Conservation Biology

Special Section

# Characterizing Spatial Uncertainty when Integrating Social Data in Conservation Planning

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**Abstract:** *Recent conservation planning studies have presented approaches for integrating spatially referenced social (SRS) data with a view to improving the feasibility of conservation action. We reviewed the growing conservation literature on SRS data, focusing on elicited or stated preferences derived through social survey methods such as choice experiments and public participation geographic information systems. Elicited SRS data includes the spatial distribution of willingness to sell, willingness to pay, willingness to act, and assessments of social and cultural values. We developed a typology for assessing elicited SRS data uncertainty which describes how social survey uncertainty propagates when projected spatially and the importance of accounting for spatial uncertainty such as scale effects and data quality. These uncertainties will propagate when elicited SRS data is integrated with biophysical data for conservation planning and may have important consequences for assessing the feasibility of conservation actions. To explore this issue further, we conducted a systematic review of the elicited SRS data literature. We found that social survey uncertainty was commonly tested for, but that these uncertainties were ignored when projected spatially. Based on these results we developed a framework which will help researchers and practitioners estimate social survey uncertainty and use these quantitative estimates to systematically address uncertainty within an analysis. This is important when using SRS data in conservation applications because decisions need to be made irrespective of data quality and well characterized uncertainty can be incorporated into decision theoretic approaches.*

**Keywords:** conservation opportunity, conservation planning, elicited values, public participation GIS, social research, spatial data quality, spatial uncertainty, systematic conservation assessment

Caracterización de la Incertidumbre Espacial cuando se Integran Datos Sociales a la Planeación de la Conservación

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**Resumen:** *Estudios recientes de la planeación de la conservación han presentado estrategias para integrar datos sociales con referencia espacial (SRE) con miras a mejorar la viabilidad de las acciones de conservación. Revisamos la creciente literatura de conservación sobre los datos SRE, enfocándonos en las preferencias obtenidas o mencionadas derivadas de métodos de encuestas sociales como los experimentos de opción y los sistemas de información geográfica de participación pública. Los datos SRE obtenidos incluyeron a la distribución espacial de la disposición de vender, de pagar, de actuar y evaluaciones de los valores culturales y sociales. Desarrollamos una tipología para evaluar la incertidumbre de los datos SRE obtenidos, la que describe cómo la incertidumbre de las encuestas sociales se propaga cuando se proyecta espacialmente y la importancia de responder a la incertidumbre espacial como los efectos de escala y la calidad de datos. Estas incertidumbres se propagarán cuando los datos SRE obtenidos se integren con datos biofísicos para la planeación de la conservación y pueden tener consecuencias importantes para evaluar la viabilidad de las acciones de conservación. Para explorar más a fondo este tema, llevamos a cabo una revisión sistemática de la literatura sobre datos SRE obtenidos. Encontramos que la incertidumbre de encuestas sociales se probaba comúnmente, pero que estas incertidumbres se ignoraban al proyectarse espacialmente. Con base en estos resultados desarrollamos un marco de trabajo que ayudará a los investigadores y a los practicantes a estimar la incertidumbre de las encuestas sociales y a usar estos estimados cuantitativos para señalar sistemáticamente a la incertidumbre dentro de un análisis. Estos es importante cuando se usan datos SRE en aplicaciones de la conservación ya que las decisiones deben tomarse sin importar la calidad de los datos y una incertidumbre bien caracterizada puede ser incorporada a las estrategias de decisión teórica.*

**Palabras clave:** calidad de datos espaciales, evaluación de la conservación sistemática, incertidumbre espacial, investigación social, oportunidad de conservación, planeación de la conservación, SIG de participación pública, valores obtenidos

## Introduction

One of the great challenges to conservation planning is accounting for the feasibility of conservation actions, which requires an understanding of the complex social, economic, and institutional environments in which conservation occurs (Knight et al. 2006). Recent conservation planning studies have presented tools for utilizing mapped quantitative social data with the view toward quantifying opportunities for conservation interventions. Although tools for assessing conservation opportunities have considered social and cultural values (Brown 2012), governance characteristics (Mills et al. 2013), and self-reported behavior (Curtis et al. 2005; Raymond & Brown 2011) these tools rarely consider the uncertainties associated with mapping these attributes. This can have the perverse result of recommending actions that have neutral or even negative conservation outcomes.

There are numerous methods for deriving mapped social data for conservation planning. These range from modeling preferences based on land use (Goldberg et al. 2011), property prices (Polyakov et al. 2015), or travel costs (Van Berkel & Verburg 2014) to implicitly integrating social values using interactive GIS software (Lesslie 2012) (Fig. 1). We focused on a subset of those methods where data on elicited or stated preferences are derived through social science survey methods which could be or are used directly in a spatial context for conservation planning. Social survey methods include the use of survey techniques to assess general community values, attitudes, and beliefs (see Babbie [2007] for an overview), and the use of public participation GIS (PPGIS) to assess place-based values and preferences (e.g., Brown 2005), and choice experiment (e.g., Campbell et al. 2009) (Fig. 1). Hereafter we refer to data collected and then mapped derived from elicited social survey methods for conservation planning as elicited spatially referenced social (SRS) data. These methods are used in the majority of research where mapped social data are incorporated into conservation planning.

Given that the use of elicited SRS data within conservation planning is a growing area of research, it is an opportune time to evaluate the methods and associated uncertainty that results from the use of mapped social data in conservation planning. In broad terms, we define *uncertainty* as sources of uncertainty within the inputs, outputs, and analysis that may be measureable (e.g., GPS error); related to difficult-to-define concepts; related to future events that are difficult to predict; and related to uncertainty in models associated with a lack of knowledge or due to generalizations (see extended definition in Supporting Information). In the social sciences, the uncertainties associated with the collation of social data are well documented and include measurement validity, response bias, and representativeness (Haslam & McGarty 2001; Hair et al. 2009). Further, the spatial and ecological sciences have characterized a suite of uncertainties associated with mapping and modeling of spatial data, including scale issues and classification error (Devillers & Jeansoulin 2010; Lechner et al. 2012*a*; Rocchini et al. 2012).

Uncertainty in SRS data is especially concerning because it can compound existing uncertainty present within biophysical data such as species distribution

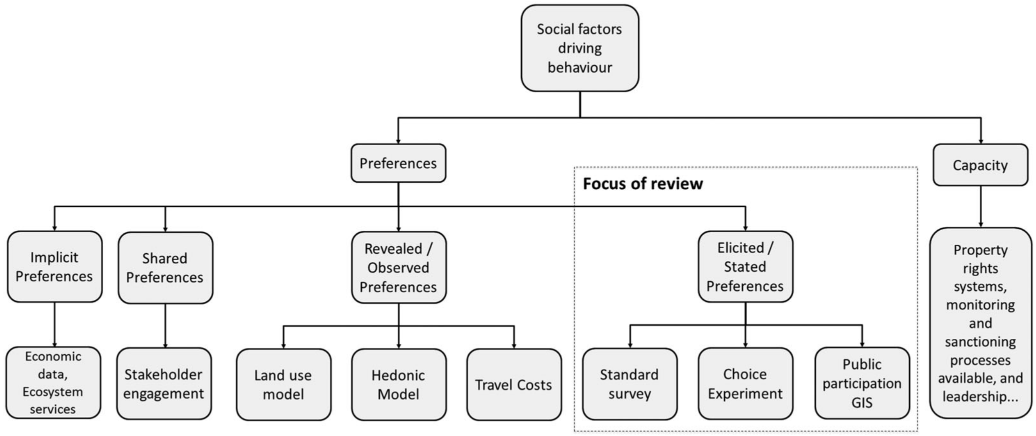


*Figure 1. Methods for assigning preferences to spatially referenced social data (Supporting Information for full version with examples) (dotted-line rectangle, scope of review).*

models and when used within systematic conservation planning (SCP) tools. Combining SRS data with biophysical data may result in greater levels of uncertainty as these multiple forms of uncertainty may interact (e.g., Lechner et al. 2013) and multiply (e.g., Langford et al. 2011). For example, using simulated data Visconti et al. (2010) found that data on vulnerability to habitat loss should only be included in SCP when uncertainty in this data is <20–30%. They showed that with greater uncertainty it was counterproductive to utilize this data and better results could be obtained using biodiversity value alone. A key motivation for including SRS data is to make plans more implementable, but data uncertainty could result in less accurate or implementable plans—the direct opposite of the desired outcome.

We addressed the question of how to manage uncertainties in SRS data by identifying the types of social data analyzed and the common types of geospatial processing methods used for creating elicited SRS data; developing a typology of SRS data uncertainty based on a review of the types of uncertainty identified in the social and spatial science literatures associated with the social survey and geospatial methods used; reviewing whether existing conservation planning studies are addressing SRS data uncertainty as defined by the typology; and using the results of the reviews to develop a process for more effectively managing uncertainty issues in future conservation planning studies. We also considered research directions required to systematically address these uncertainties and the implications this has for conservation planning in general.

## Geospatial Methods for Deriving Elicited SRS Data

We focused specifically on elicited SRS data which meets all the following criteria: one of the final outputs is a map describing individual preferences elicited directly through social science survey methods for use in conservation planning; mapping outputs aim to characterize the whole of the study area; and there is a potential for these mapped outputs to be integrated with spatially explicit biophysical data for use within SCP (e.g., Zonation [Moilanen et al. 2011]).

Three broad methods for eliciting social data are commonly used for deriving elicited SRS data: PPGIS, choice experiments, and standard survey methods. The PPGIS is a suite of techniques for engaging local communities through the use of a GIS whereby participants locate points or regions on maps describing values related to conservation outcomes (Brown 2012). In contrast, a choice experiment is a survey technique where respondents are asked to choose between different bundles of (environmental) goods, which are described in terms of their attributes, or characteristics, and the levels that these attributes take (Hanley et al. 1998; Adamowicz 2004). By a standard survey we mean commonly applied methods of eliciting information through questionnaires or interviews.

A range of geospatial and statistical methods can be used to spatially project elicited social data for integration with biophysical data (Table 1). These methods have been used to map social data including the perceptual values individuals associate with landscapes (e.g., Campbell et al. 2009; Raymond et al. 2009) and stated preferences which describe the preference for products and services such as willingness to pay (WTP), collaborate, or sell for conservation (e.g., Knight et al. 2010; Curran et al. 2012). Spatial layers using data of perceptual values are produced using a range of processing methods based on geographic units defined either by a raster grid or areal boundary (Table 1 & methods 2 and 4). In contrast, stated preferences in some cases requires no geospatial processing as individual social data are linked directly to their spatial locations (such as owners properties) (Table 1 & method 1).

**Table 1. Geospatial characteristics of elicited spatially referenced social (SRS) data.**[a]

| | *Geospatial method* | | | | |
|---|---|---|---|---|---|
| | *1. Areal data-individual* | *2. Areal aggregation*[b] | *3. Areal data-predictive method* | *4. Point pattern analysis (e.g., PPGIS)* | *5. Local statistics (e.g., kriging)* |
| Example | landowners place values on their properties assets or willingness to sell of his/her property; Curran et al. 2012 | aggregated social data from multiple individuals such as census data; no example of elicited SRS data available | derive statistical relationship between social data and subcatchment; Brouwer et al. 2010 | social or economic values individuals attach to multiple places on the landscape; Brown & Donovan 2013 | kriged social data; Campbell et al. 2009 |
| Input data | n/a | points—quantitative | n/a | points—nominal | points—quantitative |
| Method of deriving value | descriptive | descriptive | statistical | descriptive | statistical |
| Geospatial processing method | none | point to area | none | point to area | point to surface |
| Geographic unit | property boundary | areal—census boundary | areal—census area or catchment | areal—grid | areal—grid |
| Geospatial processing method description | associate individual social data with single spatial object (e.g., property) | derive descriptive statistic (e.g., mean) based on aggregation unit such as census district or government boundary | derive statistical relationship between land-cover type and social data; non-spatial analysis undertaken and results projected spatially | point pattern analysis (e.g., identifying areas with high number of occurrences) | interpolate values between point locations |
| Output data type | quantitative—continuous | quantitative—average (Gaussian) | quantitative—average (Gaussian) | quantitative—counts (binomial) | quantitative—fields orraster grid |

[a] *See Supporting Information for spatial data graphical examples.*
[b] *This type of analysis was included in this table even though it was not present in the review as it represents a very common type of geospatial analysis method used with social data.*

Stated preferences may also require interpolation to map preferences in areas where there is no data. This is done using a range of statistical methods such as predictive (e.g., Brouwer et al. 2010) (Table 1 & method 3) and Kriging (e.g., Campbell et al. 2009) (Table 1 & method 5).

## Typology for Assessing SRS Data Uncertainty

We developed a typology for assessing SRS data uncertainty by synthesizing insights from the social science and spatial science literatures with respect to the range of geospatial methods used for deriving these data and integrating the data within analysis. The typology describes uncertainties associated with: the collation and interpretation of social data; the projection of social data spatially; and the integration of elicited SRS data with other data sources such as biophysical data.

The many different forms of uncertainty in the social sciences have been eloquently categorized in a paper by Haslam and McGarty (2001) into internal and external methodological uncertainties (Table 2), in addition to statistical uncertainty. Internal methodological uncertainty is related to whether an observed effect has been correctly measured and interpreted (Hair et al. 2009) and depends on face validity, content validity, and construct validity (Table 2). External methodological uncertainty arises when researchers are unsure whether results can be generalized to the wider population of interest. It requires a consideration of the sampling strategy, sample size, representativeness of the sample, and associated nonresponse bias. A more detailed discussion of social survey methods uncertainty and methods to address it are in Supporting Information.

When projecting social data spatially, the methodological uncertainty associated with social surveys can be considered in the same way as data accuracy within spatial models in terms of uncertainty propagation. Social survey data accuracy can be measured as the deviation from the true value (e.g., the deviation from the correct value of WTP estimated for an individual on a property). Data accuracy is a general aspect of a suite of uncertainty sources known as data quality (Devillers & Jeansoulin 2010; Shi 2010). Data quality considerations include, but are not limited to: completeness, logical consistency, positional accuracy, temporal accuracy, thematic accuracy, coverage, lineage, accessibility, and interpretability (Aspinall & Pearson 1996; Devillers & Jeansoulin 2010; Shi 2010). Uncertainty associated with data quality has unique characteristics when considered in space. For example, as error is spatially distributed across the landscape, it can magnify when combined with other data or when used in a model (Congalton 1988; Heuvelink et al. 1989; Gergel et al. 2007).

Sources of uncertainty that are specific only to spatial data principally arise from the modifiable areal unit problem (MAUP) (also known as the zoning effect or scaling problem) and the related ecological inference problem and change of support problem (COSP) (Openshaw 1984; Gotway & Young 2002) (Table 3). The MAUP results from the many ways in which nonoverlapping spatial units can be used to divide a study area for the purposes of analyses such as a raster grid or census district boundaries (Openshaw 1984). Although COSP is a broader term referring to changing the types, size, and shape of the spatial units within any single study, for example, point, lines, areas, and pixel (Dungan et al. 2002; Gotway & Young 2002). The ecological inference problem (also known as the ecological fallacy) is a specific case of the COSP that is the result of making conclusions about individuals based only on analysis of aggregated data (e.g., at the district level) (King 1997). Whenever social survey data is projected spatially the choice of spatial units in terms of their size and shape (e.g., property boundary, grid cell, catchment) and the relationship with the spatial patterns of the social value or perception being represented will impact on spatial analysis and in some cases render the outputs meaningless (Openshaw 1984; Jelinski & Wu 1996; Wu et al. 1997; Lechner et al. 2012*b*). In any single analysis, there will be multiple potential sources of the COSP (which includes the MAUP and the ecological inference problem) and data quality associated uncertainty which together affect both modeling and inference undertaken with the data (Gotway & Young 2002). An extended discussion of COSP and data quality uncertainty and methods to address them is in Supporting Information.

When using elicited SRS data for conservation planning, other types of data such as biophysical data (e.g., land cover and species distributions maps and spatial information on threats and costs) are required and all contain uncertainty. In the case of species' distribution modeling, uncertainties originate from both input data and the process of mapping the species distributions (Elith et al. 2002; Rocchini et al. 2012). Along with SRS data uncertainty, these other sources of uncertainty need to be addressed when conducting analysis.

Based on the geospatial, ecological, and social science literature we have devised a typology that describes the propagation and sources of uncertainty resulting from projecting elicited SRS data spatially and utilizing it within an analysis (Fig. 2). Uncertainty first arises in the social survey data due to methodological uncertainty (nonspatial uncertainty) (Fig. 2a). This social data can then be used in a broad range of ways to map elicited SRS data resulting in uncertainty being propagated to other parts of the analysis. The simplest way to use the social data is to convert to a spatial unit based on the geolocation of the social data (Table 1 & methods 1, 2, and 5). This results in uncertainty taking on a spatial dimension, whereby uncertainty can be treated as classification accuracy (Fig. 2b)

**Table 2. Types of social survey uncertainty.**

| *Type of uncertainty* | *Definition* | *Means of management* | *Tests to consider in social values studies (e.g., PPGIS)* | *Tests to consider in stated preference studies* |
|---|---|---|---|---|
| Internal | confidence that the output shows what it is believed to show | research design controls, including validity testing | face validity, content validity, construct validity reliability | face validity, content validity, construct validity, preference uncertainty |
| External | the confidence in the results being generalizable | research design controls, including validity testing | sample strategy and size, representativeness, concurrent validity, predictive validity | preference uncertainty, sample strategy and size, representativeness, concurrent validity, predictive validity, hypothetical bias |

*Adapted from Haslam and McGarty (2001) (Supporting Information for extended discussion).*

**Table 3. Types of spatial uncertainty associated with elicited spatially referenced social (SRS) data.**

| *Type of uncertainty* | *Definition* | *Source* | *Potential methods to consider* |
|---|---|---|---|
| Accuracy | difference between measured value and true value | social survey methodological uncertainty, statistical model uncertainty | simulate uncertainty in geographic units based on uncertainty bounds from social survey methodology or statistical model; uncertainty quantified with statistical model, for example, standard errors and Bayesian approaches; variations include Monte-Carlo methods, simulating the spatial distribution of uncertainty and local versus global sensitivity analysis |
| Change of support problem (COSP) | uncertainty due to the many ways of integrating different types of spatial data | area to point—-ecological inference problem | cross-classification with other variables, Quadrat counts |
| | | point to area | dasymetric mapping, use of areal centroids |
| | | point to surface | geostatistical methods such as kriging, cokriging |
| | | area to area—the modifiable areal unit problem (MAUP) (e.g., combining multiple spatial data sets) | areal interpolation, incompatible/misaligned zones, pixel aggregation, Bayesian areal regression models, multiscale spatial tree models, hierarchical models |
| | | area to surface | pycnophylactic interpolation |

*Supporting Information for extended discussion.*

(e.g., transcription error). These uncertainties interact with uncertainty that arises from data quality (e.g., transcription error), choice of spatial units, and the method for aggregating the data (e.g., average value for a raster cell) (data quality and COSP) (Fig. 2b). Alternatively, social survey data uncertainty can affect the analysis as an input into a statistical model when using other elicited SRS data geospatial methods (e.g., Table 1 & methods 3 and 4). Regardless of how uncertainty arises in elicited SRS data (Fig. 2c), it will propagate when combined with other forms of data and potentially interact if that data also includes uncertainty (Fig. 2d). Additional error will also arise in studies that use statistical analyses even if the social data is 100% accurate due to sample error, model choice, generalizability, etc. We did not consider the mechanisms associated with a statistical analysis because these forms of uncertainty are common to most scientific studies. All the uncertainties associated with the production and analysis of elicited SRS data will be present in the final modeling or mapping output used in conservation planning (Fig. 2e).

## Review of Elicited SRS Data Literature

We reviewed a subset of the literature on elicited SRS data in order to summarize what social data is being mapped and the geospatial methods used and assess whether uncertainty is being addressed. We identified 16 papers in our systematic review as meeting the criteria for elicited SRS data described above from a Web of Science keywords search (“*conservation planning*” OR “*systematic conservation planning*” OR “*spatial prioritization*”) AND Topic = (“*willingness to sell*” OR “*willingness to participate*” OR “*willingness*” OR “*conservation opportunity*” OR “*social value*” OR “*preference*”) we conducted in October 2013. We also asked participants attending a workshop on conservation opportunity to identify potential papers (Supporting Information for full description). The studies reviewed included a broad range of conservation objectives, methods, and environments. Conservation objectives included improving water quality (Brouwer et al. 2010), managing ecosystem services (Bryan et al. 2010), and designing protected area

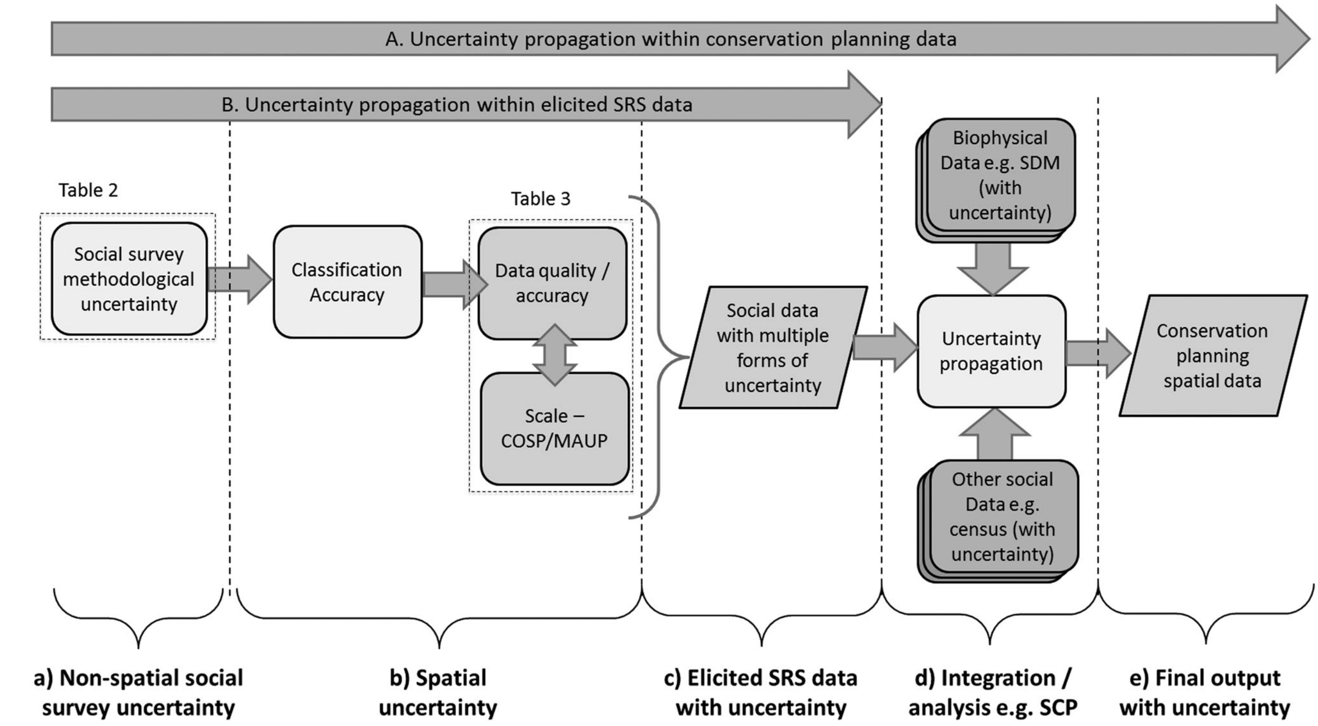


*Figure 2. Conceptual diagram describing the steps in the processing and analysis of elicited spatially referenced social (SRS) data and other forms of data (e.g., SDM, species distribution model) and the propagation of nonspatial methodological uncertainty and spatial uncertainty (COSP, change of support problem; MAUP, modifiable areal unit problem). Uncertainty propagation can be tested in the production of elicited SRS data and for the outputs of a spatial analysis for conservation planning.*

networks (Guerrero et al. 2010) (Table 4) and included a range of environments including both terrestrial and marine. Social data were gathered using interviews, mail surveys, and Web-based surveys with sample sizes ranging from 29 (Curran et al. 2012) to 766 individuals (Campbell et al. 2009) (Table 4) and response rates, where reported, (10 of 16 studies) ranged from 11.6% to 100%. The size of the study areas ranged from small local scale (Curran et al. 2012) to country-wide (Campbell et al. 2009).

We categorized the studies into 3 groups based on use of similar social survey and geospatial methods. The first group was individual property owners, in which the likelihood of undertaking a conservation related action on the respondent's property was measured directly (Table 4 & Geospatial method–Areal data descriptive individual's property) based on "willingness to steward" (Pasquini et al. 2010) or "willingness to sell" (Knight et al. 2010). These studies commonly used interview survey techniques with small sample sizes ($n = \sim 50$) but with large response rates (89–100%), indicating high or complete coverage of the relevant stakeholders. The second group of studies was the choice survey group, which included only 2 studies (Campbell et al. 2009; Brouwer et al. 2010). They both attempted to measure the likelihood of paying for conservation actions with choice survey methods. This group included the 2 largest sample sizes ($n = \sim 700$), which reflects the large data requirements for this experimental approach. The third group was the PPGIS group and included 9 out of 16 studies. They measured collective perceptions of biological importance (or value) (Brown et al. 2004; Raymond et al. 2009; Whitehead et al. 2014). These studies were commonly undertaken at the regional scale involving large sample sizes ($n = 54$–$500$) with moderate response rates (11.6–100%) and used PPGIS methods (Table 4).

The geospatial methods used in each study were influenced by the method used to gather social data and by the size of the study area because it is impractical for studies that occur over large areas to sample the total population. The most common geoprocessing method was based on PPGIS (9 out of 16 studies) (Table 4). These PPGIS studies assumed that collective measures of community perceptions of biological importance (or value), or threats to values, were directly related to conservation actions. Our review also included 2 examples where statistical methods were applied to mapping social data. Brouwer et al. (2010) used a statistical model to assess WTP for water quality improvements for subbasins across a river basin, whereas Campbell et al. (2009) used the

**Table 4. Summary of papers on elicited spatially referenced social (SRS) data describing the type of social data, the geospatial methods used, and whether uncertainty is addressed.**

| *Reference*[a] | *Conservation objectives* | *Social data* | *Method* | *Data gathering* | *Sample size (%)*[b] | *Geospatial method* | *Data integration* | *Social data uncertainty*[c] | *Spatial data uncertainty*[c] |
|---|---|---|---|---|---|---|---|---|---|
| Brouwer et al. 2010 | water quality improvement | willingness to pay | choice experiment | interviews | 619 | areal data predictive | overlay | yes | yes |
| Brown & Donovan 2013 | national forest planning | acceptable land uses | PPGIS[d] | web survey | 244 (11.6) | point pattern analysis | overlay | no | no |
| Brown et al. 2004 | biodiversity conservation | environmental values | PPGIS | mail survey and workshop | 542 (31) | point pattern analysis | overlay | no | no |
| Bryan et al. 2010 | ecosystem services | landscape social values and threats | PPGIS | interviews | 84 (100) | point pattern analysis | overlay | yes | no |
| Bryan et al. 2011 | ecosystem services | social values for natural capital and ecosystem services and perceived threats | PPGIS | interviews | 54 | point pattern analysis | overlay | yes | no |
| Campbell et al. 2009 | landscape improvement | willingness to pay | choice experiment | interviews | 766 (78.33) | local statistics | mapping | yes | yes |
| Curran et al. 2012 | carbon credit restoration | willingness to sell or collaborate or participate, restoration opportunity and conservation related social values | standard survey | interviews | 29 | areal data descriptive individual's property | mapping | yes | no |
| Guerrero et al. 2010 | expanding protected areas | willingness to sell | standard survey | interviews | 48 (100) | areal data descriptive individual's property | SCP[e] | yes | no |
| Knight et al. 2010 | conservation action on private land | social values related to conservation success and willingness to collaborate | standard survey | interviews | 48 (100) | areal data descriptive individual's property | SCP | yes | no |

*Continued*

**Table 4. Continued.**

| *Reference*[a] | *Conservation objectives* | *Social data* | *Method* | *Data gathering* | *Sample size (%)*[b] | *Geospatial method* | *Data integration* | *Social data uncertainty*[c] | *Spatial data uncertainty*[c] |
|---|---|---|---|---|---|---|---|---|---|
| Knight et al. 2010 | conservation action on private land | willingness to sell | standard survey | interviews | 48 | areal data descriptive individual's property | SCP | yes | no |
| Pasquini et al. 2010 | conservation on private land | willingness to steward | standard survey | interviews | 50 (89) | areal data descriptive individual's property | mapping | no | no |
| Raymond & Brown 2006 | identifying future national park | landscape social values | PPGIS | mail survey | 500 | point pattern analysis | overlay | no | yes |
| Raymond & Brown 2011 | climate change risks | landscape social values and perceived climate change risks | PPGIS | mail survey and workshop | 375 (61) | point pattern analysis | overlay | yes | no |
| Raymond et al. 2009 | ecosystem services | landscape social values and threats | PPGIS | interviews | 54 | point pattern analysis | overlay | yes | no |
| Tyrväinen et al. 2007 | open space values | landscape social values | PPGIS | mail survey | 421 (42) | areal data descriptive individual's property | mapping | yes | no |
| Whitehead et al. 2014 | SCP with social and biological data | landscape social values | PPGIS | mail survey | 395 (40) | point pattern analysis | SCP | yes | no |

[a] *Supporting Information for full version of references.*
[b] *% refers to the response rate.*
[c] *Whether papers quantified or explicitly addressed one or more forms of uncertainty.*
[d] *Public participation GIS.*
[e] *systematic conservation planning*

geostatistical Kriging techniques to interpolate between sampled locations to produce a WTP for landscape improvement surface.

### Social Survey Uncertainty

Two-thirds of the studies reviewed (69%) conducted some kind of assessment of social data uncertainty (Table 4 & Fig. 2a), however, the type of tests used differed between studies. Most commonly, studies with large sample sizes (PPGIS group) but low to moderate response rate assessed the representativeness of the sample size used. Alternatively, those studies that had small sample sizes (individual property owners group) but complete coverage of the targeted group (e.g., total sample) such as Curran et al. (2012) and Knight et al. (2006) tested for internal methodological uncertainty such as construct validity (extent to which a test measures what it is designed to measure) and reliability. Such analyses enabled the systematic identification of different dimensions of conservation opportunity, with the view toward applying and externally validating them in other study areas. In these studies there is no need to test for sample bias or representativeness as it is assumed that the total population has been sampled (e.g., all relevant landholders). These smaller studies also tended to have a larger number of response variables derived from long questionnaires and thus have more options for testing construct validity. For example, Knight et al.'s (2010) questionnaire had 165 questions that were then reduced to 12 factors.

The PPGIS and choice survey studies had a greater range of uncertainty sources because they did not sample the total population and because they aggregated data unlike the individual property owners group. The PPGIS and choice survey studies commonly tested for external methodological uncertainty such as respondent bias. However, they did not test for internal methodological uncertainty (such as construct validity), most likely due to the paucity of response data (e.g., short questionnaires) that is a result of the practical difficulty in gathering more data using this method. For example, PPGIS techniques are commonly conducted at the regional scale and are more time consuming because survey respondents are asked to plot their values on a map. In contrast, the individual property owners group is likely to be more robust to internal methodological uncertainty because this method commonly uses a total sample and has longer questionnaires (describing multiple constructs with redundant questions for the same construct); however, due to small sample sizes and small extents this method will have external methodological uncertainty related to the difficulty in generalizing outside the study area.

### Spatial Uncertainty

Uncertainty associated with the creation of elicited SRS data is dependent on the spatial data types and processing methods used—specifically point data inputs represented spatially as areal data (Table 1 & methods 2, 4, and 5) and areal data derived from statistical analysis (Table 1 & method 3). For geospatial method 1 (Table 1), individual social data are linked to property locations and the sources of spatial uncertainty are likely to be insignificant. In contrast, PPGIS methods often start as social value data associated with a point location, which are then aggregated to a grid. Each geospatial process has the potential for uncertainty (Table 3 & Fig. 2b).

In contrast to social data uncertainty only 2 out of 16 studies tested for spatial uncertainty (Table 4). Raymond and Brown's (2006) PPGIS study assessed differences in the outcome of their analysis depending on whether a vector or raster model was used to aggregate the data—an example of testing for issues resulting from the MAUP (and thus the COSP). Campbell et al. (2009) assessed the error of the Kriging estimates, a common output produced using this type of analysis. The group individual property owners is likely to be relatively unaffected by spatial error such as those associated with the COSP because individual respondents provide information about their own property. The COSP does not pose a problem because no aggregation takes place, but there is potential for data quality uncertainty.

### Uncertainty Propagation

No study attempted to understand how the uncertainty in the SRS data propagated (Fig. 2c & 2d). This would have affected all studies to varying degrees due to uncertainty associated with combining elicited SRS data (Fig. 2c) with other spatial data (Fig. 2d). In many cases, social data were integrated with biophysical data (such as biodiversity surrogates) through overlaying both data sets and identifying patterns in the overlap between biophysical values and social values for conservation. Integration with SCP tools was undertaken in 4 of the papers reviewed including one PPGIS study and 3 individual property owners group study (Table 4). In each of these cases uncertainty was not tested.

## Framework for Managing Uncertainty

Based on the typology of elicited SRS data uncertainty and the literature review, we propose a framework for more effectively managing uncertainty in the production and use of elicited SRS data. Our framework describes a process that can account for the range of geoprocessing methods and social data types discussed here, but we acknowledge that the technical methods for the management of uncertainty is often context specific and data dependent.

Our framework presents 2 possible pathways for addressing uncertainty. The first pathway describes the most common currently used approach for addressing

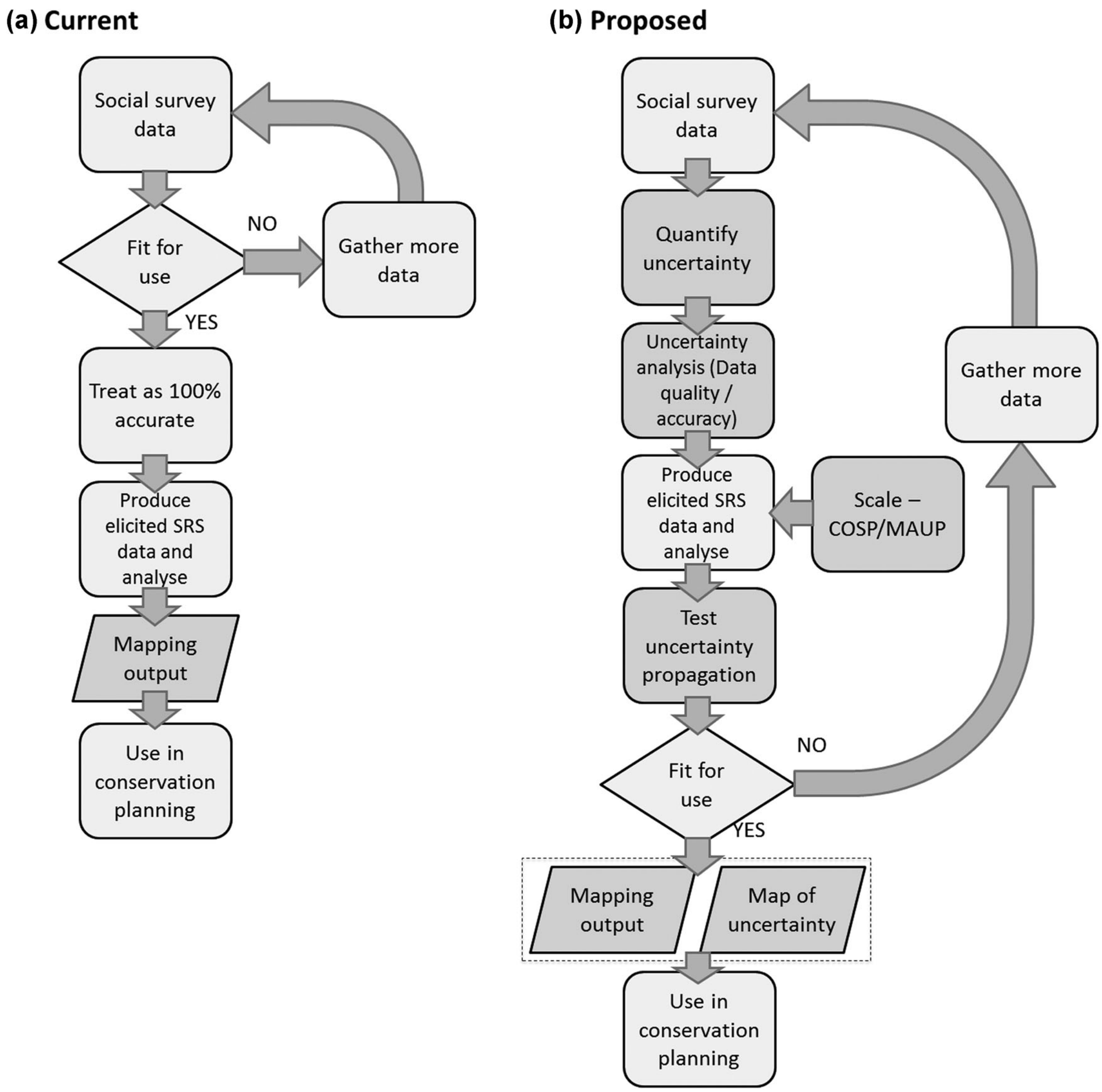


*Figure 3. Process for addressing uncertainty in elicited spatially referenced social (SRS) data: (a) current method used in producing elicited SRS data and (b) suggested method for dealing with uncertainty (COSP, change of support problem; MAUP, modifiable areal unit problem).*

uncertainty (Fig. 3a), but for the second pathway we propose a new method based on integrating existing geospatial methods for addressing social survey uncertainty (Fig. 3b). The current standard practice in social science is assessing fitness for use for methodological uncertainty as opposed to quantifying uncertainty and deriving estimates of its distribution (Fig. 3a). The fitness for use method rejects data if not up to a standard. In cases where data are not fit for use, more data are acquired or research questions may be abandoned. Even if some uncertainty is observed (but not beyond levels that is considered unusable), the data are, in most cases, used as if they were 100% accurate (Fig. 3a). The assessment of the levels of uncertainty that are appropriate is also generally expert based.

There were no examples in the papers we reviewed where the uncertainty in the social survey was carried over into analysis. Yet, two-thirds of the papers reviewed described some kind of assessment of social survey methodological uncertainty (Table 4). This suggests those papers assessed fitness for use but ignored social survey uncertainty when projecting the social data spatially or when using the projected data in further analysis. Furthermore, the standard method for producing and analyzing elicited SRS data issues in most cases failed to account for any forms of spatial uncertainty such as data quality, the COSP, and uncertainty propagation (except for 2 of the papers reviewed).

Our proposed process requires that social survey methodological uncertainty are quantitative (Fig. 3b) rather than only an assessment of fitness for use. This will require social scientists to build on existing methods for assessing fitness for use and explicitly quantify uncertainty. There is a need to derive reasonable estimates on the bounds of uncertainty when using social science survey methods. As such, social survey uncertainty can be interpreted as a form of data accuracy that can be quantified and addressed using a number of existing methods within the spatial sciences such as sensitivity analysis. Importantly, the quantification of uncertainty allows us to explicitly account for it in conservation planning (Carvalho et al. 2011; Williams & Johnson 2013) and therefore provides substantial advantages over the fit for use approach.

Along with the quantification of social survey method uncertainty, there is a need to address the COSP because all spatial processing methods we identified (especially processing methods 2–4) (Table 2) were commonly projected spatially with arbitrary geographic units that were not statistically determined (administrative boundaries, catchment boundaries). Uncertainty can then propagate as a result of projecting the social survey data spatially (Fig. 2 & arrow B) and from combining it with other data sets that also contain uncertainty (Fig. 2 & arrow A). Figure 3 suggests that social survey uncertainty needs to be tested in conjunction with the COSP effects as this form of uncertainty will potentially magnify existing uncertainties. Uncertainty also increases with the number of input data sets and the complexity of models. Finally, along with the output maps of social values or conservation priorities, there needs to be a corresponding map that describes the spatial distribution of uncertainty.

### Quantifying Uncertainty in Social Data

In the social sciences, no procedures have ever been agreed upon for measuring or estimating methodological uncertainty; however, a lot is known about how to minimize methodological uncertainty (see above and Supporting Information). For example, internal methodological uncertainty can be addressed through appropriate validation of measures whereas external methodological uncertainty can be reduced through appropriate sampling and the development of social science theory. Figure 3 clearly illustrates the need for the employment of specific tests of internal and external methodological uncertainty on the social data to derive the quantitative estimates that can be assessed within an analysis using accuracy assessment methods. The development of these methods is a fertile ground for further research and will allow for the quantification of uncertainty arising from these sources.

### Estimating and Addressing Uncertainty

Depending on the social data, biophysical data, and geospatial methods, there are numerous approaches for addressing uncertainty. Methods for addressing specific forms of uncertainty are outlined in Supporting Information; however, a common method for quantifying all forms of uncertainty involves testing the contribution of varying model inputs (such as mapped data layers) to variation in the model output, known as sensitivity and uncertainty analysis. These methods can be used for testing all forms of mapping and modeling uncertainty (Crosetto et al. 2000). A common approach for spatial data is to use Monte Carlo simulation methods whereby each uncertainty source is treated as having a probability density function (PDF) with a known mean and variance for each spatial object (e.g., point, pixel or area), then values are randomly drawing from the PDF and the analysis is rerun with different values for each spatial object to produce confidence bounds (Burrough & McDonnell 1998). Variations on this method include testing for the interaction of uncertainty sources (Saltelli & Annoni 2010) and modeling error in more realistic ways by incorporating the spatial distribution of error (Congalton 1988; Heuvelink 2002). Such methods could be used to develop confidence bounds for social data prior to integration with biophysical data. The inclusion of quantified social uncertainties through this method (or similar) within elicited SRS data analysis is the fundamental difference between current approaches used in the studies we reviewed and our proposed approach (Fig. 3).

Testing for the COSP sensitivity in the creation of elicited SRS data or combining elicited SRS data within a model can be achieved by simulating multiple zoning and scale configurations. This method is a useful first step; however, it is difficult to test for the COSP in a probabilistic way because there are infinite ways to modify spatial boundaries or aggregate data, thus more sophisticated approaches may potentially be used. Testing for this kind of uncertainty should be done for most elicited SRS mapping tasks (except for individual property data) and for all studies that integrate these data with biophysical data.

In many cases, complex methods will be required if a sensitivity analysis demonstrates high levels of scale dependent uncertainty. Some of these methods for addressing uncertainty are specific to one of the 4 different geospatial processing methods and some are more generally applicable. A summary of potential methods that can be applied for addressing specific kinds of the COSP can be found in Table 4 and Supporting Information. These methods range from geostatistical treatments (Gotway & Young 2002) to use of cross-classification with other sociodemographic variables (e.g., sex, race) to address the ecological inference problem (King 1997).

## Implications of Uncertainty

In conservation, decisions need to be made even when uncertainty is large. Yet, if these uncertainties can be quantified, decision theoretic approaches can be used to deal with them. Building on previous enquiry (Burgman et al. 2005), we argue the explicit treatment of spatial uncertainty in SRS data needs to become routine and should use the approach outlined in Fig. 3(b) instead of the current fitness for use approach (e.g., Fig. 3a). The choice of the methods used for including social data and assessing uncertainty within conservation planning will depend on resources, the complexity of the study area, and its size. However, addressing spatial uncertainty and uncertainty propagation is rarely undertaken and can be challenging for workers without significant expertise in GIS, statistics, and writing source code (Heuvelink 2002; Devillers et al. 2010). For example, it is rare for a map to explicitly represent uncertainty in spatial data (Schmit et al. 2006). The difficulty of addressing uncertainty is compounded by numerous forms of uncertainty that have been identified, making it challenging to analyze the consequences of each (King et al. 2004; Chen 2008; Devillers et al. 2010; Lechner et al. 2012*a*).

Uncertainty associated with SRS data should be rigorously assessed to ensure that the benefits of including social data into conservation planning outweigh the impact of adding additional sources of uncertainty. Existing literature on SCP indicates that the most variable data included will tend to drive the conservation priorities identified and this is most commonly the socioeconomic data (Ferraro 2003; Bode et al. 2008). However, given that existing uncertainties associated with spatial data as SCP inputs are often not adequately dealt with (Visconti et al. 2010; Langford et al. 2011), it is important to weigh up the benefits and costs of incorporating this uncertain SRS data into conservation planning (Tulloch et al. 2014 [this issue]).

Value of information theory can be used to explicitly evaluate the degree to which the current SRS data (or additional SRS data) will reduce uncertainty and improve conservation decisions (Raiffa & Schlaifer 2000; Yokota & Thompson 2004; Forsberg & Guttormsen 2006). Social data are collected with the expectation they will reduce uncertainty about cost, feasibility, and opportunities. However, if cost of collecting that data exceeds the value of that information because uncertainty levels are high, it may be better to not invest in that social data. Quantifying uncertainty in SRS data and then undertaking a value of information analysis can help us make this decision from a conservation planning perspective. Most of the papers in the peer reviewed literature on SRS data are theoretical in nature, and it is not yet possible to assess whether the inclusion of social data have made planning more implementable.

When seeking to apply the uncertainty measurements derived from the process outlined in Fig. 3(b), conservation planners should consider how this uncertainty intersects with biological priorities. It is useful to consider SRS data uncertainty through a framework of error types analogous to Type I and Type II statistical errors. Type I errors (false positives) occur when SRS data indicate that conservation actions are feasible, when in fact they are not. Type II errors (false negatives) occur when SRS data indicate that conservation actions are not feasible, when in fact they are. Uncertainties that result in false negatives are more costly in terms of unsuccessful conservation actions, especially in areas of high biological priority. False positives may conversely result in inefficient use of resources. Conservation practitioners should therefore prioritize ground truthing to account for the likely impacts of these different types of errors and be guided by spatially explicit maps of SRS data uncertainty (Fig. 3b).

It is also important to compare alternative approaches to including the social dimension of conservation planning such as land use modeling and participatory approaches (Fig. 1). Participatory approaches to conservation planning may explicitly account for social values in conservation as a substitute for a spatial analysis where the focus is on the decision making process and building relationships rather than a final output from a model. For example, collective bargaining of the final location of protected areas (e.g., Game et al. 2011) may be a more effective way to ensure protected areas are implemented than selecting areas based on their predicted social acceptability (e.g., quantifying willingness to protect). However, this type of participatory planning may not be realistic for larger planning regions, where the number and diversity of stakeholders may make it too difficult to negotiate consensus.

## Future Research

The inclusion of elicited SRS data in conservation planning is a new and promising area of research that allows conservation planners to consider conservation opportunity. However, the dynamic nature of social systems, including their susceptibility to external shocks, can result in high level of uncertainty in SRS data, as we show here. Although ecological systems are also dynamic, social systems have the potential for very rapid change, for example, when new information becomes available. When combining SRS data and biophysical data, the potential for uncertainty propagation is very real. Failure to explicitly account for this uncertainty could result in erroneous conservation priorities and feasibility of implementation could be reduced, counter to the desired outcomes from inclusion of the SRS data. Our typology for assessing SRS data uncertainty and the process we devised for more effectively managing uncertainty issues in conservation planning studies begin to address these concerns. Future research should explicitly consider whether inclusion of elicited SRS data has achieved desired outcomes of making conservation planning more implementable or if uncertainty outweighs the benefits of including SRS data.

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## Supporting Information

A version of Fig. 1 with examples (Appendix S1), an extended definition of uncertainty (Appendix S2), spatial data graphical examples for Fig. 2 (Appendix S3), extended discussions of social data uncertainty (Appendix S4) and spatial uncertainty associated with projecting SRS data (Appendix S5), review criteria and methods (Appendix S6), and complete references for Table 4 (Appendix S7) are available on-line. The authors are solely responsible for the content and functionality of these materials. Queries (other than absence of the material) should be directed to the corresponding author.

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