THE USE OF CROWDSOURCED AND GEOREFERENCED PHOTOGRAPHY TO AID IN VISUAL RESOURCE PLANNING AND CONSERVATION: A PENNSYLVANIA CASE STUDY

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Abstract.—This paper uses a Pennsylvania case study to discuss opportunities for using crowdsourced and georeferenced photography to aid in visual resource conservation and planning. Studies have shown that clustering of georeferenced photos indicates interest in a point of view within the landscape or a particular visual or cultural resource. This clustering can also aid in prioritizing visual resource conservation efforts by indicating preference for certain locations over others. The present research began by examining where in Pennsylvania people were taking photos using Google Earth imagery sourced from the now nonoperational (as of November 2016) Website Panoramio. We analyzed the content and locations of 7,309 photos. To provide some context for conservation, we focus here on photos taken in areas of Pennsylvania with natural gas "fracking" activity. However, this method can also be applied to situations with other forms of landscape impacts related to climate change, population growth, and urban/suburban sprawl.

INTRODUCTION

In their introduction to landscape-scale conservation planning, Trombulak and Baldwin (2010) emphasize that:

> "…[C]onservation planning is a multilayered, systematic process that progresses in an orderly fashion from conservation vision to science, to communication of results and engagement of stakeholders, to design, and finally to implementation" (p. 8); and

> "[It is important to select] the proper temporal and spatial scale for the conservation goals chosen, considering both cultural and natural history, responding to present and emerging economic trends, engaging both stakeholders and experts, developing multivariate measures of threats and opportunity, and practicing patience, creativity, and collaboration" (p. 13).

Visual and cultural conservation may also need to be done at scales larger than those typically addressed by cultural landscape studies. At the regional scale, specialist consultants, designers, policy-makers, NGO stakeholders, and scientists, to name a few, may all need to collaborate in order to establish a satisfactory conservation plan (Steinitz 2012, Trombulak and Baldwin 2010). For problems that occur at the regional scale, it is often difficult to find current data that cover the entire affected area.

Visual Resource Assessment

Traditional methods of visual resource assessment in landscape architecture and allied disciplines have long included the use of photographs and video, both analog and digital. In one type of assessment, the investigator provides images for test respondents to analyze and rank, sometimes allowing for projection of preference across the landscape. This top-down approach is usually used with respondents who are removed from the actual landscape experience. In another method, trained landscape architects (typically) apply principles of formal aesthetics to judge the value of landscape settings. Daniel (2001) and Zube (1984) warn against this "expert" approach, indicating that it may not take into consideration all of the public's values and perceptions. Finally, as Riley (1997) suggests, all of these forms of visual analysis tend to be atemporal.

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To address these shortcomings, another approach asks research participants to bring a camera into the field and take photographs either at their whim or in response to a prompt (such as photographing what they consider to be "scenic" or "beautiful"). The photographer gives photos to the investigators for later analysis; the investigator may have asked the subjects to record their reasons for photographing. These approaches, termed "visitor employed photography" or "photovoice," while addressing weaknesses in other methods, require that the subjects are aware that they are part of a study, which may sway their intentions or influence the subject matter of their photos.

We postulate that crowdsourced data from photographs taken voluntarily in situ remedy both the atemporal and top-down problems in visual analysis.

Big Data, Crowdsourced Photography, and Social Media

The advent of Web 2.0 and the growth of social media platforms have fostered a new environment for the taking and sharing of photos. Social media Websites like Flickr and Panoramio (previously the image hosting site for Google Earth, closed as of November 2016) allow users worldwide to upload and share georeferenced photographs. A New York Times (2011) survey about online sharing via social media (n = 2,500) found that:

- 68 percent of respondents share photos or other information to give people a better sense of who they are and what they care about;
- 73 percent share information because it helps them connect with others who share their interests;
- 84 percent share because it is a way to support causes or issues they care about; and
- 94 percent carefully consider how the information they share will be useful to the recipient.

These findings suggest that most social media posting is meaningful to the user and not haphazardly done.

These new resources also allow investigators to access large reserves of photographic images taken in situ, many with substantial metadata and geographic coordinates. Images are taken without prompt and contributed voluntarily to various image hosting Websites. The photos represent what the individual was observing in the landscape at a particular moment and their decision to share the image suggests a positive valuation of the photo and the view.

Recent studies that have used publicly available online data to understand people's perceptions of the environment or landscape include Dunkel (2015) and Newsam (2010). Some studies have looked specifically at scenic-ness as their metric (Alivand and Hochmair 2013, Hochmair 2010, Xie and Newsam 2011).

One way to coalesce impact data across a region is to crowdsource it by deliberately requesting that people provide images that fit a particular theme. FrackTracker Alliance and its Website fractracker.org, for example, use crowdsourced photography and videos to document impacts of unconventional shale gas development in the United States and other countries. The volunteered media can be sorted by theme (e.g., air quality concerns, rigs, water impoundments, pipelines, etc.) or by location such as state or country. While the photos are not georeferenced, they do have locational information in their descriptions so at least municipal level location can be determined for impact assessment. It is possible to combine this information with photographic preference data to see where spatial overlaps occur between impacted areas and sites or areas with special significance to the photographers.

Similarly, our work uses photographs posted voluntarily online to address visual and cultural conservation at larger scales. Beyond the kinds of records traditionally collected at the site scale, these big data allow for more efficient visual landscape assessment at the regional scale and a broader representation of stakeholder viewpoints throughout the impacted region. At larger scales, photographs may reveal broad patterns in the landscape including preference for certain land cover types and ease (or lack of) access to visual and cultural resources.

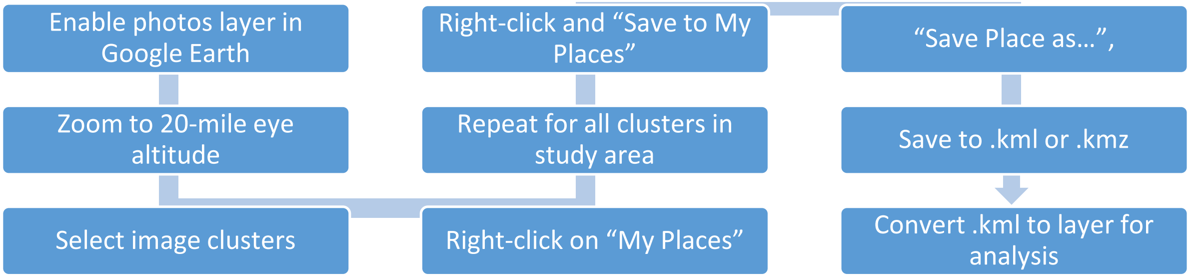


Figure 1.—Data collection process.

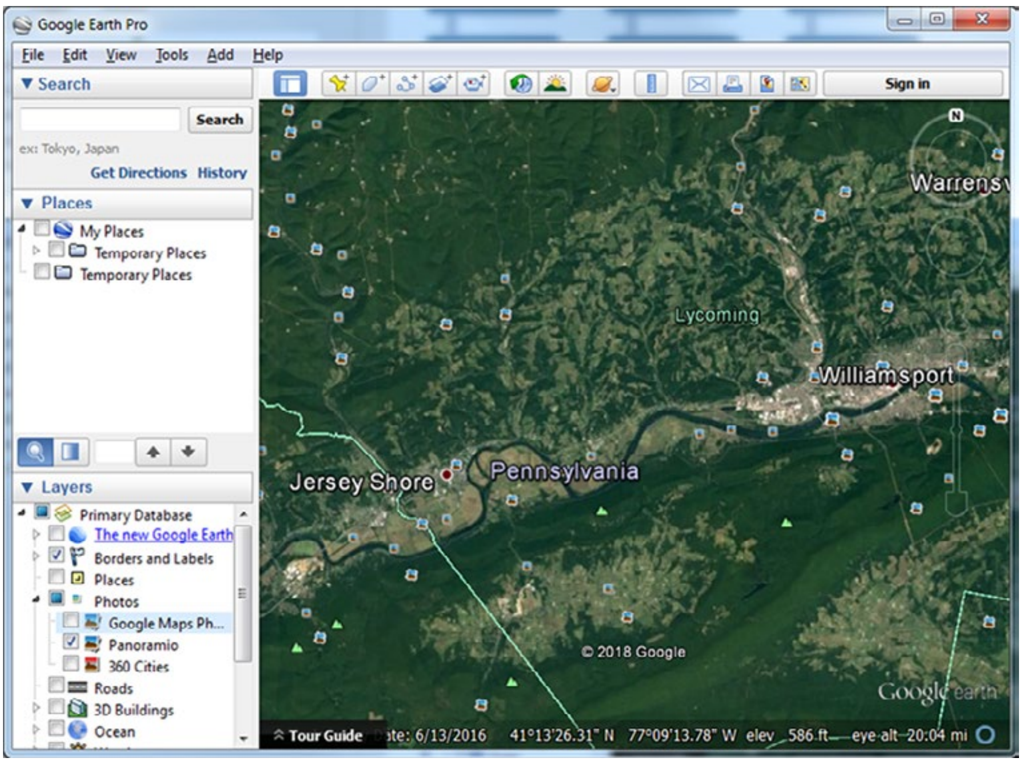


Figure 2.—Computer screen shot using Google Earth with Panoramio photos. Google Earth Pro.

OBJECTIVES OF THIS RESEARCH

The onset of Marcellus Shale natural gas development in the State of Pennsylvania, together with the rapidly widening availability of crowdsourced citizen photography, provided a valuable opportunity to study crowdsourced and georeferenced photography as an aid in visual resource conservation design and planning. Following Trombulak and Baldwin (2010), the goals for this work include: 1) identifying spatially explicit measures of change in the landscape, 2) predicting spatially explicit threats to the landscape, 3) recognizing sites within the region that are important or irreplaceable, and 4) prioritizing areas for conservation action to address pressures and preserve/ conserve exceptional sites in the future.

METHODS

The data collection process (Fig. 1) involved gathering photos from Google Earth's Panoramio layer. Panoramio clusters photos differently at different scales so that zooming away from the Earth's surface condenses photos into fewer clusters while zooming in separates them into more clusters with fewer photos.

We collected photos at a 20-mile eye altitude zoom level (Fig. 2). At this distance, only clusters with multiple photos were selected, based on the assumptions that multiple photos indicate interest in a location and that multiple users photographing and uploading in a location demonstrates consensus (Alivand and Hochmair 2013, Dunkel 2015, Hochmair

2010). When saving the cluster, the metadata and embedded title provided by the user were saved from the most popular photo (most viewed or liked/favorited photo) within that cluster. The resulting data points saved from the cluster locations thus represent interest in a place, but not necessarily in the photo itself.

This process was repeated all over Pennsylvania, working county by county, using the right-click "Save to My Places" command within Google Earth. Each county was then exported as a KML file by right-clicking on "My Places," then "Save My Place as …," then "Save to .kml" and named for the county. After all counties were inventoried, we added all of the county KML files back into Google Earth and exported a master KML file for the entire state. The master file contained 7,309 photos (and corresponding location points).

We then applied a 1-km buffer to the point locations to help document and describe the physical context of each photo using 2011 National Land Cover Dataset (NLCD), 30-meter resolution (Homer et al. 2015). Using the Geospatial Modelling Environment (GME) software program, we calculated the representative area of all land cover types for each of the 7,309 1-km buffers. For this task, the GME "isectpolyrst" (intersect polygons with raster) function offers a benefit over traditional spatial joins and similar tools in ArcGIS, which do not include overlapping polygon areas in the calculations. Finally, we calculated percentage of land use/land cover within the 1-km buffers and classified the 7,309 photo location points by the majority land cover type found within their respective buffers.

In addition to evaluating the physical context of the 7,309 photos, we classified and categorized metadata included with the photos to integrate our work more fully with the broader Appalachian Landscape Conservation Cooperative pilot study. The goal was to categorize the images using a classification system based on the key categories in the National Register of Historic Places. We chose the National Register of Historic Places because it is a well-known and long-established program that coordinates public and private efforts to identify and protect America's historic and archaeological resources.

Initial categories included The Arts, Infrastructure, Religion, Economy, Society, Education, Military, Environment, and Transportation. These were amended to add a Scenic category (to catch images whose subject looks out over a mixed landscape in a long-distance view), and Ephemeral (to catch images whose subjects are fleeting, such as weather, seasons, etc.). The Environment category was subdivided into Human Environment and Natural Environment to help understand the nuances between environments and landscapes that are clearly touched by people and those that appear more "natural." Images were classified by their titles, initially using a keyword search, and then manually for those not captured by the keyword search. Untitled images (704) and those whose titles were not intuitively descriptive were visually inspected and classified according to their subject matter.

RESULTS

Using 2010 U.S. Census data, 3,019 images fell within areas classified as urban and the other 4,200 were in non-urban areas. Figure 3 shows the point density for the distribution of the photos, and units of density are points per square meter represented in 500-meter pixels.

Comparison with the NLCD classifications shows that the majority of people took photos in areas with forest land cover; 52.4 percent depicted deciduous forest, 1.8 percent showed mixed forest, and 0.3 percent included evergreen forest for a combined 54.5 percent total forest classification. The next highest category was developed open space, such as parks, at 10.6 percent. All results are shown in Table 1.

Interestingly, even when we separated urban and non-urban areas according to the 2010 Census data, deciduous forest was still the highest ranked land cover type. After deciduous forest, in urban areas, the most photos were taken in developed open space and developed low and medium density areas. In nonurban areas, deciduous forest was followed by hay/pasture areas and cultivated crops.

Figure 4 shows the geographic distribution of all of the photo buffers and their dominant land cover types. Development is represented in reds, pinks, and purples, and these aggregate in the urban areas. The length of the Susquehanna River is clearly displayed in blue.

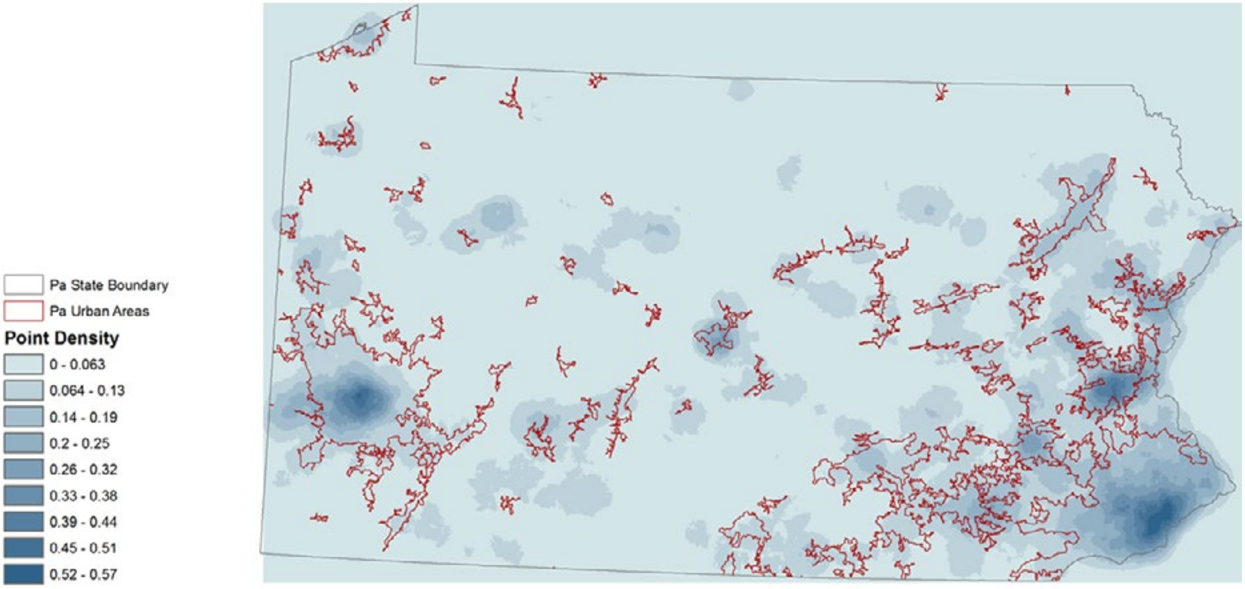


Figure 3.—Point density of photos in Pennsylvania areas and delineation of urban areas.

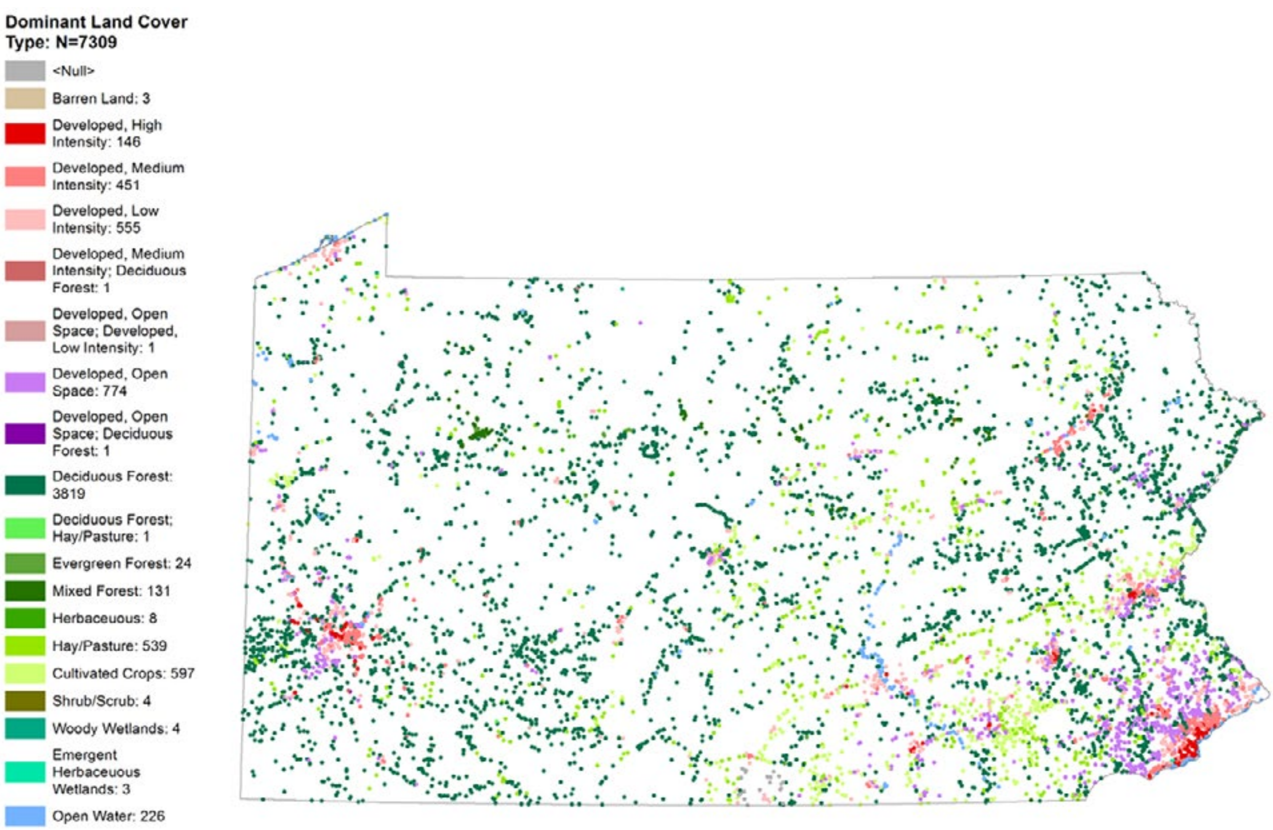


Figure 4.—Distribution of photos and land cover type in Pennsylvania.

Table 1.— Percentage land cover type: urban vs. nonurban (colors [red-through-green] denote 5 most prevalent categories in the combined "all" list and show where these categories fall in the "urban" and "nonurban" sub-areas)

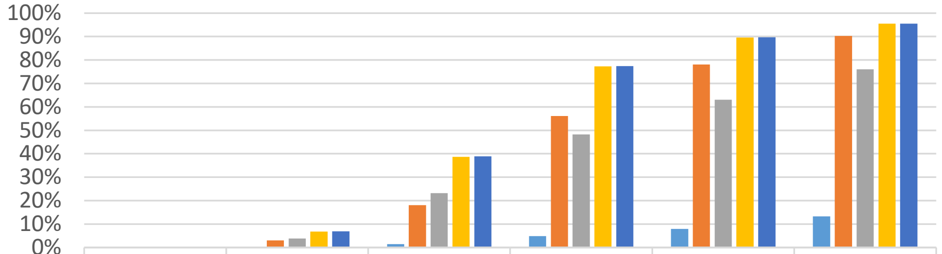
Classification	urban	nonurban	all
Deciduous forest	33.8%	72.9%	52.25%
Developed, open space	19.5%	0.6%	10.6%
Cultivated crops	7.2%	9.2%	8.2%
Developed, low intensity	14.3%	0.1%	7.6%
Hay/pasture	5.3%	9.6%	7.4%
Developed, medium intensity	11.7%	0.0%	6.2%
Open water	3.7%	2.4%	3.1%
Developed, high intensity	3.8%	0.0%	2.0%
Mixed forest	0.2%	3.6%	1.8%
Evergreen forest	0.0%	0.7%	0.3%
Herbaceous	0.0%	0.2%	0.1%
Shrub/scrub	0.1%	0.0%	0.1%
Woody wetlands	0.0%	0.1%	0.1%
Barren land	0.1%	< 0.1%	< 0.1%
Emergent herbaceous wetlands	0.1%	< 0.1%	< 0.1%
Developed, medium intensity; deciduous forest	< 0.1%	< 0.1%	< 0.1%
Developed, open space; deciduous forest	< 0.1%	< 0.1%	< 0.1%
Developed, open space; developed, low intensity	< 0.1%	< 0.1%	< 0.1%

Another interesting pattern that emerged relates to access. Figures 5 and 6 show that 95.5 percent of all photos were taken within 0.5 kilometers of a road. This equates to about four blocks or an 8-minute walk. The textual analysis also yielded useful results. While we expected a high number in the "natural environment" category based on the geographic distribution and land use analyses, we did not expect transportation to be the second largest category. Table 2 shows the category percentages and Table 3 shows the number of photos in each category and subcategory.

DISCUSSION

This research used crowdsourced georeferenced photos in a manner similar to Alivand and Hochmair (2013) and Hochmair (2010), who suggest that a location or artifact is scenic if more than one photo, posted by unique users, is located in a particular place. As an artifact, each photo is a spatial event. Relying on analogies from ecology, we recognize that these events occur in a spatial context. In order to capture or model that context, we buffered each location. With scenic vistas, there are often several vantage points from which a view can be seen, so a distance buffer is required for those images. Similarly, an artifact such as a building can be photographed from multiple sides and locations, again requiring a buffer to associate those images with one another. In this case, we filtered metadata tags (Dunkel 2015) to find relationships between images.

As has been found in much of scenic conservation research and literature, natural or naturally appearing areas and greenery were common in the photos we analyzed. The geospatial analysis showed that deciduous forest was the most photographed land cover type in Pennsylvania, in both urban and nonurban areas. In urban areas, developed open space (parks and similar) were second. In nonurban areas, people photographed and shared hay/pasture and cultivated crops second and third, respectively. Compared with the textual analysis, this makes sense as the natural environment category was the most popular. However, one issue is that small water bodies in forested areas would not be visible at the NLCD 30-meter scale (water was the most popular subcategory in the textual analysis). The next steps for this work would be to combine and cross-validate the geographic and textual analyses.



	0m	1m	10m	100m	.25km	.5km
Unpaved	0.0%	0.2%	1.5%	4.8%	8.0%	13.3%
Local	0.0%	3.0%	18.1%	56.1%	78.0%	90.2%
State	0.0%	3.8%	23.2%	48.2%	63.1%	76.1%
Improved	0.0%	6.8%	38.7%	77.3%	89.6%	95.5%
All	0.0%	6.9%	38.9%	77.4%	89.7%	95.5%

Unpaved Local State Improved All

Figure 5.—Photo locations as a percent and their proximity to roads types.

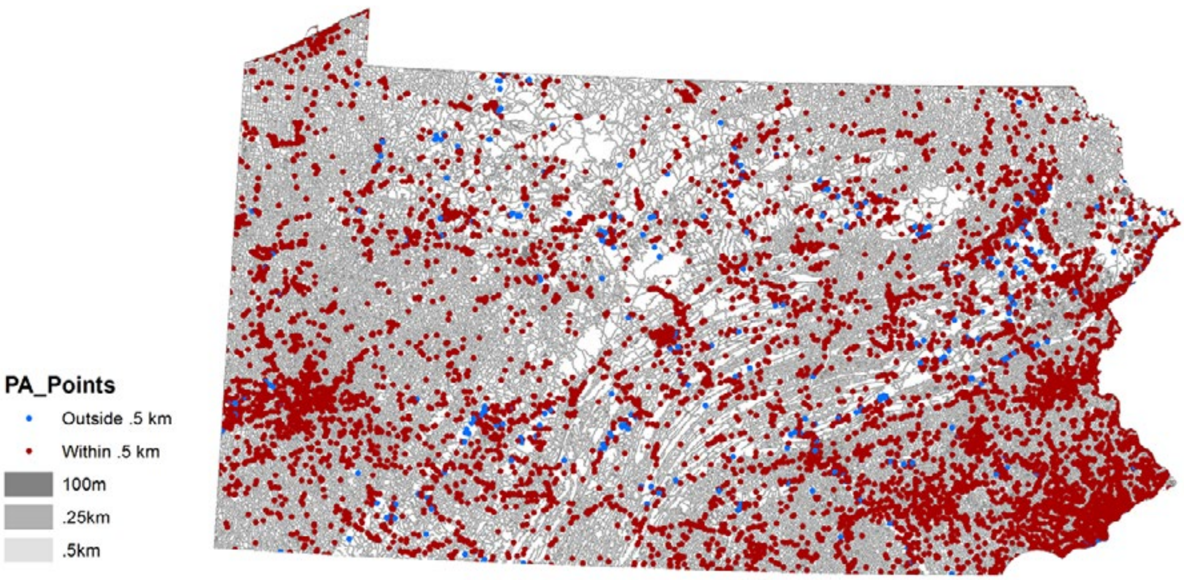


Figure 6.—Photo proximity to roads.

Table 2.—Textual analysis results

Category	percent
Natural environment	18.5%
Transportation	18.3%
Human environment	17.2%
Cultural	14.9%
Economic	8.1%
Religion	6.0%
Infrastructure	5.2%
Ephemeral	3.8%
Scenic	3.6%
Education	2.2%
The arts	1.5%
Military	0.7%

Table 3.—Textual classification index.

Natural environment	count
Water	627
Waterfall	133
Vegetation	116
Forest	103
Animals	89
Geology	79
Mountains	61
Field	38
Nature preserve	35
Valley	16
Wetland	14
Island	13
Disaster	9
Beach	5

Transportation	count
Road	470
Bridge	288
Covered bridge	152
Railroad	150
Tunnel	47
Air	45
Transportation	30
Gas station	28
Train	26
Vehicle	26
Canal	23
Boat	21
Dock	10
Parking lot	7
Port	4
Disaster	1

Infrastructure	count
Sign	113
Energy	100
Firehouse	24
Hospital	23
Telecommunication	21
Post office	17
Courthouse	15
Fire tower	15
Water tower	13
(Storm)water management	9
Town hall	9
Utilities	6
Prison	4
Police	3
Springhouse	3
Senior living	2
Turnpike commission	1
Plaque	1

Cultural	count
House	321
Town/city	319
Recreation	241
Ruins	42
Memorial	28
People	22
Monument	21
Festival	17
Civic center	14
Object	13
Cultural	9
Visitor center	6
Cultural/historical society/center	5
Historic site	5
Historic/cultural district	4
Historical marker	4
Plaque	4
Archaeological site	3
Political	2
Mound	1

Economic	count
Business	201
Restaurant	99
Hotel	81
Industry	66
Store	62
Mill	60
Quarry	12
Bank	5

Religion	count
Place of worship	271
Cemetery	148
Religious symbol	7
Religion	4
Plaque	1

Scenic	count
Vista	262

Education	count
School	72
Education	66
Library	9
Schoolhouse	8
Arboretum	4
Plaque	1

Military	count
Military	38
Memorial	10

Human environment	count
Park	280
Trail	211
Farm	156
Barn	100
Agriculture	83
Countryside	68
Dam	65
Building	41
Reservoir	29
Structure	27
Domestic animals	26
Cabin	25
Yard	25
Object	23
Decay	14
Disaster	14
Fountain	9
Garden	9
Fair grounds	8
Dump	6
Square	6
Lighthouse	5
Wall	5
Human environment	4
Courtyard	2
Construction	1
Greenhouse	1
Interior	1
Plaque	1
Wrong	1

Ephemeral	count
Sunset	81
Snow	53
Autumn	39
Weather	31
Sunrise	23
Clouds	15
Rainbow	13
Winter	9
Moon	5
Spring	4

The arts	count
Art	37
Architecture	27
Museum	18
Theater	15
Statue	11
Arts	2

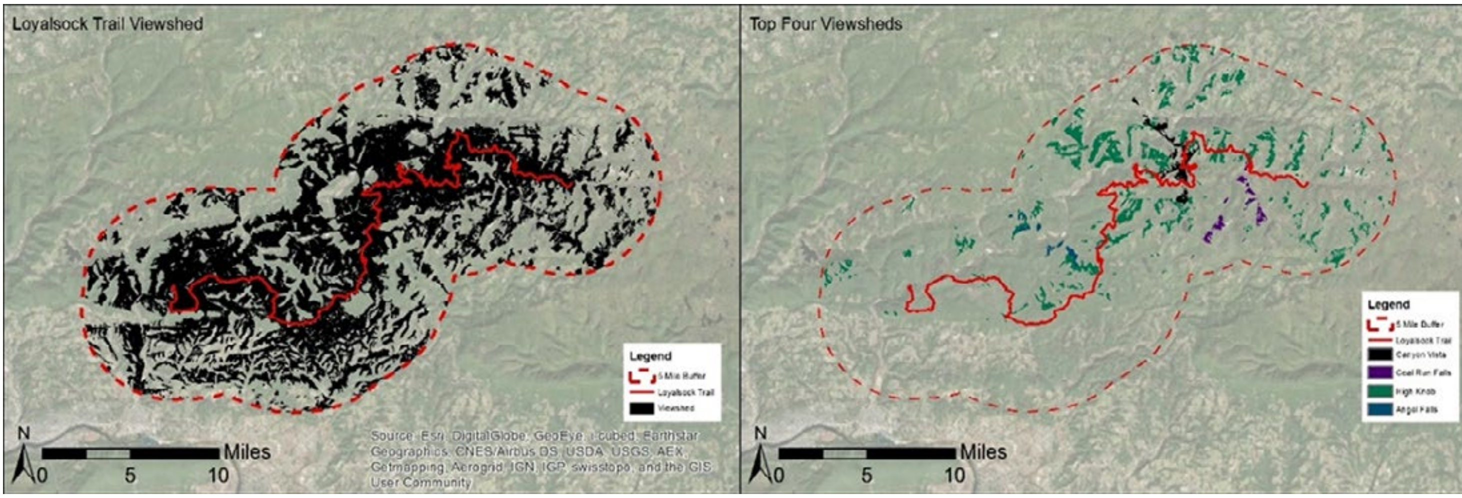


Figure 7.—Loyalsock Trail: entire viewshed and top four sub-viewsheds.

One unexpected finding was the popularity of transportation as a photographic subject in the textual analysis. About 35 percent of transportation-related photos showed roads and many were obviously taken from a vehicle. These included streets and intersections, highways, and images specifically titled as “xxxx Street” (or Road, Boulevard, etc.). Further research is needed to better understand why roads are so important and so frequently photographed. One obvious hypothesis is that roads enable people to visit a location and take a photo; therefore, if people cannot drive to a location, they are unlikely to visit and photograph it.

This has implications for conservation in that if people cannot visit or see something, they will not value it (Whyte 1968). On the other hand, limiting vehicular access to an area may prevent many people from visiting it, which can be good for sensitive landscape areas and habitats.

Examples of Potential Applications

The work described here has several additional potential applications. First, our findings suggest that locations with the most crowdsourced photos (from unique contributors) may be obvious priorities for conservation efforts. An example of this from a related project (Goldberg 2015) looked at the 113,743-acre viewshed of the Loyalsock Trail, a historic 60-mile hiking trail in central Pennsylvania. In the midst of Marcellus Shale development, the Loyalsock Trail spans two counties, eight municipalities, and two conservation regions (the Pennsylvania Wilds and Endless Mountains regions). To focus limited resources along the trail, crowdsourced photos were analyzed and areas with the most photos (from unique contributors) were listed in rank order. This allowed sub-viewsheds along the length of the trail to be dealt with individually and in order of scenic and cultural importance (Fig. 7).

A second potential application is analyzing how areas of Pennsylvania that are visually and culturally important are being impacted by energy development. Figure 8 shows where Marcellus Shale gas well development locations and photo point locations co-occur. This rough analysis quickly draws focus to the northeastern part of the state where densities of both kinds of locations are high. This region is known as the Northern Tier or the Endless Mountains region and is highly valued for its rolling hills, beautiful forests, and bucolic scenes. As seen in the figure, these valued areas and the associated scenery are at risk from shale gas development.

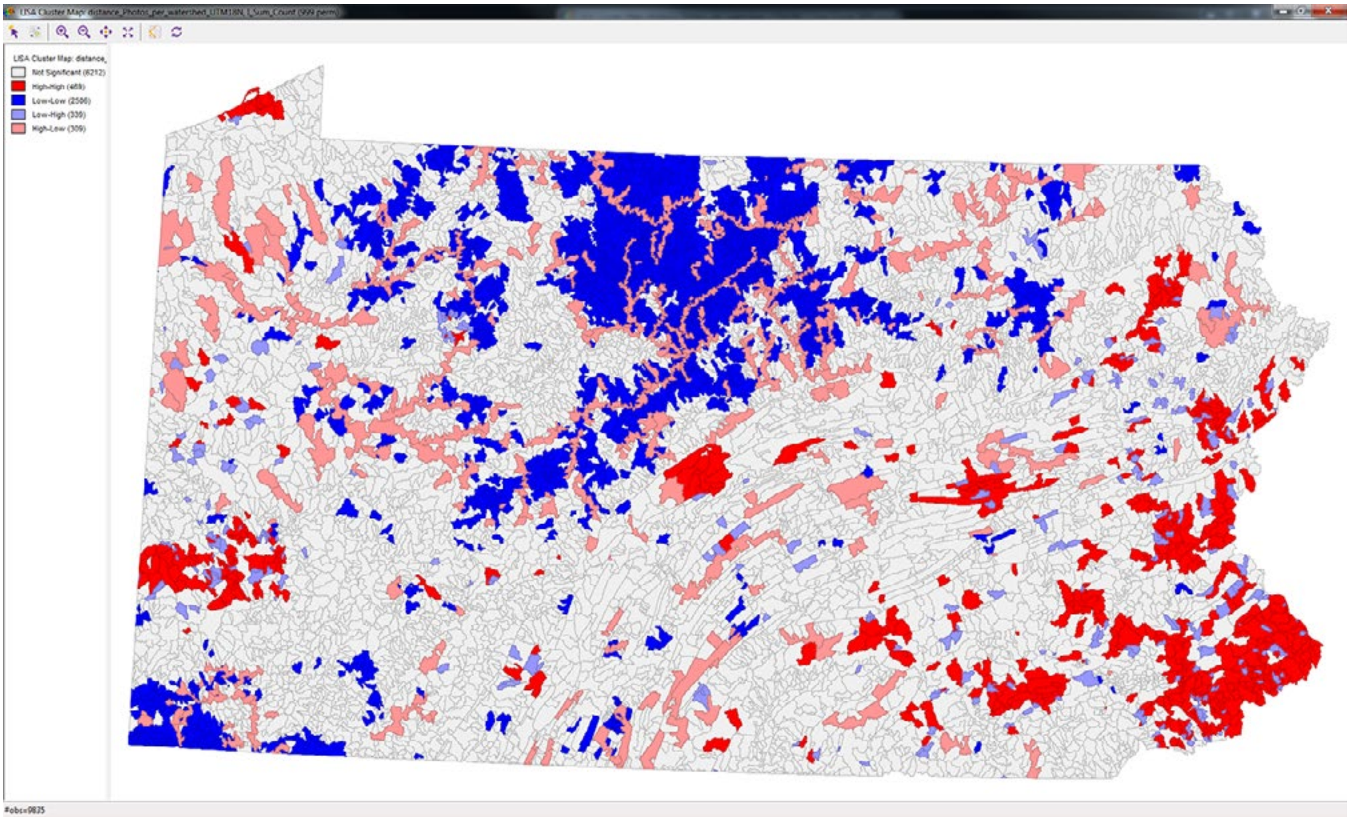


Figure 8.—Marcellus Shale gas well and photo point density overlay.

CONCLUSIONS

This paper examines several forms of crowdsourced data and their utility and versatility in visual resource planning and conservation. As this study shows, crowdsourced photos can reveal where people are visiting and taking photographs in a landscape. The next step of subsequent sharing to social media indicates that the photographers value these locations. Repeat photographs in a particular location suggest consensus among those visiting, seeing, and sharing these visual and cultural landscapes and amenities.

Crowdsourced data does have its faults. It is a convenience sample and may not represent the opinion or views of all stakeholders, particularly those without access to transportation, technology, or social media. The photos themselves may be labeled with incorrect locations, have missing or incomplete metadata, and may depict subjects that are unclear to the researcher without further explanation. However, big data, as the name suggests, are large data sets, inexpensive or free for use in a multitude of analyses.

This work aims to inform a broader pilot study of the Appalachian Landscape Conservation Cooperative Network.

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