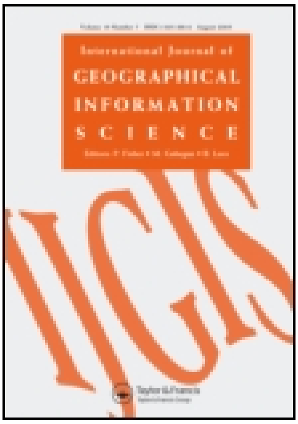

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An evaluation of the use of points versus polygons in public participation geographic information systems using quasi-experimental design and Monte Carlo simulation

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The collection of spatial information through public participation geographic information systems (PPGIS) is most frequently implemented using either point or polygon spatial features but the research trade-offs between the two methods are not well-understood. In a quasi-experimental PPGIS design, we collected four attributes (aesthetic, recreation, economic, and biological values) as both point and polygon spatial features in the same PPGIS study. We then used Monte Carlo simulation methods to describe the relationship between the quantity of data collected and the degree of spatial convergence in the two methods for each of the four PPGIS attributes. The results demonstrate that the same PPGIS attributes identified by points and polygons will converge on a collective spatial 'truth' within the study area provided there are enough observations, however, the degree of spatial convergence varies by PPGIS attribute type and the quantity of data collected. The use of points for mapping PPGIS attributes and aggregating areas through density mapping constitutes a conservative approach to spatial inference about place significance, but the data demands for point collection are considerably higher than for polygon features. Based on our results, we provide heuristic guidelines for future PPGIS research when using point or polygon spatial attributes. We argue that other variables such as the cognitive complexity of the PPGIS mapping process and stronger claims of external validity favor the use of point features, but these advantages must be weighed against the significantly higher sampling effort required.

Keywords: public participation GIS; geographic information systems; spatial analysis; Monte Carlo simulation

Introduction

The term 'public participation geographic information systems' (PPGIS) was conceived in 1996 at the meeting of the National Center for Geographic Information and Analysis in the United States to describe how GIS technology could support public participation for a variety of applications with the goal of greater inclusion and empowerment of marginalized populations. PPGIS combines the practice of GIS and mapping at local levels to produce knowledge of place. The formal definition of the PPGIS remains 'nebulous' (Tulloch 2007) and 'inconsistent across applications' (Schlossberg and Shuford 2005) with use of the term 'PPGIS' emerging from developed-country contexts while the term participatory GIS or 'PGIS' is often used to describe participatory planning approaches in rural areas

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of developing countries, the result of a merger between Participatory Learning and Action methods and geographic information technologies (Rambaldi *et al*. 2006). Since the 1990s, the use and range of PPGIS applications has been extensive, ranging from community and neighborhood planning to environmental and natural resource management to mapping traditional ecological knowledge of indigenous people (see Brown 2005, Sieber 2006, Dunn 2007; and Sawicki and Peterman 2002, for reviews of PPGIS applications and methods). For example, Sawicki and Peterman cataloged over 60 PPGIS programs in the United States alone nearly a decade ago and Chapin *et al*. (2005) provided a review of spatial methodologies for mapping indigenous lands including sketch mapping techniques.

With the development of Google® Maps and Google Earth 'mashups' through an application programming interface, the availability of open source Geoweb software such as MapServer, and the development of open source base maps such as the OpenStreeMap project, the number of PPGIS applications will continue to increase. Further, there is a growing inventory of user-volunteered geographic information (VGI) (Goodchild 2007) and Web 2.0 geospatial applications (Hall *et al*. 2010) where participants can identify different spatial features. VGI involves the creation and dissemination of geographic data provided voluntarily by individuals and overlaps with PPGIS in that both involve the investigation and identification of locations that are important to individuals (Tulloch 2008). A potential difference between VGI and PPGIS relates to the purpose or motivation for participation; PPGIS projects are often implemented to inform planning and policy issues while VGI systems may have no explicit purpose other than participant enjoyment.

The context of this research is most applicable, though not exclusively, to the genre of PPGIS methods in developed countries that seeks to expand and enhance public participation and community collaboration in governmental processes for environmental planning and management. These PPGIS studies often target a regional cross-section of the general public for participation, usually through random sampling.

The potential social impact of PPGIS systems will be determined by the utility of the applications. An important methodological question yet to be addressed for data collection in PPGIS systems, which has both practical and theoretical implications, is when it is most appropriate to solicit and capture PPGIS attributes using point versus polygon spatial features. A PPGIS attribute is any characteristic, social or physical, that can be described as having a spatial extent that is requested to be identified spatially in a PPGIS. They are identified on a map by a participant using point, polygon, or line features. The purpose of this article is to empirically determine how the choice of data collection method (point vs. polygon) in PPGIS influences the mapping results, and to provide some heuristics based on the convergence or divergence of results to provide future research guidance.

The validity of PPGIS methods depends on public participation rates and related sampling issues and the quality of the data collected. Participation rates are affected by the quality and design of the spatial data collection method and supporting instructions, among other variables. For example, in a recent PPGIS study, Pocewicz *et al*. (2010) found about a third of the non-response was related to the content of the PPGIS. Minimizing cognitive complexity and enhancing ease of use for the PPGIS participant appears essential to increasing participation rates. And yet, there may be a contrary relationship between the simplicity of the PPGIS data capture methods and the resulting quality of the spatial data. Survey researchers have long recognized that social data collection must balance participant engagement with the length and complexity of the survey instrument as well as the manner in which certain types of questions are framed. For example, both paper and web survey research results may be influenced by the wording, sequencing of questions, and visual layout (see e.g., Christian and Dillman 2004, Tourangeau *et al*. 2004). Similarly, with PPGIS, the spatial feature chosen for soliciting spatial information may influence both the empirical results and the inferences that can be made.

The collection of spatial information and attributes from the general public through PPGIS can be implemented using multiple methods and technologies. For example, one can use low-level technology such as paper maps and markers of some type (e.g., pencil, pen, stickers) or one can use higher-technology solutions such as electronic maps and markers that are now commonly available in Internet PPGIS applications. Common to all types of PPGIS data capture is the need to symbolically represent the spatial attribute of interest on a map. Depending on the specific application, some researchers have chosen to solicit PPGIS spatial attributes as polygon features while other researchers have preferred point features. Presumptively valid, but conflicting arguments can be made for the choice of a particular PPGIS data collection method.

Precision versus accuracy in PPGIS

There is an important distinction between spatial precision in mapping and accuracy in PPGIS-mapped attributes. Virtually in all PPGIS systems participants have to identify spatial attributes of some type. For example, a partial list of spatial features identified with PPGIS include landscape values (Brown and Reed 2000, Brown *et al*. 2004, Brown and Alessa 2005, Brown and Raymond 2007, Alessa *et al*. 2008, Beverly *et al*. 2008, Brown and Reed 2009, Clement and Cheng 2010, Zhu *et al*. 2010, Nielsen-Pincus in press, Sherrouse *et al*. 2011), climate change risks (Raymond and Brown 2011), transportation corridor qualities (Brown 2003), development preferences, (Brown 2006, Nielsen *et al*. 2010), urban park and open space values (Brown 2008), national park experiences and perceived environmental impacts (Brown and Weber in press), knowledge of landscape conditions (Pocewicz *et al*. 2010), recreation resources (McIntyre *et al*. 2008), and ecosystem services (Brown et al. in press).

Precision is a measure of the exactness in placing the PPGIS marker on the map, either paper or digital. In PPGIS systems that do not involve obtaining spatial locations from global positioning system technology, the participant will place or draw some type of marker on the map to represent the attribute as a point, polygon, or line/arc. The precision of marker placement on the map depends on a number of variables including marker size and map scale as well as participant characteristics such as visual acuity and physical dexterity. Flexible mapping environments that provide multiple map scales and marker sizes such as Google® Maps can, in theory, enhance the precision of marker placement.

For PPGIS attributes used in regional planning applications conducted at a larger scale, concern with mapping precision is relatively small compared to the accuracy of the geographic area represented by the marker. Accuracy reflects how well the marker approaches the true spatial dimensions of the attribute being mapped. Accuracy in PPGIS is influenced by a number of variables including the nature of the PPGIS attribute being mapped (i.e., clarity in operational definitions and instructions enhance accuracy), the quality of the mapping environment (e.g., what base map features are included), and respondent characteristics such as map literacy.

The nature of the PPGIS attribute being identified, in particular, affects accuracy. For some PPGIS attributes, especially subjective judgments about landscape qualities, the level of accuracy may be indeterminate. For example, when a PPGIS participant is asked to identify recreation values on a map with a point, does the point represent a campground, a trail, the catchment or watershed, or a broader region? When a participant is asked to identify scenic or aesthetic areas with a point, does the point represent the center of polygonal scenic area? How large is the polygon? If the participant identifies the scenic region with a polygon, does the scenery stop at the polygon boundary? How much accuracy can be imputed to polygon boundaries? Limiting PPGIS attributes to landscape features where accuracy can be objectively verified is not a solution to the accuracy problem because some of the most relevant PPGIS attributes for land-use planning and management are respondent perceptions whose accuracy is not easily determined.

In mapping a PPGIS attribute with a point, the spatial attribute of interest is presumed to extend outward from the point in some unknown distance in some unknown direction. For PPGIS attributes identified as polygons, the participant is required to create boundaries that necessarily bifurcate the PPGIS attribute on the landscape, many of which are best viewed as continuous. For polygons, one can argue that the inaccuracy of a single point to represent the spatial attribute is replaced by the inaccuracy of an infinite number of points along the polygon's edge. Alternatively, one can argue that some areal boundaries are better than none and increase the accuracy, even if indeterminate, of the attribute being identified.

The inherent spatial inaccuracy of point data for PPGIS attributes can be managed, but not avoided by inductively creating polygons through point densities. The analyst must still subjectively determine a density threshold to create a discrete polygon boundary. At what density does an aggregation of points become a concentrated 'hot spot' or *de facto* polygon? For landscape values, Brown and Reed (in press) and Alessa *et al*. (2008) suggest a heuristic kernel density threshold of greater than 0.67 for standardized point densities while Zhu *et al*. (2010) suggest using the Getis–Ord Gi* spatial statistic to identify statistically significant spatial concentrations of high point densities. Because point-based PPGIS attributes can have highly variable spatial distributions, density heuristics may need to be developed for the specific PPGIS attributes being measured. The simplicity of point placement for the participant in PPGIS necessarily results in greater complexity in spatial interpretation for the analyst (Brown 2005).

Research questions

In a 2005 PPGIS study of the Otways Region in Victoria, Australia, a quasi-experiment was conducted in which a subset of sampled residents in the region were requested to map the same landscape value attributes using polygons rather than the majority of sampled residents that were instructed to identify attributes with point features. This quasi-experiment provides a unique opportunity to compare the results of two PPGIS methods that were similar except that one sampling group identified the features as points while another group as polygons.

Specific research questions for this study include: (1) does the use of point versus polygon spatial features for the same PPGIS attribute yield similar spatial results, (2) under what conditions are the spatial results similar or divergent for the two methods, and (3) can heuristics be developed, based on the empirical results, to guide future PPGIS research?

Methods

Data collection

In 2005, researchers conducted a PPGIS study in the Otways region of Victoria, Australia, to identify regional landscape values and to determine resident and visitor preferences for residential and tourism development in the region (Raymond and Brown 2007). In the corpus of the study, residents from 44 Otways region communities ($n = 1400$) were randomly selected for receiving a PPGIS survey packet containing a 1:125,000 grayscale map (810 mm × 750 mm) of the Otways region and accompanying map legend containing 12 rows of sticker dots (6 mm diameter) for each of 12 landscape values, ranging from aesthetic value to wilderness values, as well as sticker dots representing development preferences and special places. An operational definition for each value appeared adjacent to the respective row of sticker dots. Participants were instructed to place their sticker dots on the map locations representing the landscape values, development preferences, and special places. A total of 563 individuals responded representing an overall response rate of 40%. The maps with the point data was digitized into a GIS for analysis resulting in 21,423 total points available for spatial analysis representing the different PPGIS attributes.

The spatial mapping quasi-experiment consisted of sending 200 randomly selected residential households in the Otways region the same grayscale map and PPGIS attribute definitions but with different mapping instructions. Instead of sticker dots, colored pencils ($n = 100$) or black markers ($n = 100$) were included with the survey with instructions to draw the PPGIS attributes on the map using polygons. Each colored pencil represented a unique PPGIS attribute and participants were instructed to draw polygons on the map with the colored pencils representing the PPGIS attributes. The black marker technique instructed participants to draw polygons with the marker and place a pneumonic code (e.g., 'A' for aesthetic value) in the polygon representing the different PPGIS attributes. Of the two experimental techniques for drawing polygons, the black marker technique was deemed superior as the legibility of the polygons drawn by respondents with colored pencils on the glossy-finished paper map was generally poor. Taking a conservative approach to data quality, we only digitized respondent maps containing clearly legible and interpretable polygons. Approximately 30% of the colored pencil polygons were not used in the analysis due to legibility compared to less than 5% for the black marker technique.

Data analysis

Four PPGIS attributes with sufficient point and polygon data were selected for comparative analysis. These attributes are landscape values that (1) express a wide range of landscape qualities – aesthetic, recreation, biological, and economic; (2) provide varying quantities of point and polygon data for analysis (aesthetic – most data, biological – least data); and (3) provide different spatial distributions with aesthetic and recreation values being most clustered, and economic and biological values less clustered. The PPGIS attribute definitions, number of respondents, and quantity of spatial data used in our analysis appear in Table 1. The table also shows the degree of spatial clustering for the point data with the R statistic. R is a ratio of observed distances between points to the expected distances between points if the points were randomly distributed. R ranges from $R = 0$ (completely clustered) to $R = 1$ (random) to $R = 2.149$ (completely dispersed).

To answer the first research question, whether point and polygon features yield similar spatial results, we modeled the spatial overlap of point and polygon areas in the study region using Monte Carlo methods. These methods rely on repeated random sampling to compute results and are appropriate for modeling phenomena with significant uncertainty in inputs, as is the case with PPGIS-generated data.

Description of Monte Carlo procedure

The general approach is to test how different sample sizes for one type of spatial feature collection process compare with the overall area determined by another process. We sampled different numbers of points to compare with the area obtained by polygons, and we sampled different numbers of polygons to compare with the area obtained by point data.

Table 1. PPGIS attributes used in the comparative spatial analysis.

	Points			Polygons				
PPGIS attribute and operational definition	Number of points mapped	Number of respondents	R^a	Number of polygons mapped	Number of respondents	Area[b] largest	Area[b] smallest	Area standard deviation
Aesthetic/scenic value – I value these places for the attractive scenery, sights, smells, or sounds.	1816	400	0.33	272	42	511.2	0.1	65.7
Recreation value – I value these places because they provide outdoor recreation opportunities.	1569	377	0.34	145	30	389.1	0.2	46.3
Economic value – I value these places for economic benefits such as tourism, forestry, agriculture, or other commercial activity.	1425	361	0.38	74	24	5044.2	0.2	602.8
Biological value – I value these places because they provide for a variety of plants, wildlife, marine life, or other living organisms.	1143	304	0.48	68	18	326.7	0.5	66.6

Note: [a]R is a ratio of observed distances between points to the expected distances between points if the points were randomly distributed. R ranges from $R = 0$ (completely clustered) to $R = 1$ (random) to $R = 2.149$ (completely dispersed). From the R statistic, a standardized z score is computed to test the hypothesis that the point distribution deviates from randomness, either toward clustering or uniformity. The hypothesis of complete spatially random (CSR) distribution of points is rejected for all four PPGIS attributes.
[b]Area in square kilometers.

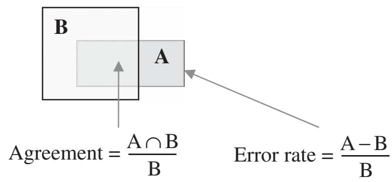

Figure 1. Area-based performance measures indicating agreement and error rate between a sample area A and test area B assumed to be the 'truth'.

Because there is no 'true' value to compare to, we compared the methods with each other to measure performance in terms of: (1) spatial agreement, and (2) error rate. We defined the performance measures as follows: A sample obtained by method 'a' determines a spatial area of influence, called A. This is compared with the overall area estimate obtained from method 'b', called B. The calculation of the performance measures are shown in Figure 1. Note that these comparisons are based on binary areas; we discuss the means used to convert sets of points and polygons to areas below.

$$\text{Agreement} = \frac{\text{AreaofoverlapbetweenAandB}}{\text{AreaofB}}$$

$$\text{Error rate} = \frac{\text{Area of A outside B}}{\text{Area of B}}$$

The performance measures for agreement and error rate are based on a single trial of feature selection, but it was necessary to generate many sample sizes as trials to describe the

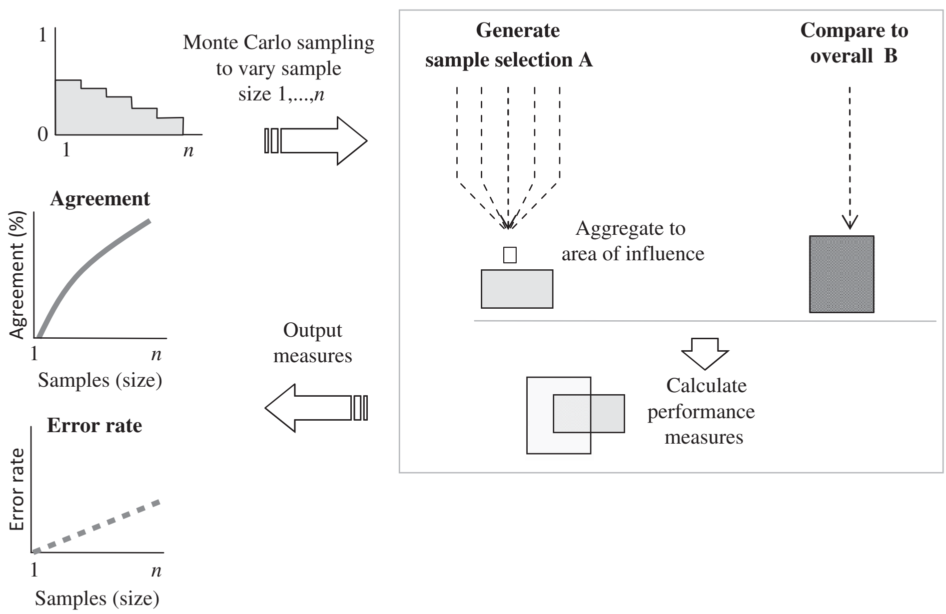

Figure 2. Illustration of Monte Carlo procedure to perform repeated random sampling of spatial data to create a selection A, to spatially aggregate this set and compare it with B, and to report performance measures as output.

overall relationship. Figure 2 shows the procedure using Monte Carlo methods to generate probabilities for random selections from A. To illustrate, for one trial, 20% of the points may be randomly selected to create an area of influence and this result is compared with the overall area of the polygons. Typically, 100 trials are considered the minimum for sampling to achieve accurate results. Because we are sampling from a finite set with different sample sizes, we biased the sampling probability for smaller sample sizes as these have greater variability. For example, there is greater sampling variability when sampling 20% of the points compared to sampling 100% of points which always yields the same sample selection. The output measures from the Monte Carlo trials are charted as a function of the sample size. If the processes for identifying areas of influence by points and polygons are similar, one would expect to see increasing agreement with increasing – but flatter – error rate.

In the first Monte Carlo analysis, we established point-generated areas as the baseline 'truth' using kernel density estimation in ArcGIS Spatial Analyst® and ran trials by varying the number of randomly selected polygons within probability groups ranging from the minimum to the maximum number of polygons. Kernel density estimation (Rosenblatt 1956, Parzen 1962) is a nonparametric technique for estimating the probability density function of a random variable (in this case, a landscape value) based on observed point locations. By convention (see Alessa *et al*. 2008), we established significant point areas (i.e., 'hotspots') as standardized kernel densities greater than 0.67 using a grid cell size of 500 m and a search radius of 3000 m.

The choice of grid cell size and search radius was a heuristic judgment based on the size of the sticker dot, some assumed level of precision/error in placing the dot on the map, and the distance in which these types of PPGIS attributes might be expected to cluster. We experimented with grid cell sizes of 500 or 1000 m based on the size the sticker dot (between 700 and 800 m in diameter in map units). We chose 500 m because it visually appeared to provide a better fit with the map scale. The search radius was a judgment about an assumed level of precision in placing a point and the distance at which these PPGIS attributes might be presumed to cluster. Empirical research (Nielsen-Pincus in press) suggests that the type of PPGIS attributes mapped in this research tend to cluster between 3 and 6 km. The level of precision in placing a sticker dot on the map based on participant vision and dexterity suggest a common potential error of —two to three times the size of the sticker if the participant is imprecise in placing the sticker dot on the intended map location. For these reasons, we selected 3 km as the search radius.

The 0.67 standardized kernel density threshold for determining hotspots from point data is a heuristic developed from previous analysis of similar PPGIS data. This threshold works to identify the higher densities of clustered points as hotspots while avoiding creating hotspots based on isolated points or smaller numbers of clustered points. It is important to study the hotspot areas generated using different thresholds and ask whether they make sense for the particular PPGIS attribute. Over multiple data sets, the 0.67 cut-off has yielded the most consistent, interpretable results.

Approximately 115 trials were tested for the separate PPGIS attributes and outputs generated for spatial agreement and error rates. For each trial and PPGIS attribute, we plotted the percent of area of agreement and area outside (i.e., error) as x, y pairs to generate an approximate function of the spatial relationship based on the number of points and polygons selected in the trial. A best-fit trend line function (polynomial) was superimposed to show the spatial convergence between the point and polygon PPGIS measures. The results of this Monte Carlo analysis are plotted in part (a) of Figures 4–7.

In the second analysis, we followed a similar procedure but instead established the union of polygon areas as the baseline 'truth' and ran trials ($n = 115$) by varying the number of randomly selected points within probability groups ranging from the minimum to the maximum. The results of this Monte Carlo analysis appear in part (b) of Figures 4–7.

Results

Descriptive maps of the four PPGIS attributes appear in Figure 3. The descriptive maps show point distributions and generated hotspots at the 0.67 standardized density threshold in the upper portion of the figure, and the distribution and overlap of polygons in the lower portion of the figure, color-coded to indicate increasing spatial overlap. Both aesthetic and recreation values show spatial convergence along the coastal areas and in selected hinterland locations in the study region. Economic values, both points and polygons, spatially converge on communities in the study region, but there are large polygons drawn by some respondents that take in virtually the entire study area. Of the four PPGIS attributes, biological value is the most dispersed in the study region based on nearest-neighbor analysis of point data ($R = 0.48$), but there is clear agreement between point and polygon measures on the importance of the Cape Otway peninsula (southern-most land feature).

The results of the Monte Carlo trials for each of the four PPGIS attributes appear in Figures 4–7. The plots and trend lines of polygon overlap on point data for aesthetic and recreation attributes appear in part (a) of Figures 4 and 5 while the overlap of point data on polygon data appears in part (b) of the same figures. The plots and trend lines of polygon data on point data for economic and biological attributes appear in part (a) of Figures 6 and 7 while the overlap of point data on polygon data appears in part (b) of the same figures.

The spatial overlap of aesthetic polygons on points reaches near 100% with all polygons (Figure 4a). However, a visual examination of the trend line indicates a diminishing return on new information provided by additional aesthetic polygons beyond approximately 120 polygons. This diminishing spatial information relationship is accompanied by an increasing polygon spatial area identified outside the point hotspots. If the point density hotspots represent true aesthetic areas, the polygon area outside the point hotspots may be said to represent potential spatial error from using polygons.

For recreation values, the spatial overlap of recreation polygons on point hotpots never reaches 100% (Figure 5a) but indicates a similar trend toward diminishing information and greater potential error with increasing numbers of polygons beyond about 100 polygons.

When the spatial overlap of point hotspots on polygons is simulated for aesthetic (Figure 4b) and recreation (Figure 5b) attributes, the extent of spatial overlap reaches a maximum of about 24% for aesthetic and 35% for recreation. This occurs because the spatial area identified by polygons, in general, far exceeds the areas identified by point densities. The area represented by point hotspots outside polygon areas exhibit a small, but increasing rate, reaching a maximum of 1% for aesthetic and 10% for recreation. If polygons are assumed to represent the true attribute area, the potential spatial error from mapping points remains very small for aesthetic value, regardless of the number of points mapped, while the potential error for recreation value increases significantly beyond approximately 500 points.

The results for the economic PPGIS attribute (Figure 6) demonstrate what happens when one or more respondents identify very large attribute polygons in the study region. The spatial overlap of economic polygons on point hotpots (Figure 5a) results in a dichotomous distribution with 100% overlap of all point hotspots when large polygons are

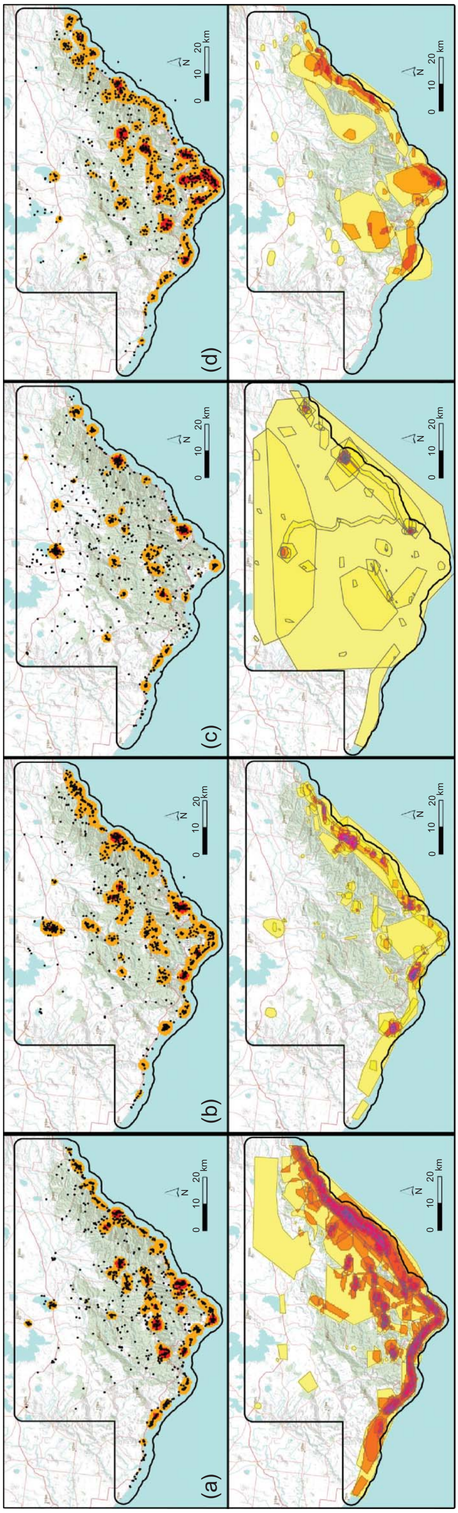

Figure 3. Distributions of point (*top*) and polygon (*bottom*) features for four PPGIS landscape values: (a) aesthetic/scenic; (b) recreation; (c) economic; (d) biological.

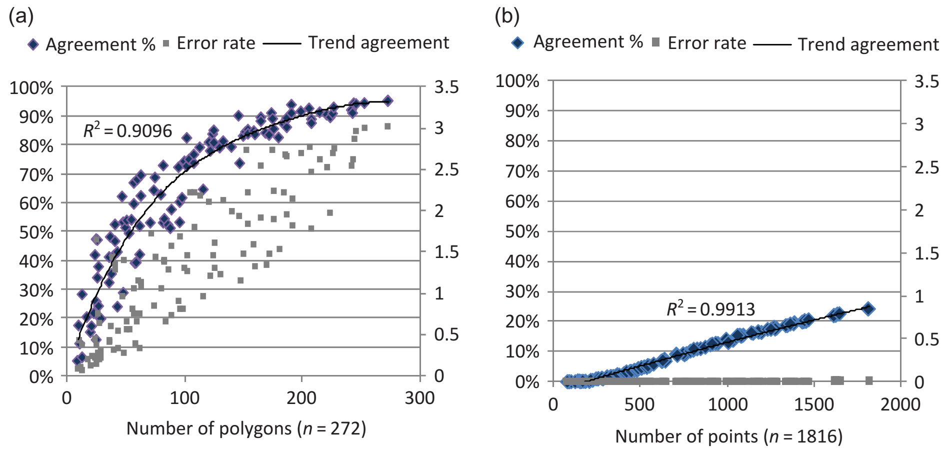

Figure 4. Plots for aesthetic attributes for agreement and error rate from Monte Carlo simulation: (a) polygons on points; (b) points on polygons. The left vertical axis is the percent of spatial agreement and the right vertical axis is the error rate expressed as a proportion.

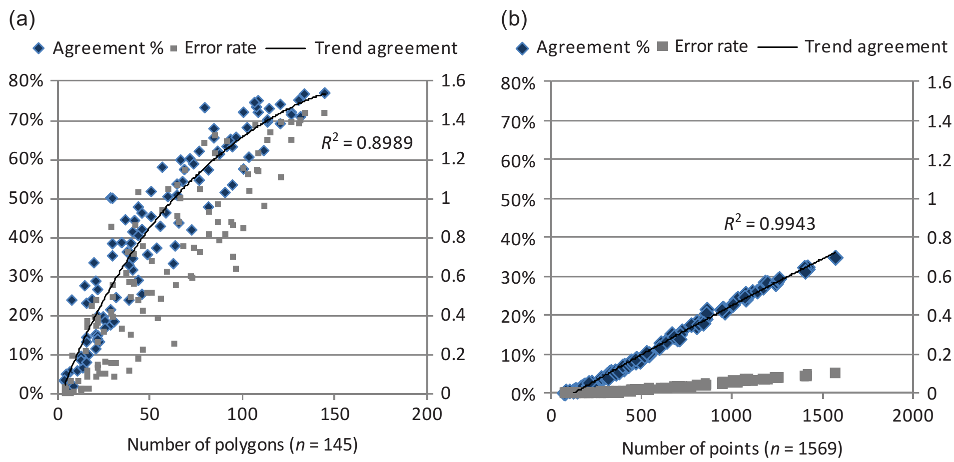

Figure 5. Plots for recreation attributes for agreement and error rate from Monte Carlo simulation: (a) polygons on points; (b) points on polygons. The left vertical axis is the percent of spatial agreement and the right vertical axis is the error rate expressed as a proportion.

selected in the Monte Carlo trials. The trend line has a poor fit when there is such large variation in the size of the polygons and the potential spatial error (amount of polygon area outside the point area) can be up to 18 times greater than the point hotspot area. The point on polygon analysis for economic value (Figure 5b) also produces unusual results in that there are no point areas outside the polygons (no potential spatial error) regardless of the number of the points identified, while the total amount of spatial overlap does not exceed 6%.

The results for the biological PPGIS attribute (Figure 7) demonstrate outcomes when there is less PPGIS data collected and when the point attributes are more spatially dispersed. The spatial overlap of biological polygons on points only reaches about 65% with all 68 polygons (Figure 7a). The trend line exhibits a steeper slope indicating that each additional polygon adds significant new information to the outcome. With relatively fewer

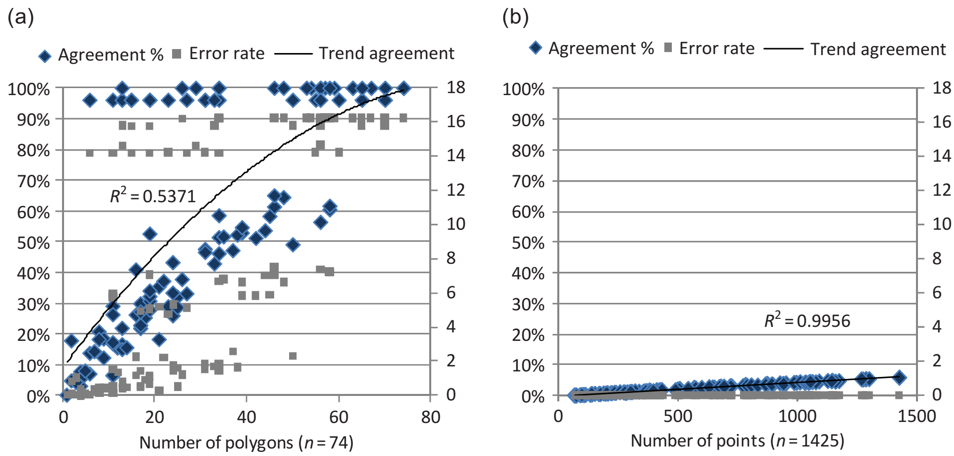

Figure 6. Plots for economic attributes for agreement and error rate from Monte Carlo simulation: (a) polygons on points; (b) points on polygons. The left vertical axis is the percent of spatial agreement and the right vertical axis is the error rate expressed as a proportion.

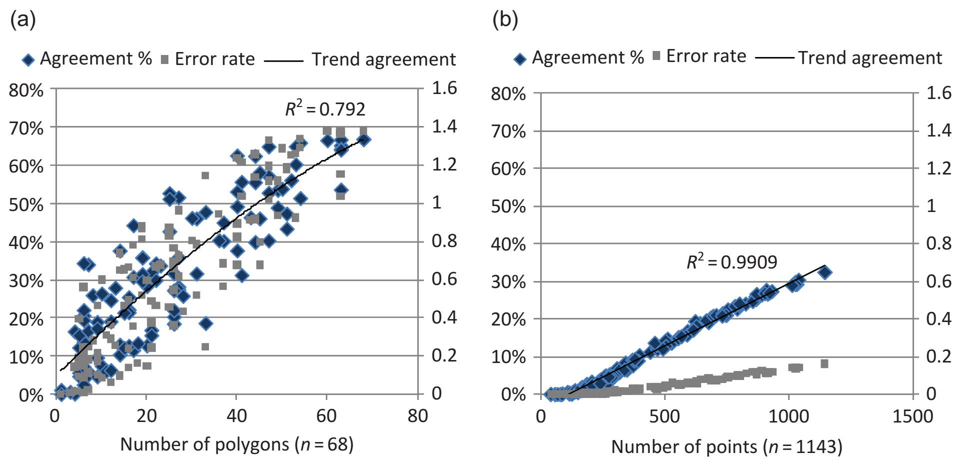

Figure 7. Plots for biological attributes for agreement and error rate from Monte Carlo simulation: (a) polygons on points; (b) points on polygons. The left vertical axis is the percent of spatial agreement and the right vertical axis is the error rate expressed as a proportion.

polygons, the potential spatial error of using polygons over point features is often more than double the actual point area covered. The results of simulating points on polygons indicate similar explanatory power as aesthetic and recreation attributes (up to 35% spatial overlap), however the potential spatial error is much higher with up to 16% of the point areas outside the polygon areas.

Discussion

The development and implementation of PPGIS systems is likely to increase in the future and points and polygons will necessarily be the two primary spatial options for collecting areal PPGIS attributes. Understanding the strengths and limitations of these spatial features in PPGIS systems is essential to address research validity issues that may determine their rate of adoption in decision support systems.

The quasi-experimental results presented herein demonstrate that the same PPGIS attributes identified by points and polygons will converge on a collective spatial 'truth' within a region provided there are enough observations in the study area. However, points and polygons do present different data information demands and spatial error trade-offs. One limitation of this research was the selection and use of a single, standardized kernel density threshold for creating polygon areas from points. Although we selected the best kernel density threshold based on our judgment, the choice of kernel density threshold will affect the size of the polygon areas generated from points which will alter the results. We recommend that future research include sensitivity analysis that varies the kernel density threshold to determine the effect on spatial agreement and error.

The use of points for identifying PPGIS attributes and aggregating areas through density mapping constitutes a conservative approach to spatial inference. Using point densities to create polygon areas results in a smaller probability of accepting spatial areas as collectively significant, when in fact, they are not. The use of polygons increases the probability of accepting spatial areas as collectively significant, when in fact, they are not. The researcher must decide which type of inferential error is more acceptable given the PPGIS research context.

There are also trade-offs about the PPGIS data collection effort required for each spatial feature. To provide the PPGIS research community with guidance on sampling effort, we present some heuristics for the use of points and polygons based on the results of our analysis (see Table 2). The ratio of the number of point to polygon respondents to achieve spatial convergence ranged from 28:1 with high variability in the economic polygon attributes, to 15:1 for recreation attributes. Thus, the sampling effort to achieve spatial agreement varies significantly by the type of PPGIS attribute collected. The research effort required to solicit and recruit 30 participants to draw polygons can be significantly less than the effort to recruit 300+ participants to identify point features. However, it is essential that the sample size be sufficiently large to claim regional representativeness regardless of whether points or polygons are the chosen method.

Our methodological preference is to use points in PPGIS systems as these tend to produce conservative estimates of collective spatial significance. Perhaps more important, based on pre-testing and debriefing of individuals that tried both methods, PPGIS participants found the placement of points less ambiguous than identifying polygons and thus participants are more likely to complete the PPGIS mapping activity. In a social climate

Table 2. Heuristic guidelines for using point and polygon spatial features in PPGIS based on quasi-experimental results.

PPGIS attribute	Mean number of points per respondent	Mean number of polygons per respondent	Estimated number of polygons that provide comparable information to points in Monte Carlo trials	Suggested minimum number of polygon respondents	Suggested ratio of point to polygon respondents
Aesthetic	4.5	6.5	120−150	23	17:1
Recreation	4.2	4.8	100−120	25	15:1
Economic	3.9	3.1	40	13	28:1
Biological	3.8	3.8	68	18	17:1

where survey research has become ubiquitous and marginalized by both poor design and the pursuit of socially insignificant information, sustaining high participation rates has been increasingly challenging for social researchers. The choice of data collection methods that reduce the probability of withdraw or incompletion because of task difficulty, ambiguity, or frustration is important. Although there are no absolutes, we suggest that polygon methods appear better suited for structured interviews, group-administered surveys, or workshops that provide face-to-face support for completion, whereas points may be a better choice for self-administered surveys.

A significant limitation of using point features is the sampling and recruitment effort. To achieve the point densities required to make meaningful inferences about place significance, our results suggest a minimum of 350 respondents, recognizing that PPGIS item non-response will vary depending on the attribute. In the analysis reported herein, the four PPGIS attributes evaluated had relatively high mapping rates, but with increased numbers of PPGIS attributes included in the study, and with attributes less familiar to participants, the average number of points mapped per attribute will decrease. With reported general public response rates of Web-based PPGIS systems in the 10–12% range (Brown and Reed 2009, Pocewicz *et al*. 2010), mapping points could require in excess of 3000 contacts for a Web-based PPGIS study. For mail-based PPGIS systems and targeted respondent groups, response rates have been reported in the 40–50% range requiring just over half the number of invitations. The research trade-offs between Web-based digital and mail-based paper PPGIS systems are discussed by Brown and Reed (2009), but the relevant point for this research is that spatially significant areas can be determined with fewer polygon observations and thus less participant recruitment effort.

For PPGIS researchers inclined to use polygons for identifying PPGIS attributes, we suggest obtaining at a minimum, the number of respondents needed for the most demanding of the PPGIS attributes to achieve spatial parity with point data. Based on the results of this analysis, we would advise a minimum of 25 respondents for polygon-based PPGIS systems assuming 4–5 polygons identified per attribute per respondent on average. It is highly probable that some polygons will have to be excluded from the analysis because some respondents will select between 50% and 100% of the study region as a PPGIS polygon which does little to identify collective spatial significance while simultaneously increasing potential error. The threat to internal study validity from inadequate or erroneous spatial information is in addition to the well-understood threats from sampling error. Our empirical results indicate diminishing information returns with some polygon PPGIS attributes such that additional participant sampling and recruitment effort would provide little additional information. However, the benefit of this effort would come from stronger claims of regionally representative results.

It appears inevitable that PPGIS data and decision support systems will be used to make inferences about place attributes to support and justify land-use decisions ranging from conservation to development. Given the newness of PPGIS research, we have attempted to provide some guidance on the number of participants and the quantity of spatial observations needed to generate comparable spatial information for point and polygon features. But the larger research question about determining the collective, spatial significance of mapped PPGIS attributes is not purely reducible to the number of study participants or the quantity of spatial information generated. For example, how many PPGIS respondents are required to identify the same spatial location for it to be collectively, spatially significant for a particular land-use decision? More spatial agreement among respondents equates to higher confidence in place attributes, but there can be no definitive answer.

As PPGIS systems become more common in land-use decision support systems, there is a need for research that describes the various thresholds for concluding collective, spatial significance in particular decision contexts. Until such experience is accumulated in the design and use of PPGIS systems, a pragmatic approach would be to encourage methodological plurality and increased use of experimental design to assess the effects of different PPGIS methods on outcomes, as has been common in survey research. A reasonable next step would be to experiment with including point and polygon features within the same PPGIS study with the same participants to refine estimates of point and polygon spatial agreement and error.

References

Alessa, L., Kliskey, A., and Brown, G., 2008. Social-ecological hotspots mapping: a spatial approach for identifying coupled social-ecological space. *Landscape and Urban Planning*, 85 (1), 27–39.

Beverly, J.L., *et al*., 2008. Assessing spatial attributes of forest landscape values: an internet-based participatory mapping approach. *Canadian Journal of Forest Research*, 38 (2), 289–303.

Brown, G., 2003. A method for assessing highway qualities to integrate values in highway planning. *Journal of Transport Geography*, 11 (4), 271–283.

Brown, G., *et al*., 2004. A comparison of perceptions of biological value with scientific assessment of biological importance. *Applied Geography*, 24 (2), 161–180.

Brown, G., 2005. Mapping spatial attributes in survey research for natural resource management: methods and applications. *Society & Natural Resources*, 18 (1), 1–23.

Brown, G., 2006. Mapping landscape values and development preferences: a method for tourism and residential development planning. *International Journal of Tourism Research*, 8 (2), 101–113.

Brown, G., 2008. A theory of urban park geography. *Journal of Leisure Research*, 40 (4), 589–607.

Brown, G. and Alessa, L., 2005. A GIS-based inductive study of wilderness values. *International Journal of Wilderness*, 11 (1), 14–18.

Brown, G., Montag, J., and Lyon, K., in press. Public participation GIS: a method for identifying ecosystem services. *Society & Natural Resources*.

Brown, G. and Raymond, C., 2007. The relationship between place attachment and landscape values: toward mapping place attachment. *Applied Geography*, 27 (2), 89–111.

Brown, G. and Reed, P., 2000. Validation of a forest values typology for use in national forest planning. *Forest Science*, 46 (2), 240–247.

Brown, G. and Reed, P., 2009. Public participation GIS: a new method for national forest planning. *Forest Science*, 55 (2), 166–182.

Brown, G. and Reed, P., in press. Social landscape metrics: measures for understanding place values from public participation geographic information systems (PPGIS). *Landscape Research*.

Brown, G. and Weber, D., in review. Public participation GIS: a new method for use in national park planning. *Landscape and Urban Planning*.

Chapin, M., Lamb, Z., and Threlkeld, B., 2005. Mapping indigenous lands. *Annual Review of Anthropology*, 34, 619–638.

Christian, L.M. and Dillman, D.A., 2004. The influence of graphical and symbolic language manipulations on responses to self-administered questions. *Public Opinion Quarterly*, 68 (1), 57–80.

Clement, J.M. and Cheng, A.S., 2010. Using analyses of public value orientations, attitudes and preferences to inform national forest planning in Colorado and Wyoming. *Applied Geography*, 31, 393–400.

Dunn, C.E., 2007. Participatory GIS—a people's GIS? *Progress in Human Geography*, 31 (5), 616–637.

Goodchild, M., 2007. Citizens as voluntary sensors: spatial data infrastructure in the world of Web 2.0. *International Journal of Spatial Data Infrastructures Research*, 2, 24–32.

Hall, G.B., *et al*., 2010. Community-based production of geographic information using open source software and Web 2.0. *International Journal of Geographical Information Science*, 24 (5), 761–781.

McIntyre, N., Moore, J., and Yuan, M., 2008. A place-based, values-centered approach to managing recreation on Canadian crown lands. *Society & Natural Resources*, 21 (8), 657–670.

Nielsen-Pincus, M., *et al*., 2010. Predicted effects of residential development on a northern Idaho landscape under alternative growth management and land protection policies. *Landscape and Urban Planning*, 94 (3), 255–263.

Nielsen-Pincus, M., in press. Mapping a values typology in three counties of the interior northwest, USA: scale, geographic associations among values, and the use of intensity weights. *Society & Natural Resources*.

Parzen, E., 1962. On estimation of a probability density function and mode. *Annals of Mathematical Statistics*, 33, 1065–1076.

Pocewicz, A., Schnitzer, R., and Nielsen-Pincus, M., 2010. *The social geography of southern Wyoming: important places, development, and natural resource management*. Lander, WY: The Nature Conservancy, 16. Available from: http://www.nature.org/wyoscience [Accessed 28 Dec 2010].

Rambaldi, G., et al., 2006. Participatory spatial information management and communication in developing countries. *EJISDC*, 25 (1), 1–9.

Raymond, C. and Brown, G., 2007. A spatial method for assessing resident and visitor attitudes toward tourism growth and development. *Journal of Sustainable Tourism*, 15 (5), 520–540.

Raymond, C. and Brown, G., 2011. Assessing spatial associations between perceptions of landscape value and climate change risk for use in climate change planning. *Climatic Change*, 104 (3), 653–678.

Rosenblatt, M., 1956. Remarks on some nonparametric estimates of a density function. *Annals of Mathematical Statistics*, 27, 832–837.

Sawicki, D.S. and Peterman, D.R., 2002. Surveying the extent of PPGIS practice in the United States. *In*: W.J. Craig, T.M. Harris, and D.M. Weiner, eds. *Community participation and geographic information systems*. London: Taylor & Francis, 17–36.

Schlossberg, M. and Shuford, E., 2005. Delineating 'public' and 'participation' in PPGIS. *Journal of the Urban and Regional Information Systems Association*, 16, 15–26.

Sherrouse, B.C., Clement, J.M., and Semmens, D.J., 2011. A GIS application for assessing, mapping, and quantifying the social values of ecosystem services. *Applied Geography*, 31 (2), 748–760.

Sieber, R., 2006. Public participation geographic information systems: a literature review and framework. *Annals of the Association of American Geographers*, 96 (3), 491–507.

Tourangeau, R., Couper, M.P., and Conrad, F., 2004. Spacing, position, and order: interpretive heuristics for visual features of survey questions. *Public Opinion Quarterly*, 68 (3), 368–393.

Tulloch, D., 2007. Public Participation GIS (PPGIS). In *Encyclopedia of Geographic Information Science*, SAGE Publications. Available online at http://www.sage-ereference.com/geoinfoscience/Article_n165.html.

Tulloch, D., 2008. Is VGI participation? From vernal pools to video games. *GeoJounal*, 72, 161–171.

Zhu, X., Pfueller, S., and Whitelaw, P., 2010. Spatial differentiation of landscape values in the Murray River region of Victoria, Australia. *Environmental Management*, 45 (5), 896–911.