User gender could not always be determined, especially for Panoramio for which we had to rely on gender-normative naming conventions. For Flickr and Instagram, we used the listed gender or the apparent gender from the profile photograph when available on the profile page. Gender matters because if the effect of gender and origin were unknown, and the findings were applied to the beneficiary population, unrepresentative and potentially misleading inferences could result. When the user was a business, institution, or group, we did not assign a gender. In some cases, where it was not given in the user's public profile, we were able to determine the user's origin by examining the mapped locations of all the user's public photographs (an automated feature in Flickr). We classified user origin as local (in or adjacent to the Duluth/Superior or Milwaukee metropolitan area), regional (in Minnesota, Wisconsin or a surrounding state), international plus non-regional states, or unknown. We classified origin based on current location unless the listed hometown was Duluth/Superior or Milwaukee, in which case we classified the origin as local. We used the *G*-test of independence (=likelihood ratio chi-square, SAS 9.4, SAS Institute, Cary, NC) to compare the proportions of photographs depicting each benefit among levels of a second variable such as AOC, PSS, origin or gender.

We used the Directional Distribution tool in ArcGIS Pro 10.4 (ESRI, 2017) to create unweighted standard deviational ellipses to show the distribution of geotagged photographs. This method calculates the standard deviation of the x-coordinates and y-coordinates from the mean location to define the axes of the ellipse. The ellipse reveals the central tendency of points, contains about 68% of the points (one standard deviation), and shows if the distribution of points has a particular orientation in the AOC.

The classification scheme was developed and all photographs were classified by the first author; any classification errors are his. We provide a link to the data used in this study (Appendix B) and encourage different perspectives.

Results

Scope of the data

Excluding photographs with bad links or that were taken outside the AOC's boundaries, 21,552 photographs were classified (Table 3). The overall date range for photographs was 2000–2016. Based on the mean year, available Instagram photographs were more recent (2015.4–2015.7) than Flickr (2011.9) or Panoramio photographs (≤ 2011). Mean month was between May and July, inclusive, in all cases. In the raw classified data (with redundant photographs not removed), the mean number of photographs posted per social media user was 3.2 (Table 3). For the data that we downloaded, Flickr users posted more photographs (6.4–14.6 photographs/user) than users of other social media (1.6–4.0 photographs/user). Users who posted at least one photograph depicting a service or benefit, posted, on average, 1.6 photographs (redundant photographs excluded).

Social media photographs depicting a benefit

After removing redundant photographs, 2547 photographs depicting a benefit remained (Table 3). Mean year of these photographs was, on average, one year more recent than all photographs. Mean month was June as for all photographs. The percent of classified photographs depicting a benefit varied between AOCs and among photo-sharing sites (Fig. 1) A greater percent of Instagram photographs depicted a benefit (22–25%) than Flickr (11–15%) or Panoramio (8–20%). After eliminating photographs of "indoors" subjects, an even greater percent of Instagram photographs depicted a benefit relative to other PSSs (Fig. 1).

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Table 2
Examples of the photograph classification linked to FEGS-CS. Beneficiary categories may include two levels of sub-categories. See Appendix A2 for complete details.

Online photograph	Photograph classification		FEGS-CS		Is an ecosystem benefit depicted?	Explanation
	Subject 1	Subject 2	Final ecosystem service	Beneficiary category and sub-categories		
Water-level view of kayakers	Boating	Human-powered boating	Water safe and suitable for human powered boating and water contact	Recreational boaters-human powered	Yes	Example presumes the photographer is a participant and directly benefits from the service.
Distant view of kayakers (e.g., from beach or bridge)	Boating	Human-powered boating-np	Water safe and suitable for human powered boating and water contact	Recreational boaters-human powered	No	Example presumes photographer is a non-participant (np) and does not directly benefit from the service.
Butterfly on a flower	Fauna	Invertebrate	The non-captive invertebrate	Recreational viewers and experiencers-invertebrates	Yes	May be combined with other groups of organisms into "fauna and flora."
Beach-level view of sunbathers on a beach	Recreation	Beach	The beach	Recreational Swimmers, boaters, and divers-beach use	Yes	Example presumes photographer is a participant in beach use. If the photograph were of the beach with no humans or pets, the beneficiary would be recreational viewers and experiencers.
Al fresco diners at a riverside cafe	People/pet	Outdoors	The river	Resource dependent businesses-food service	No	The primary beneficiary of the river is the restaurant owner.
Lift bridge	Built	Bridge	Not a service	Not applicable	No	Built infrastructure is not an ecosystem output.
Fish in aquaria	Other	Indoors	Not a service	Not applicable	No	Specific fish in aquaria are not necessarily an output of the ecosystem in question.
Wild rice harvesting by tribal members	Subsistence	Wild rice	The harvested wild rice	Subsistence-food subsisters-Native Americans	Yes	Example presumes wild rice provides an important nutritional subsidy for harvesters.

The complete results for classified photographs depicting a FEGS or benefit are given in ESM Table S2. We combined several of the original classifications into composite benefits to make the findings more robust (fewer classifications with few occurrences). Table 4 shows the percentage occurrence of each composite benefit. The data suggest that passive recreation such as scene experiencing and viewing (30–38% of photographs) and fauna and flora experiencing and viewing (7–14% of photographs) were less frequent among Instagram photographs than among Panoramio and Flickr photographs (scene: 34–64%; fauna and flora: 11–35%). In contrast, several active forms of recreation including hiking, biking, public greenspace use (e.g., field sports), recreation with dogs, and human-powered boating were in nearly all cases more frequent among Instagram photographs than among Flickr or Panoramio photographs.

From the perspective of potential ecosystem service "supply", a major difference between the St. Louis River AOC (as defined herein) and the Milwaukee Estuary AOC is that the St. Louis River AOC does not have a Great Lake beach, which is reflected in the proportion of photographs depicting beach recreation (Table 4). We rejected the hypotheses that the relative proportions of photographs in each composite benefit classification were independent of AOC or PSS ($G > 20$, $P < 0.05$ for all comparisons), meaning that the proportions of depicted benefits were different among PSSs and between AOCs. When we retabulated the photographs excluding photographs classified as beach recreation or scenes of beaches (Table 5), we still rejected the null hypotheses of independence ($P < 0.05$) for all comparisons except for Panoramio photographs from Milwaukee and the St. Louis River ($G = 14.2$, $P = 0.12$) meaning that the proportions of depicted benefits among composited Panoramio photographs from these two AOCs were similar.

Social media photographs not depicting a benefit

We did not focus on the content of photographs we judged to not depict a FEGS or benefit, but these photographs provide added insight into variation among the PSSs and between the two AOCs. Overall, the most common classification of photographs not depicting an ecosystem benefit was "other-indoors" which includes photographs of food, drink,

Table 3
Scope of social media photograph data used in this study.

Great Lakes Area of Concern	Photo-sharing site	Number of classified photographs	Year range	Mean year	Mean month	Mean photographs per user
All photographs (redundant photographs not removed)						
Milwaukee Estuary	Flickr	4968	2004–16	2011.9	6.8	6.4
Milwaukee Estuary	Instagram	6058	2011–16	2015.7	5.2	1.7
Milwaukee Estuary	Panoramio	1345	2006–14	2010.7	6.4	4.0
St. Louis River	Flickr	6348	2000–16	2011.9	7.3	14.6
St. Louis River	Instagram	1483	2012–16	2015.4	5.9	1.6
St. Louis River	Panoramio	556	2006–14	2009.9	6.9	3.0
All	All	20,758	2000–16	2013.1	6.4	3.2
Photographs depicting an ecosystem service or benefit (redundant photographs removed)						
Milwaukee Estuary	Flickr	392	2005–16	2011.4	6.4	2.7
Milwaukee Estuary	Instagram	1190	2012–16	2015.6	5.5	1.3
Milwaukee Estuary	Panoramio	181	2007–14	2010.7	6.2	1.7
St. Louis River	Flickr	411	2003–16	2012.9	6.7	4.5
St. Louis River	Instagram	339	2012–16	2015.4	6.0	1.3
St. Louis River	Panoramio	34	2007–13	2010.4	6.1	1.6
All	All	2547	2003–16	2014.1	6.0	1.6

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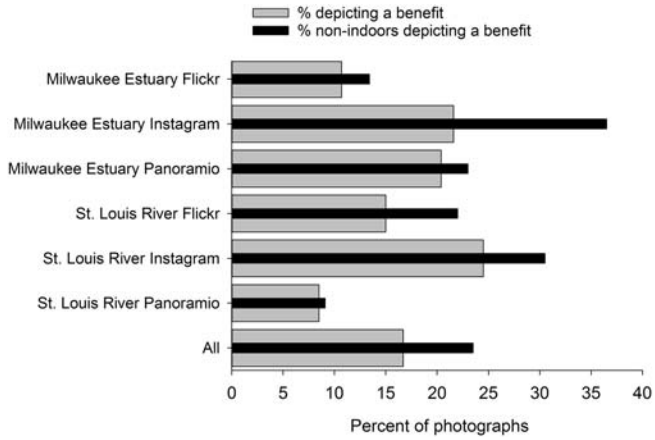

Fig. 1. Percent of all classified photographs depicting an ecosystem benefit and percent of classified photographs from outdoors depicting an ecosystem benefit by Great Lakes AOC and photo-sharing site. See Table 3 for sample sizes.

furnishings, consumer goods, and architectural elements. The next four most common classifications were "people/pet-indoors", "people/pet-outdoors", "built-bridge", and "built-cityscape" (see Appendix A3) for percentages by AOC and PSS. The main difference between the AOCs was that photographs of bridges and ships were much more frequent among photographs for the St. Louis River, which can be explained by the presence of the iconic Canal Park Lift Bridge within the AOC where ships can be closely viewed.

Photographs depicting people or pets were rare among Panoramio photographs. Photographs of built infrastructure, including cityscapes, railroads, and commercial buildings were less frequent among Instagram photographs than other PSSs. Photographs of people taken indoors were much more frequent among Instagram photographs than other PSSs.

User gender

We were able to determine the user's gender for 89% of all classified photographs. The failure rate was higher for Panoramio (28%) than for Instagram (12%) or Flickr (6%). About 61% of Instagram photographs were posted by female users, compared to 11% female Flickr users and 16% female Panoramio users (Fig. 2). Relatively more of the photographs depicting a benefit were posted by female than male users. For example, about 29% of all photographs were posted by female users, but 37% of photographs depicting a benefit were posted by female users.

For both Milwaukee Estuary photographs pooled across PSSs and St. Louis River photographs pooled across PSSs, the proportions of photographs among benefits was different for female and male users ($G > 74$, $P < 0.001$). For Flickr and Instagram photographs pooled across AOCs, the proportions of photographs among benefits was different for female and male users ($G \geq 41$, $P < 0.01$; sample size was too small for Panoramio for a reliable test). Across AOCs and PSSs, photographs of active riparian recreation, including hiking, biking, and recreation with dogs, were posted more frequently by female users (Fig. 3; complete results given in ESM Table S4). Beach recreation was also depicted more often in photographs posted by female users. Photographs of scenes, angling, sailing, and fauna and flora were posted more frequently by male users (Fig. 3).

User origin

We were able determine the user origin for photographs posted to Flickr in 95% of cases. For the St. Louis River, 39% of photographs were posted by local users, 46% were posted by regional users, and 10% by international users or users from non-surrounding states. For the Milwaukee Estuary 73% of photographs were posted by local users; 12% were posted by regional users, and 10% by international or non-surrounding state users.

For both the St. Louis River and Milwaukee Estuary, local users posted relatively more photographs depicting a benefit than did regional or international plus non-surrounding state users (Fig. 4). Thirty-one percent of the Flickr photographs posted by users local to Duluth/Superior depicted a benefit compared to 3% of photographs posted by regional users (i.e., non-local users from Minnesota, Wisconsin, Iowa, North and South Dakota). Twelve percent of the Flickr photographs posted by users local to Milwaukee, WI depicted a benefit compared to 5% of photographs posted by regional users (i.e., non-local users from Wisconsin, Illinois, Iowa, Minnesota, or Michigan).

Content of photographs depicting benefits was different for local and non-local users for the St. Louis River ($G = 72$, $P < 0.0001$) but were similar (independent of origin) for the Milwaukee Estuary ($G = 14$; $P = 0.13$). On the St. Louis River, non-local Flickr users tended to post more photographs of fauna and flora experiencing and viewing, and fewer photographs of scenes than local Flickr users (Fig. 5). Duluth/Superior is a popular travel destination for bird watching (Thayer, 2017) which could partly account for this finding.

Geospatial variation

The mean geotag location of all photographs depicting a benefit was farther from the mean geotag location of photographs not depicting a

Table 4
Percent of photographs by composite benefit depicted for each AOC and photo-sharing site. Composites: Power boating and cruising combined into power boating; all angling photographs combined into angling; all bird, animal, and flora photographs combined into fauna and flora; all learning combined; all inspirational combined; biking and trail use combined; ice recreation and excursion railroad combined into other recreation; swimming and beach recreation combined into beach recreation.

Composite benefit	Milwaukee Estuary			St. Louis River			All photos
	Flickr	Instagram	Panoramio	Flickr	Instagram	Panoramio	
	$N = 392$	$N = 1190$	$N = 181$	$N = 411$	$N = 339$	$N = 34$	$N = 2547$
Scene experiencing/viewing	45.4	37.8	64.1	34.0	30.4	55.9	39.5
Fauna/flora experiencing/viewing	28.8	7.3	10.5	35.0	13.9	17.6	16.3
Beach recreation	10.7	13.8	7.7	0.5	1.5	0.0	8.9
Hiking and biking on trails	2.3	11.9	3.9	3.4	10.3	11.8	8.3
Public greenspace use	7.7	9.0	3.9	1.7	3.8	0.0	6.4
Recreation with dogs	0.8	10.7	1.1	2.9	3.8	0.0	6.2
Sailing	2.0	2.1	4.4	13.4	3.8	2.9	4.3
Human-powered boating	1.5	3.0	0.6	1.2	9.7	0.0	3.2
Power boating	0.0	3.1	0.6	1.5	4.4	8.8	2.4
Angling	0.3	0.6	2.2	2.7	8.0	2.9	2.0
Other recreation	0.0	0.0	1.1	1.0	8.3	0.0	1.3
Learning	0.0	0.2	0.0	2.4	0.6	0.0	0.6
Inspirational experience	0.5	0.5	0.0	0.2	1.5	0.0	0.6

Table 5
Percent of photographs by composite benefit depicted for each AOC and photo-sharing site, with beach benefits and swimming removed.

Composite benefit	Milwaukee Estuary			St. Louis River			All photos
	Flickr	Instagram	Panoramio	Flickr	Instagram	Panoramio	
	$N = 309$	$N = 951$	$N = 150$	$N = 409$	$N = 334$	$N = 34$	$N = 2187$
Scene experiencing/viewing	44.3	39.4	66.0	34.2	30.8	55.9	39.9
Fauna/flora experiencing/viewing	36.6	9.1	12.7	35.2	14.1	17.6	19.0
Hiking and biking on trails	2.9	14.9	4.7	3.4	10.5	11.8	9.7
Public greenspace use	9.7	11.3	4.7	1.7	3.9	0.0	7.5
Recreation with dogs	1.0	13.4	1.3	2.9	3.9	0.0	7.2
Sailing	2.6	2.6	5.3	13.4	3.9	2.9	5.0
Human-powered boating	1.9	3.8	0.7	1.2	9.9	0.0	3.7
Power boating	0.0	3.9	0.7	1.5	4.5	8.8	2.8
Angling	0.3	0.7	2.7	2.7	8.1	2.9	2.3
Other recreation	0.0	0.0	1.3	1.0	8.4	0.0	1.6
Inspirational experience	0.6	0.6	0.0	0.2	1.5	0.0	0.6
Learning	0.0	0.2	0.0	2.4	0.6	0.0	0.6

benefit for the St. Louis River (3.4 km) than the Milwaukee Estuary (0.6 km; Fig. 6). For the St. Louis River, locations of photographs depicting a benefit tended to be upriver of photographs not depicting a benefit, which were closer to the highly developed city and port of Duluth. For the Milwaukee estuary, locations of Instagram photographs were further away from Lake Michigan (they were west of the Milwaukee River) than Flickr or Panoramio photographs. Directional standard deviational ellipses showed that the location of the photographs depicting a benefit were generally more dispersed (larger ellipse) than were photographs not depicting a benefit. Photographs from the Milwaukee Estuary were generally aligned along the Milwaukee River. In the St. Louis River, the distribution of photographs depicting a benefit was aligned with the morphology of the upper river.

Plots of Flickr photograph locations for composited benefits and associated directional ellipses show that the spatial extent of active recreation (hiking, biking, greenspace use, recreation with dogs, and other recreation) in the St. Louis River was greater than the other benefits (Fig. 7). Boating was located primarily in Superior Bay; angling extended further upriver. Two areas of the AOC for which few photographs depicting benefits were posted to Flickr were the southeast part of the estuary including Allouez Bay, and the St. Louis River upriver of Spirit Lake. As for the St. Louis River, the extent of Flickr photograph locations for active recreation in the Milwaukee Estuary was greater than other benefits (Fig. 7). Relatively few photographs were posted of benefits from upriver reaches of the Milwaukee, Menomonee, or Kinnickinnic Rivers (see area maps in Appendix A1). Despite the difference between local and non-local users in the percent of images depicting a benefit and in the content of photographs, there was not much difference in the spatial distribution of photograph locations (Appendix A6).

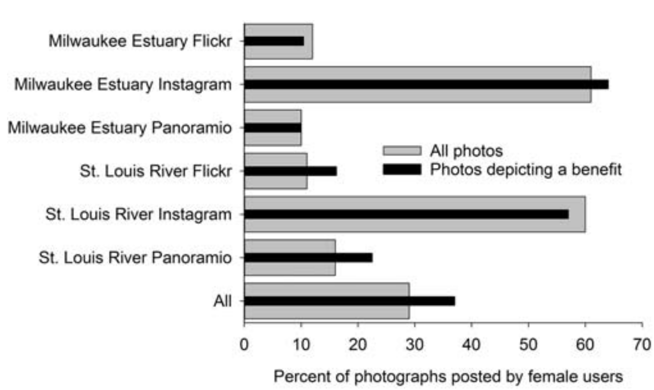

Fig. 2. Percent of all classified photographs posted by female users and percent of photographs depicting a benefit posted by female users by AOC and photo-sharing site. Percentages based on photographs for which a user gender could be determined. Sample sizes (all photographs) for St. Louis River: Panoramio, $N = 399$; Flickr, $N = 5399$; Instagram, $N = 1336$. Samples sizes for Milwaukee Estuary: Panoramio, $N = 974$; Flickr, $N = 5399$; Instagram, $N = 5272$.

Discussion

Classification of photographs

The manual classification of photographs by their final ecosystem service or benefit subject matter was time consuming. With practice, each photograph could be classified in less than a minute, but the process is necessarily iterative in the early stages and the classifier must make multiple passes through many of the photographs to insure consistency within the classification scheme. Adoption or adaptation of our classification scheme (Appendix A2) could facilitate future classification of Great Lakes social media photographs. Use of image recognition software has some potential to automate classification. However, a recent application of this tool by Richards and Tunçer (2017) suggests to us that the keyword "tags" returned for each photographs are not yet sufficiently specific for reliable classification of ecosystem benefits.

An important advantage of linking the classification of photographs to FEGS-CS was that because it is an integrated framework for the classification of both final ecosystem services and beneficiaries, it allowed us to attribute photographs that depicted a biophysical service (i.e., FEGS) or that directly depicted humans benefiting from nature with an ecosystem benefit. An aspect of our approach that might not apply for other ecosystem service classification systems was our rule

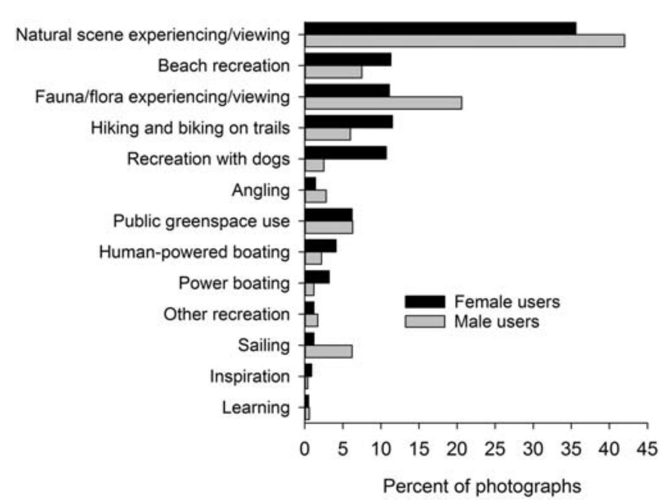

Fig. 3. Percent of photographs pooled across PSS and AOC depicting each type of benefit class by user gender. Percentages based on photographs for which a user gender could be determined. Complete data and sample sizes given in Appendix A4.

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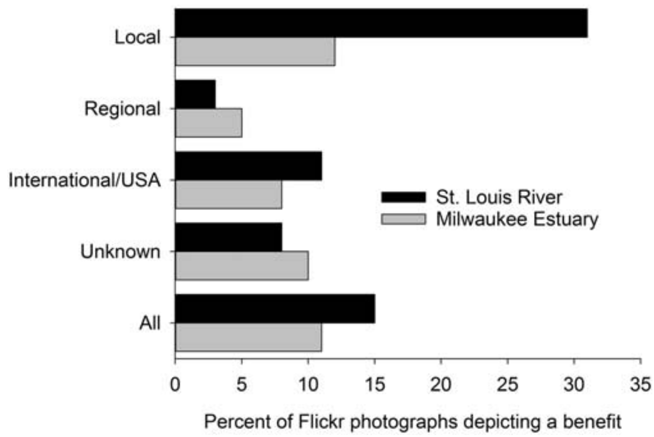

Fig. 4. Percent of Flickr photographs depicting benefit by user origin for the St. Louis River and Milwaukee Estuary. Sample sizes: St. Louis River $N = 6348$; Milwaukee Estuary, $N = 4968$.

of excluding depictions of services or benefits for which we judged the photographer was not the primary beneficiary of the service (Table 2).

Despite having a detailed classification scheme, our interpretation and classification of photos was partly subjective. For example, sometimes it was unclear what human subjects were actually doing in photographs: were they truly recreating in nature or simply posing or taking a "selfie" with no apparent nature in the foreground or background? In these cases, the classifier used best judgment. In some cases, it was not clear whether it was the intent of the photographer to depict nature or built infrastructure or both. For example, we would classify as "built-monument" a photograph of public art installed in an otherwise natural setting (e.g., greenspace), but other interpretations are possible. Likewise, some cityscape photographs contained natural habitat, often water, in the foreground. We used a practical rule wherein if more than half the photograph was natural foreground we classified it as "scene-seminatural"; otherwise we classified it as "built-cityscapes." To photographs classified as natural or semi-natural scenes, we attributed the benefit "scene experiencing and viewing." Some number of these photographs would probably more accurately be classified as inspirational for artists, rather than as spontaneous documents without an explicit artistic motivation, but we could rarely make that distinction. In a few photographs the actual process of photographing or painting a natural subject was depicted.

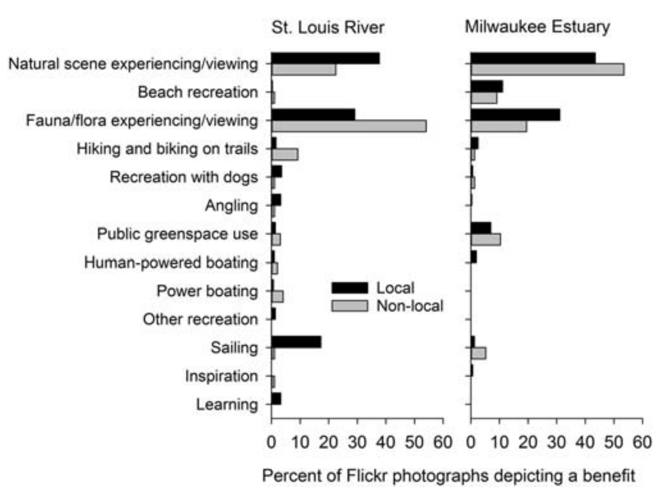

Fig. 5. Percent of Flickr photographs depicting each type of composite benefit posted by local and non-local users for the St. Louis River and Milwaukee Estuary. Sample sizes: St. Louis River local, $N = 313$; non-local, $N = 98$; Milwaukee Estuary local, $N = 315$; non-local, $N = 77$.

Some details that are lost in the composited benefits, but are preserved in the data, may be useful in some applications. For example, we sub-classified natural and semi-natural scenes into water, land, beach and atmospheric, which might be relevant for comparing among PSSs. Also, we composited fauna and flora, but we actually classified fauna into finer groups (e.g., birds, by type, mammals, invertebrates, herptiles, Appendix A2) which might be relevant for comparing among habitats provided by restoration design alternatives. Birds were depicted in photographs more frequently than other fauna or flora, but we suspect that attributing all of these to bird-watching would still underestimate preference for that activity because only some birders post photographs.

Biases

We documented several biases in the data, and we suspect others based on the experience of classifying thousands of photographs. There was a consistent difference in the subject matter of photographs posted to Instagram compared to photographs posted to Panoramio or Flickr. Overall, relatively more of the photos on Instagram depicted a benefit, and more Instagram photographs depicted active recreation by humans in nature than did the other PSSs. Photographs on Flickr more often depicted natural scenes, fauna, and flora. The underlying drivers of this variation between PSSs are not clear, but may be related to user gender, age, or differential motivations for using PSSs. Hausmann et al. (2017) used both Flickr and Instagram photographs to examine tourist preferences in a national park. Their findings qualitatively corroborate ours; Flickr users tended to be enthusiasts of biodiversity per se, whereas Instagram users tended to experience biodiversity through activities in nature. Flickr and Instagram are self-characterized somewhat differently. Flickr promotes itself as the as "the best online photo management and sharing application" (Flickr, 2017). Instagram is a place to "share the world's moments" and as a "home for visual storytelling" (Instagram, 2017).

Likely related to the differences among PSSs that we observed was a strong user-gender bias. For the Instagram photographs we classified, users were about 61: 39% female: male. For Flickr the ratio was about 11: 89% female: male. These ratios agree in direction but are skewed compared to a report from 2015 which put the user gender ratio at 52: 48% female: male for Instagram and 37: 63% female: male for Flickr (Verto Analytics, 2015). User-gender bias matters because male and female users are likely to post photographs depicting different benefits, several examples of which we documented with our analysis. Causality behind gendered preferences for benefits is beyond the scope of this study, but it is likely that there are multiple underlying factors (Kelemen et al., 2015; Kennedy and Dzialo, 2015). If necessary, the relative proportions of photographs posted by gender based on metadata could be used to rescale relative preferences to actual population gender ratios.

We showed that there were differences in the content of photographs posted by local and non-local users, both in the percent of photograph depicting a benefit and in the benefits depicted. User origin matters because although the photographs are spatially explicit, the photographers are not. It may be important to know the degree to which local beneficiaries are represented in the data, and how they value local benefits. Generally, local users posted more photographs depicting a benefit than did users from the surrounding region or further away. Local users may be less likely to post photographs of more touristic "destination" features such as iconic built infrastructure such as bridges, monuments, buildings, or industries (Wood et al., 2013). The effect of origin on the content of photographs depicting a benefit was less consistent between AOCs than was the effect of user gender.

Local expertise is required to identify benefits missing from social media photographs due to underlying biases. For the St. Louis River AOC, there were virtually no photographs of waterfowl hunting, furbearer trapping, sacred sites, or wild rice stands in situ or being

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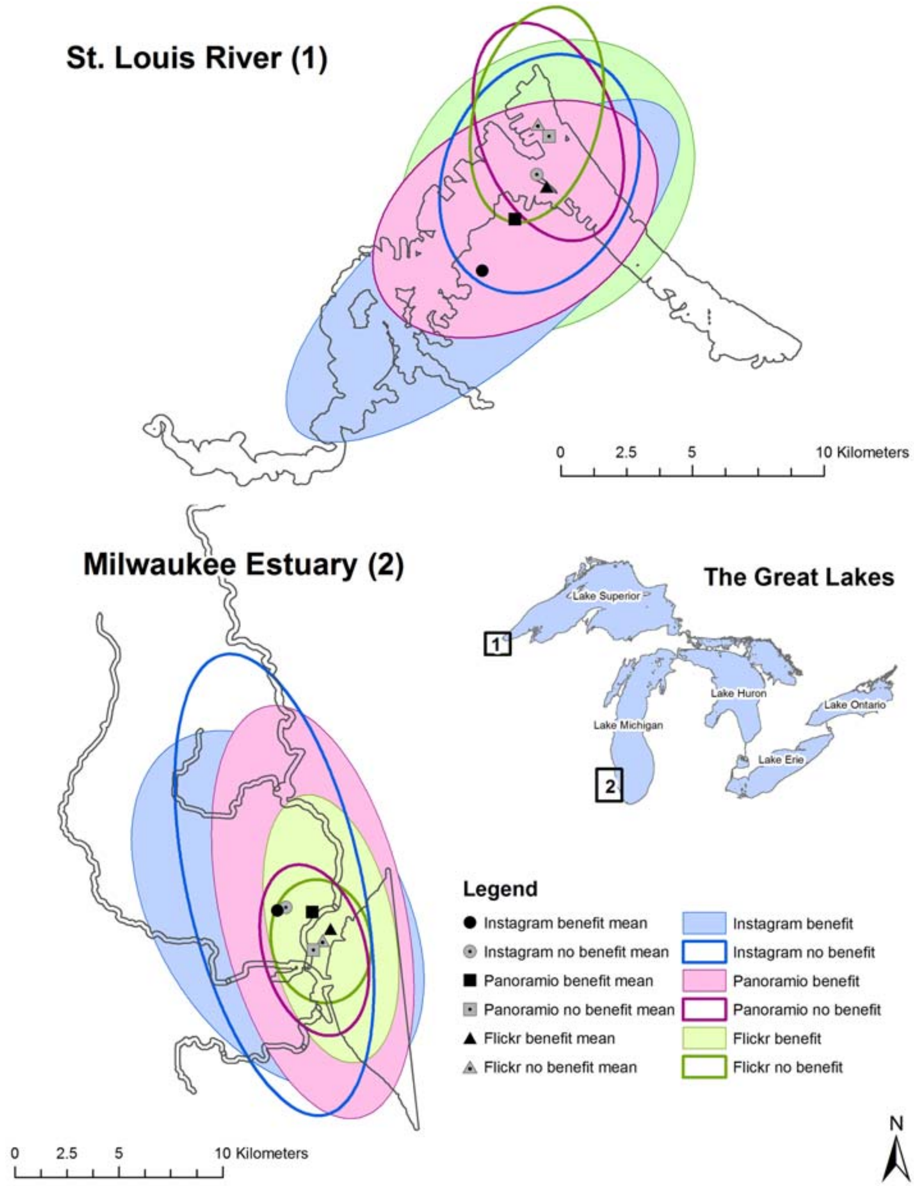

Fig. 6. Mean location and directional ellipse for photographs depicting a benefit and photographs not depicting a benefit. Ellipses include about 68% of the observations (one standard deviation). Inset map shows location of each AOC in the Great Lakes. See Appendix A1 for map detail.

harvested. However, we know that beneficiaries are present for these benefits in the AOC (e.g., Angradi et al., 2016). We can posit several potential reasons why some benefits may be missing (or underrepresented) from posted sets of photographs. The benefit may not be especially photogenic; beneficiaries may be secretive or infrequent social-media users; or the activities associated with the benefit may not be "photography friendly" (e.g., participants are too busy or too wet to take photographs; Wood et al., 2013). Beneficiaries of intangible cultural benefits (Chan et al., 2012) may see little point in taking or sharing a photograph representing the benefit, as may be the case for the spiritual value of Native American sacred sites. If users do post photographs depicting spiritual benefits, they may not be recognizable as such by the classifier.

Negative ecosystem features that may be relevant for restoration may be difficult to infer from social media photographs. Natural threats to human health and safety that undermine benefits were never unambiguously depicted in the photographs we classified. These may include terrain or navigation hazards, biting insects, poisonous vegetation, wildfire, or vegetation-impacted sight-lines. Decision-makers should recognize that relative valuation based on photographs posted to social media may not capture these social-welfare concerns related to the environment due to bias toward depicting positive experiences. Also, photographs unambiguously depicting depreciative behavior such as littering or vandalism (Dorwart et al., 2009) were virtually absent from the data, suggesting that these aspects of nature experience may be underrepresented in social media photographs.

Similarly, there may be a "curation effect" in social media wherein users tend to share photographs that depict themselves living their best possible lives (Stevens-Davidowitz, 2017). Since posted photographs still depict user's preferences for how they interact with nature (or how they want to be perceived as interacting with nature), this bias may not seriously decrease the reliability of data for relative valuation of benefits, but we do not really know. Unrecognized biases and unphotographed benefits are a major challenge for using social media data to infer preferences (Oteros-Rozas et al., 2017).

It is worth noting that similar issues apply to stated preference approaches for which reporting errors, sample selection bias, nonresponse, and other biases complicate interpretation (Keeler et al., 2015). Also, stated preference data are rarely spatially explicit in the way geotagged photographs are (Hernández-Morcillo et al., 2013).

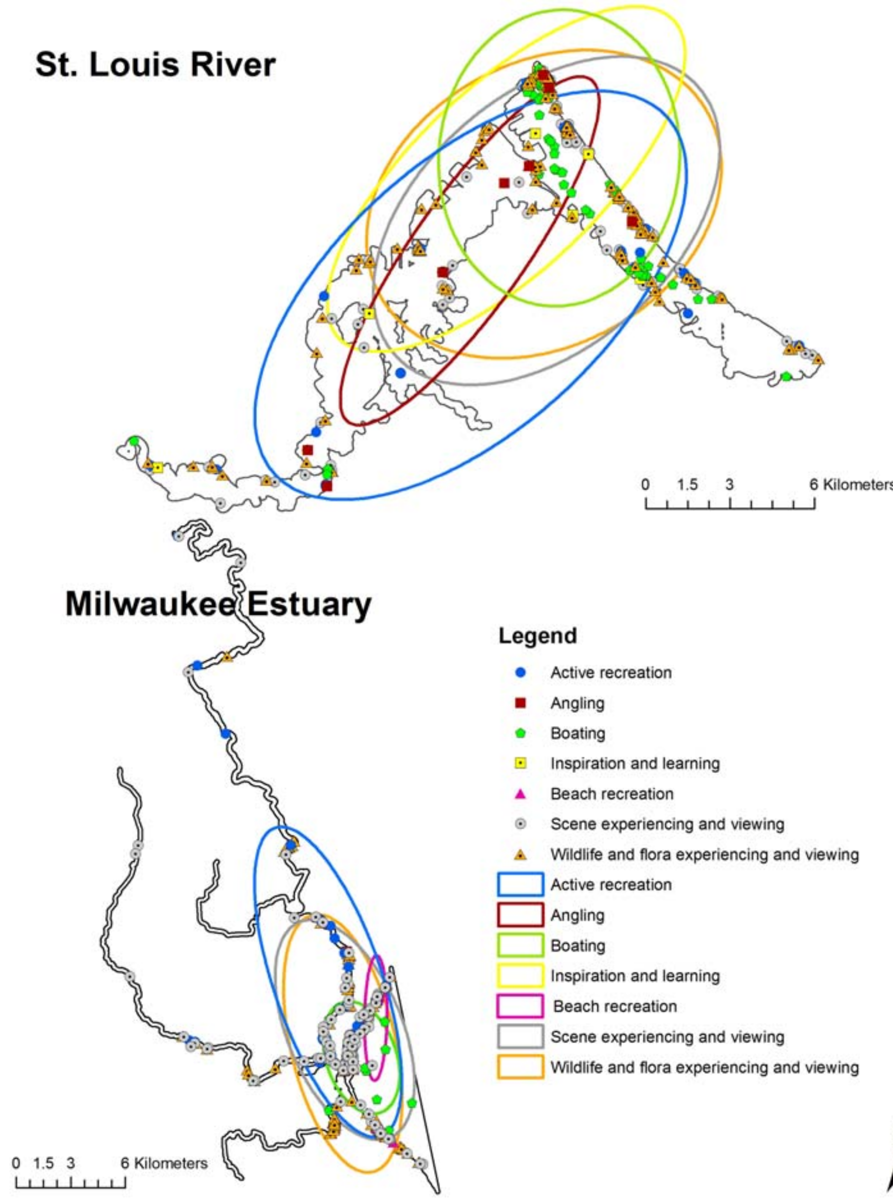

Fig. 7. Photograph geotag locations for Flickr photographs depicting an ecosystem benefit. Active recreation includes hiking and biking on trails, recreation with dogs, public greenspace use, and other recreation (see Table 4). Ellipses include about 68% of the observations (one standard deviation). See Appendix A1 for map detail.

Given that large social media data sets can often be obtained at little cost beyond the programming and processing costs of downloading large files, they are likely to be used increasingly for examining use and preference relative to other approaches, especially as methods for efficient classification are developed.

The Areas of Concern

There were some common patterns between AOCs in the proportion of images depicting classes of benefits (best shown in Table 5). Scene experiencing and viewing and fauna and flora were the most frequent subject matter in photographs from AOCs. The relative frequency of photographs depicting benefits such as boating, angling, and greenspace, varied considerably between AOCs, however. Community context can exert a strong influence on how residents and visitors interact with nature (Stedman et al., 2004), and derived preferences should be transferred across locations with caution. Variation in the demographic context (e.g., a large city like Milwaukee versus a smaller urban area like Duluth/Superior) are related to user demographics (e.g., local vs non-local), and probably age and affluence as well. The character of AOCs (e.g., mostly lake-like and partially undeveloped for the St. Louis River, mostly riverine and fully developed for the Milwaukee Estuary) influence the extent and types of natural habitats that are present. Our study shows, however, that many ecosystem benefits depicted in shared photographs occur in greenspaces and on waterways within highly developed urban areas of both Milwaukee and Duluth.

Changes over time in the subject matter of spatially explicit photographs posted to social media may be useful for assessing change in how ecosystem benefits are valued at a place. Confounding this application will be concurrent changes in the “supply” and accessibility of nature, changes in demographics, and changes in how social media are used. Another important consideration for future applications of this approach is photograph density. For Instagram, the density of geotags for posted photographs was much higher for Milwaukee (106/km^2, from Table 3) than for the St. Louis River (22/m^2), much of which is easily accessible only by boat. Likewise, for Flickr, density of geotags was 1300/m^2 for the Milwaukee Estuary compared to 100/m^2 for the St. Louis

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River. For smaller AOCs not located in urban centers, it is likely that relatively few photographs will be posted to online photo-sharing sites.

We do not think our findings are unique to Great Lakes AOCs. Very few users are likely aware that the subject matter of their photographs occurs in an AOC. Photographs posted to photo-sharing sites of non-AOC coastal communities comparable in size, demographics, and biophysical setting to the St. Louis River (Duluth, MN) or the Milwaukee Estuary will likely depict a similar set of benefits, although the relative proportions of depicted benefits will vary.

Detailed geospatial analysis of photographic geotags is beyond the scope of this paper. Our intent was to show the dispersion of photographic locations in each AOC. We showed for example that photographs depicting a benefit were consistently dispersed across a larger area than images not depicting a benefit. We speculate that this was due to the concentrating effect of urban tourist locations where the focus tends to be on non-natural amenities. At Duluth, this includes the Canal Park area near the Duluth Entry from Lake Superior (Appendix A1). At Milwaukee, this includes the Milwaukee Art Museum, other museums, entertainment venues, and other infrastructure. Our maps revealed areas in the St. Louis River and Milwaukee Estuary AOCs where relatively few shared photographs depicting a benefit were taken. In the St. Louis River this includes Allouez Bay and the Upper St. Louis River above Spirit Lake. What accounts for this is unclear. It may be due to lack of recreational access or amenities like trails, parks, and boat landings, distance from local population centers, or some other demographic factor. Similar factors may account for the relatively few photographs depicting benefits from upriver reaches in the Milwaukee Estuary.

Application

Overall, 17% of photographs from AOCs that we classified depicted an ecosystem benefit (more, 23%, if only outdoor photographs were considered). This was not surprising since these AOCs are embedded within urban or suburban mixed-use areas with an abundance of non-natural and indoor photographic subject matter. Comparable values from the literature are few and difficult to interpret with available details. >80% of social media photographs from mangrove nature reserves on Singapore depicted ecological benefits (Richards and Friess, 2015). About 60% of Instagram and 90% of Flickr social media photographs from a South African nature park depicted services (biodiversity or landscape views, Hausmann et al., 2017). Our results for the largely urban AOCs are corroborated by Guerrero et al. (2016) who found that only about 30% of Instagram photographs for Copenhagen, Denmark depicted ecosystem benefits, and Richards and Tunçer (2017) who found that about 20% of Flickr photographs from across Singapore were of nature.

Anchoring our classification of photographs in the FEGS-CS influenced our results because every photograph was judged from the perspective of the PSS user as the direct ecosystem beneficiary. Basing the classification of images on a different ecosystem services classification scheme would doubtless change the results to some degree. However, because the myriad subjects depicted in photographs must be composited into a limited number of benefit categories that can be reasonably inferred from the images, we suspect the relative distribution of depicted benefits using different classification methods will be at least broadly comparable.

We think Instagram currently has some advantages over Flickr and Panoramio for determining preferences of ecosystem beneficiaries in Great Lakes AOCs. A larger percentage of Instagram photographs could be associated with ecosystem benefits than either Flickr or Panoramio. Instagram was much less user-gender biased than the other PSSs for the photographs we classified. Instagram also has more users (800 million; Instagram, 2017) and is growing faster than Flickr (75 million registered photographers DMR, 2017). In our study, the mean date of available Instagram photographs was 2–4 years more recent than the other PSSs. An advantage of Flickr over Instagram that may be critical for some applications is the more accurate geotagging of uploaded photographs (see Methods).

No independent survey (i.e., stated preference) data were available with which to validate our finding. However, several studies have shown agreement between preference or use from surveys and preference or use revealed by analysis of photographs posted to social media (Hausmann et al., 2017, Heikinheimo et al., 2017; Keeler et al., 2015; Wood et al., 2013). Applicable user survey data are hard to come by for the coastal Great Lakes, and we encourage holders of these data to consider exploring congruence between survey findings and comparable social-media sourced data.

A recent survey of natural resource decision-makers in the Great Lakes region (Engel et al., 2017) found that most (≈65%) were at least moderately well informed about the ecosystem services paradigm and its relevance for management decisions. Unfortunately, managers also felt that research was not providing information adequate for decision-making, especially with regard to valuation of benefits (Engel et al., 2017). This disconnect is well documented in other contexts (e.g., Berghöfer et al., 2016; Posner et al., 2016). For non-market cultural benefits, which include recreational and inspirational benefits, relative valuation based on analysis of photographs posted to social media may help fill that gap. Aggregate social preference based on the proportional distribution of benefits derived from shared photographs can be readily converted to relative weight coefficients using ranks or proportions, and applied to the providing areas for benefits in restoration alternative tradeoff analyses (e.g., Angradi et al., 2016).

Exploring the feasibility of using social media data to deriving these weight coefficients for use in tradeoff analysis was our primary motivation for this study. An application of this approach to tradeoff analysis can be contemplated for a hypothetical restoration project in the St. Louis River by considering the relative proportions of benefits depicted in Instagram images (Table 4) as weights. As described in Angradi et al. (2016), with each change in aquatic or terrestrial habitat associated with a restoration project, the habitat "supply area" for ecosystem service changes. For example, upland habitat, which includes trails, viewpoints, native flora, and fauna, and which supports greenspace recreation, may increase or decrease in area as a result of habitat restoration. Area of deep-water habitat that supports sailing or power boating, or shallow water that is only accessible to human-powered boaters, may increase or decrease. Habitat for fish species valued by anglers may be created or eliminated. In many cases, there are spatially explicit models supporting the prediction of ecosystem service implications of biophysical changes in habitat associated with restoration scenarios (Angradi et al., 2013, 2016). For this set of Flickr photographs, the highest weight would be given to changes in habitat that effect landscape scene viewing. Weighting this benefit highly would help prevent negative changes in the natural scenic viewing of the project area. Fauna and flora experiencing and viewing is also highly weighted which may enhance the value within a scenario of habitats supporting diverse plant and animal communities. Based on this dataset, angling and human-powered boating were more important to beneficiaries than sailing or power boating. Hiking and biking on trails was more important than other greenspace use (e.g., sport fields), or dog walking.

This is a relatively coarse-grained example based on composited benefits. In practice for an actual set of restorations scenarios, the benefits would be composited so they corresponded to the particular changes anticipated within a project area. For example, if the biophysical changes that would result from a scenario are limited to aquatic habitat, then the benefits of angling and aquatic flora and fauna could be weighted as uncomposited benefits to assess changes in net benefits. As stated above, photograph density may limit the spatial scale at which weights are reliable. For this reason, it may make sense to consider the benefit implications across a set of restoration projects in the context of an AOC communities' aggregate inferred preferences. More

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research is needed to test how well this (or any) source of beneficiary preference information can be integrated into restoration planning.

Weights can also be incorporated into other restoration decision-making tools. Mazzotta et al. (2016) developed a method for compiling decision-relevant information about proposed wetland restoration that includes relative scarcity of habitats, beneficiary demographics, access, and other indicators for a core set of wetland benefits (reduced flood risk, natural scenes, environmental education, recreation, and bird watching). For some applications of their approach, preferences derived from shared photographs geotagged to or otherwise representative of the project area could add value to the outputs by revealing what services and benefits users photograph most frequently and value most highly.

Information derived from social media may also have utility for AOC monitoring. In addition to biophysical indicators used to measure progress toward AOC goals (e.g., Angradi et al., 2017), managers, should consider tracking social indicators (Hagger et al., 2017; Steinman et al., 2017). For example, before/after, restored/unrestored sample designs could be used to test for post-project changes in human use based on indicators derived from social media data.

As we have shown, there are a number of biases and challenges in applying preferences based to social media photographs to AOC restoration management and planning. Though imperfect for planning, these preference data may be all that is available in many decision contexts. At a minimum, geo-tagged photographs posted to photo-sharing sites are reliable cultural documents insofar as a person was at a place and they captured and shared some personally-compelling aspect of the place/experience. We suggest that AOC decision-makers avail themselves of this vast and growing body of information. Multidisciplinary research teams (e.g., ecologists, social scientists, geographers) can help translate social media and other data into information and knowledge useful to decision makers.

Insights about social preference derived from shared photographs constitute passive but spatially-explicit engagement with stakeholders. Availability of social media data does not reduce the need to foster relationships of trust between restoration decision makers and stakeholders (i.e., ecosystem beneficiaries). In some contexts, spatially-explicit preferences for ecosystem benefits based on our approach may serve as a starting point for communication between decision makers and beneficiaries about the ecosystem benefit implications of restoration efforts in Great Lakes coastal communities. When empirical evidence of what beneficiaries care about is incorporated into the decision process, the likelihood of equitable and sustainable social outcomes increases.

Acknowledgments

The opinions expressed in this article are the authors' and do not necessarily reflect EPA policy. Kathleen Williams, Dixon Landers, Rebecca Hale, and Marc Gaden provided useful comments on the manuscript.

Appendix A. Supplementary information

Supplementary information for this article can be found online at https://doi.org/10.1016/j.jglr.2017.12.007.

Appendix B. Supplementary data

Supplementary data for this article can be found online at https://doi.org/10.1016/j.jglr.2017.12.007.

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Please cite this article as: Angradi, T.R., et al., Determining preferences for ecosystem benefits in Great Lakes Areas of Concern from photographs posted to social media, J. Great Lakes Res. (2018), https://doi.org/10.1016/j.jglr.2017.12.007