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Methods and participatory approaches for identifying social-ecological hotspots

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ABSTRACT

Understanding the relationship between humans and their environment is essential for the planning and management of social-ecological systems but integration of social values with biophysical landscape information remains challenging. Identifying areas that are likely to be pivotal in land use planning decisions from both social and ecological perspectives provides one means of integration. Social-ecological "hotspots" represent valuable areas from both human and environmental perspectives but appropriate and valid methods for identifying such areas are under-developed. We applied an inductive research approach using empirical spatial data from a regional study in Australia to evaluate alternative methods for identifying social-ecological hotspots. Social data measuring the importance of the landscape was collected using public participation geographic information systems (PPGIS) while ecologically valuable areas were identified from species distributions and *Zonation* conservation prioritization software. We applied multiple importance thresholds (cut-offs) to separately identify and measure social and ecological hotspots, and then quantified the degree of spatial concurrence (overlap) when combining the layers to generate social-ecological hotspots. Based on the findings, we developed guidelines for identifying social-ecological hotspots under variable data conditions. We describe the practical implications of our findings by showing how the selected method for SES hotspot identification can enhance or limit the utility of hotspot analysis for decision support in regional conservation planning.

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1. Introduction

The social-ecological systems (SES) framework describes the interaction of complex human-environment systems (Ostrom, 2009) and provides a conceptual foundation for describing global environmental challenges such as the conservation of biological diversity (Knight, Cowling, Difford, & Campbell, 2010). A SES is a coherent, but dynamic and complex system of biophysical and social factors that regularly interact in a resilient, sustained manner at several spatial, temporal, and organizational scales to regulate the flow of critical resources (Redman, Grove, & Kuby, 2004). The SES conceptual framework has been developed extensively within the academic literature (e.g., Berkes, Colding, & Folke, 2003) with particular focus on system resilience (Walker, Holling, Carpenter, & Kinzig, 2004) and adaptive governance (Folke, Hahn, Olsson, & Norberg, 2005).

While systems level analysis and understanding is essential for addressing complex multi-scalar human–environment relationships, there is a parallel need to develop practical methods for operationalizing SES concepts for planning the governance and management of land and resource systems. Social and ecological systems are embedded within a geographic context and scale, but the rendering of spatially explicit maps that reveal critical areas of mutual importance remains an under-developed area of research and practice. Human-environment interaction occurs within geographical space that is ecologically and socially heterogeneous where some places are more important or critical to system outcomes than other places. The concept of coupled social-ecological space, also known as social-ecological "hotspots" (Alessa, Kliskey, & Brown, 2008) describes places that are both ecologically and socially important for practical application to environmental planning and management.

The SES framework has been applied to identify likely conflicts and potential trade-offs between social and ecological factors and their associated processes, for example, in the management of land

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and marine systems (e.g. Butler et al., 2011; Pollino, White, & Hart, 2007) but the integration of human dimensions spatial data for environmental management, in particular, remains a work in progress. Despite the call for better integration of humans and their activities (i.e., social data) into landscape ecology (Wu & Hobbs, 2002) and human ecology (McLain et al., 2013), the identification of important social areas that provide social and cultural ecosystem services has lagged the identification of important ecological areas in ecosystem service assessments (Plieninger, Oteros Rozas, Dijks, & Bieling, 2013). In the marine environment, St. Martin and Hall-Arber (2008) go so far as to describe the social landscape as undocumented and a "missing layer" in decision-making.

The development of participatory mapping methods described as public participation GIS (PPGIS), participatory GIS (PGIS), and volunteered geographic information (VGI), provide a means to capture spatially-explicit social data for integration with biophysical data layers in geographic information systems (Brown, 2005; Brown & Kytta, 2014), including the spatial mapping of cultural ecosystem services (see Brown & Fagerholm, 2015; for a review of applications). The ability to identify social and cultural values through participatory mapping methods has progressed toward the operationalizing of SES concepts, but also presents new challenges for data integration. Research into the identification and mapping of coupled social-ecological space or "hotspots" is relatively recent and there is as yet, little formal guidance in the current literature. The complexity, uncertainty, and potential error that characterize the identification and mapping of ecological and social data may be carried forward and amplified in the spatial integration and overlay process.

The purpose of this paper is describe and model key parameters and decision thresholds for the identification of social-ecological hotspots and to provide some guidance to inform future SES hotspot mapping. In the first study to demonstrate methods for identifying social-ecological hotspots, Alessa et al. (2008) reported that output from SES hotspot mapping were dependent on the assumptions underlying the methodology such as the quantitative parameters for determining the size of the hotspot and the specified range of standardized density values and noted that "further work is needed to explore the optimal threshold range for identifying an absolute hotspot size" (p. 38). In addition, the authors noted the limitation of using a single, convenient ecological metric such as net primary productivity for demonstrating the method when other metrics such as species richness could (and should) be incorporated into social–ecological hotspot mapping. This study addresses these research needs by using data from a regional case study in Australia whose purpose was to identify social-ecological hotspots to inform biodiversity conservation planning in the region. The specific objectives of this research were to generate social-ecological hotspots for the study region (Baffle Basin, Australia), to demonstrate how these hotspots can vary with different parameters and assumptions about the data, and to provide guidance for the generation of SES hotspots under alternative scenarios. The implications of these results for supporting regional conservation planning efforts are described.

1.1. Ecological and social values importance evaluation

A defensible method for evaluating the importance of ecological systems and their components is essential to making informed choices about conserving biological diversity. A range of approaches with different purposes have been developed including the design or expansion of conservation reserve networks (Kremen et al., 2008), the spatial prioritization of conservation actions (Moilanen, Leathwick, & Quinn, 2011), and the integration of social data into conservation prioritization models (Whitehead et al., 2014). Key criteria used to evaluate ecological values have included species richness, habitat quality, connectivity, irreplaceability, representativeness and complementarity (Margules, Nicholls, & Pressey, 1988; Moilanen, Wilson, & Possingham, 2009; Pressey, Humphries, Margules, Vane-Wright, & Williams, 1994, Pressey, Johnson, & Wilson, 1994). In this study, we evaluated the importance of ecological areas in a case study region using species distribution data and *Zonation* spatial prioritization software (Moilanen & Kujala, 2008) that generated ecological hotspots based on importance rankings.

Methods for evaluating the spatial importance of social systems and their components are less well-developed than for ecological systems given the complexity of accounting for multiple and diverse human values that can be rendered spatially explicit. However, there has been significant research effort over the last decade to operationalize spatially-explicit social values that are embedded within social-ecological systems (Alessa et al., 2008; Brown, 2005; Brown & Raymond, 2007) The development PPGIS methods (see Brown & Kytta, 2014; Sieber, 2006 for reviews) has provided the means to generate spatially-explicit social information for a variety of environmental applications such as regional conservation planning (Brown & Weber, 2013), national forest and park planning (Brown & Reed, 2009; Brown & Weber, 2011), and marine planning (Baldwin & Mahon, 2014). Methods commonly used to identify spatial areas of important social values include mapped point densities (Alessa et al., 2008) or polygon densities (Ramirez-Gomez, Brown, & Tjon, 2013).

2. Methods

An overview of the analytical methods used in this study is presented in Fig. 1. We first identified important ecological areas in the study region from species distributions using *Zonation* software (Step 1), followed by the identification of important social areas generated from density maps of social values collected using PPGIS (Step 2). Social hotspots were generated from point data using two alternative methods (global versus local). In Steps 3 and 4, we established a finite number ($n = 3$) of model parameters (importance thresholds of 10, 30, and 50%) for the evaluation of SES hotspots, while in Steps 5 and 6, we performed multiple spatial overlays of the social and ecological data using the predefined importance thresholds to compare the results under the alternative scenarios. In the final step, we present recommendations for measuring social–ecological hotspots under variable conditions.

2.1. Study area

Baffle Basin is located at the southern end of Great Barrier Reef catchment and falls within the Burnett Mary Natural Resource Management (NRM) region in Queensland, Australia (Fig. 2). Baffle basin encompasses a total of 4114 km^2 (Binney, 2008) with a population of 5822 people in 2011(Australian Bureau of Statistics, 2013). The major ecologically valuable characteristics in Baffle Basin include near pristine estuaries, threatened species of fauna and flora, two critically-endangered ecological communities (Littoral Rain forest and Coastal Vine Thickets of Eastern Australia and Lowland Subtropical Rain forest on Basalt Alluvium), a Dugong protection area, and 26 protected areas, national parks, conservation, and forest parks (Great Marine Reef Marine Park Authority, 2012). The major land uses of this region are grazing, intensive agriculture, water supply, road and rail infrastructure, and urban residential areas (Reef Water Quality Protection Plan, 2013).

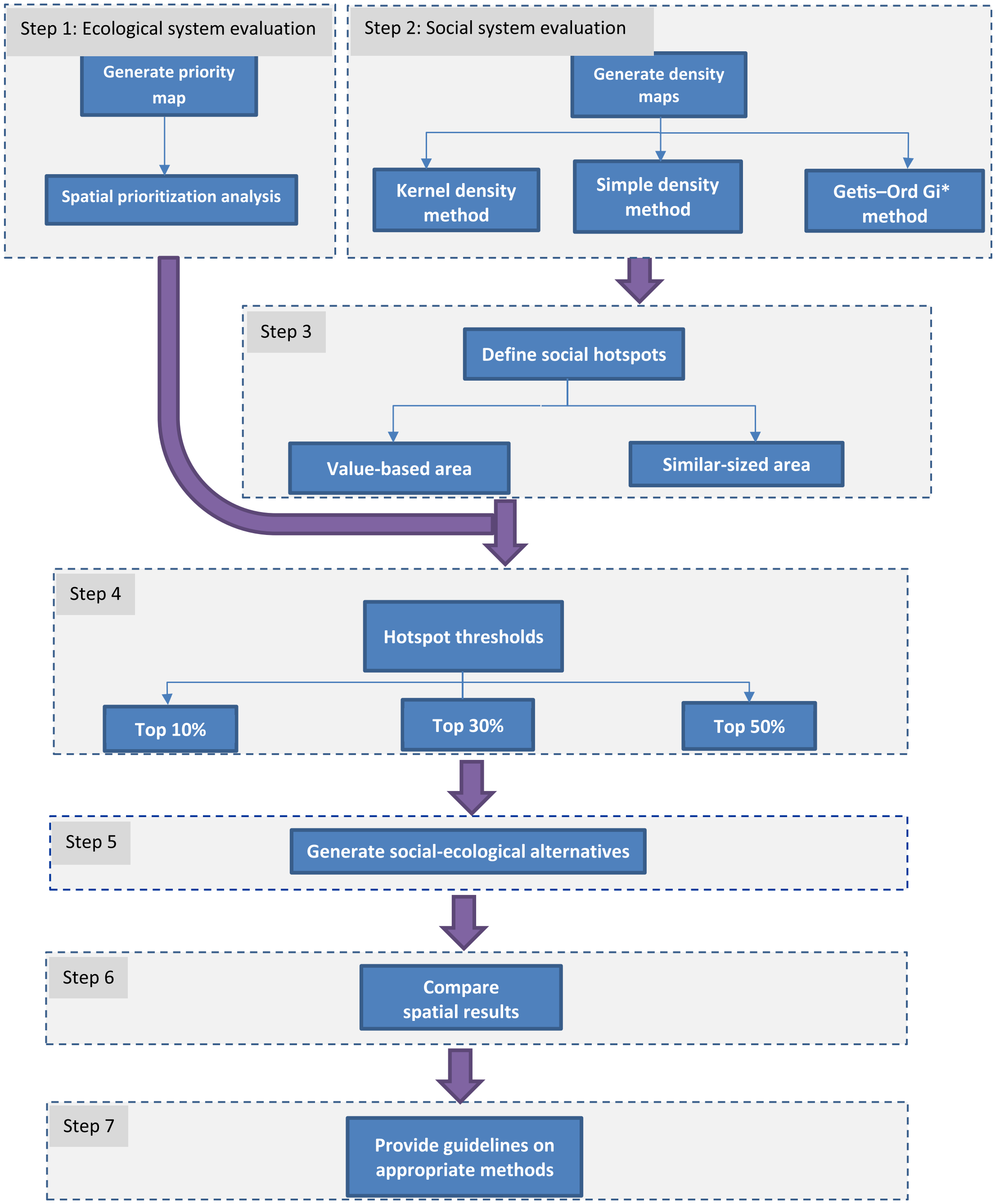

Fig. 1. Process followed to evaluate alternative social-ecological hotspot methods.

2.2. Social data collection

A mixed-methods PPGIS survey (Pocewicz, Nielsen-Pincus, Brown, & Schnitzer, 2012) was implemented to collect spatially-explicit perceived landscape values in the Baffle Basin. In order to increase the response rate, study participants were provided the option of completing an internet-based or mail-based survey. A PPGIS website was developed using a Google Maps Application Programming Interface (API) where participants were requested to drag and drop landscape value markers onto the map of the region following the methods provided to them. The landscape value typology developed by Brown (2005) was adapted after consultation with key stakeholders to identify the landscape values relevant to the study area (Table 1).

We sent letters of invitation to 2200 residential addresses provided by a marketing agency (Yell123, 2014), of which 365 were undeliverable, leaving an effective sample size of 1835 households. The letter explained the study objectives, provided the PPGIS website URL, and included instructions for participating in the study. A unique website access code was provided to each household to track responses. Two additional follow-up mailings were sent to non-respondents after the first invitation. In the third follow-up mailing, we asked whether non-participants would prefer to participate using a hardcopy version of the survey. Interested people were sent survey packages that included an A1 size map of the Baffle region, a one-page instruction explaining how to complete the survey, a legend with small, mnemonically-coded sticker dots for mapping the landscape values, and the same text-

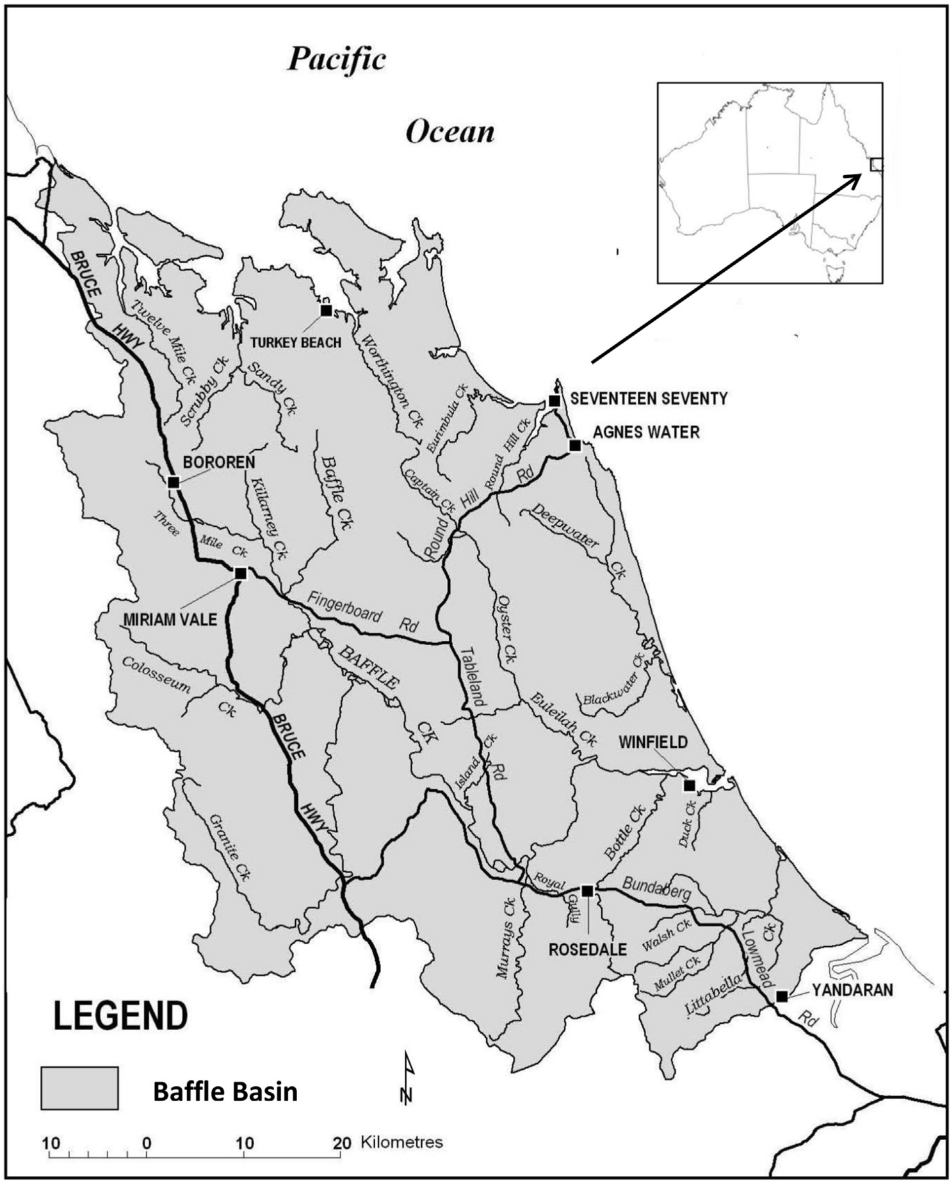

Fig. 2. Location map of Baffle Basin region in Queensland, Australia.

Table 1
Typology of perceived social values used in Baffle Basin study.

Value	Operational description
Aesthetic/scenic	These areas are valuable because they contain attractive scenery including sights, smells, and sounds.
Economic	These areas are valuable because they provide timber, fisheries, minerals, or tourism opportunities such as outfitting and guiding.
Non-water-based recreation	These areas are valuable because they provide a place for my favourite non water-based recreation activities.
Water-based recreation	These areas are valuable because they provide opportunity for water-related recreational activities such as boating, fishing.
Life sustaining/ ecological	These areas are valuable because they help produce, preserve, clean and renew air, soil and water.
Learning/scientific	These areas are valuable because they provide places where we can learn about the environment through observation or study.
[a]Biological value	These areas are valuable because they provide a variety of fish, wildlife, plants, or other living organisms.
Spiritual	These areas are valuable because they are sacred, religious, or spiritually special places or because I feel reverence and respect for nature here.
[a]Intrinsic	These areas are valuable in their own right, no matter what I or others think about them.
Historic/cultural	These areas are valuable because they represent history, or provide places where people can continue to pass down memories, wisdom, traditions, OR a way of life.
Future	These areas are valuable because they allow future generations to know and experience the area as it is now.
[a]Wilderness	These places are valuable because they are wild, uninhabited, or relatively untouched by human activity.
Social	These areas are valuable because they provide opportunities for social interaction.

[a] Identifies values used in this study.

based survey questions that were used in the internet survey. After receiving the completed maps and survey questions from the respondents, the locations of the sticker dots were digitized into GIS software and merged with the internet PPGIS spatial data.

Household sampling was augmented by a purposive sample of key informants invited by email to participate in the survey. Letters of invitation were emailed to 48 key informants who have interests or responsibility for natural resource management in the region. Key informants included Burnett Mary Regional Group (BMRG) managers, planning and conservation officers from Bundaberg and Gladstone Regional Councils, sports and recreation associations, and conservation council managers. Finally, volunteer participation in the study was encouraged through family, work, and friend referrals. Individuals that did not receive formal invitations to participate in the study could request an access code dynamically on the website.

2.3. Methods for identifying ecological importance

We used the Species of National Environmental Significance (SNES) data generated by the Australian government to identify areas of ecological importance within the Baffle Basin region (Department of Environment, 2015). To determine ecological importance, we considered all 162 species that had range maps covering the study region (53 bird, 43 fish, 22 plant, 20 mammal, and 24 reptile species). These range maps included species or habitat distributions of nationally important threatened and migratory species. This species range information was combined to identify spatial areas of high ecological value.

In our ecological model, spatial importance was determined using a complementarity-based approach in *Zonation* software (v. 3.2) that prioritizes (ranks) the individual locations of the study area based on their contributions to the overall landscape evaluation (Moilanen et al.,2009) The heuristic algorithm within *Zonation* uses all data available about the occurrence of biodiversity features (in this case, species range maps) to generate a hierarchal prioritization of the landscape (Moilanen et al., 2012). For the purpose of this study, we used core-area zonation as the cell removal rule which attempts to minimise biodiversity loss by removing cells with the lowest contributions to the overall ecological value of the landscape. The removal index δi for each cell is calculated based on the following equation (adapted from Moilanen, 2007):

$$\delta i = \max j \frac{Qij(S)}{ci}$$

where:

Qij is the extent of distribution of species
j remaining in cell **i** in the remaining set of the cell **S**
ci is the cost of adding cell
i to the prioritization analysis

According to this aggregation rule, *Zonation* starts removing the cells with the smallest contribution to overall ecological value and continues the process until no cells are left. The cells with lower $\boldsymbol{\delta i}$-values are removed sooner with the remaining cells having higher values. By removing parts of species' distribution ranges during the process, the ecological value of the remaining distributions increases. *Zonation* retains the core areas of all species as high-quality locations until the end of the cell removal process. The algorithm gives greater priorities to cells with the highest occurrence levels of the species, regardless of the extent of their distribution overlap (Moilanen et al., 2012). This hierarchical process of ranking the grid cells identifies the ecological importance of the study area based on the aggregated distribution of SNES found within the study area.

2.4. Methods for identifying social importance

To operationalize the concept of social hotspots, it was necessary to select the most relevant mapped social values (see Table 1) for analysis. To be comprehensive, we defined two scenarios that represent perceived biological importance from a social perspective. In the first scenario, we used only mapped points for biological value. In the second scenario, we combined the biological points with intrinsic and wilderness points because Brown, Weber, & de Bie, 2015 reported that these three landscape values were spatially correlated with biological importance derived from an expert assessment using species distributions. Hereafter, we refer the second scenario as the multiple-value scenario.

To identify social value hotspots, we used the following three methods: (1) kernel density function, as a non-parametric technique, to identify regional (global) hotspots, (2) simple point density which divides the number of mapped points by the cell area, and (3) Getis–Ord Gi* spatial statistic to identify local hotspots within the region. The kernel and simple density methods require the identification of a point density value "cut-off" to delineate areas of importance (hotspots) and thus we call these "value-based" hotspot methods. For value-based methods, there is single point density value for the region that determines whether social value densities comprise a hotspot. In contrast, the Getis–Ord Gi* statistic identifies hotspots by examining the distribution of points within a defined, local cell neighbourhood and thus, there is no single point density that determines importance.

2.5. Global density methods

Kernel density maps were generated as continuous surfaces using a 500 m grid cell size and 3000 m search radius, parameters that were appropriate for this analysis based on the point distributions and the scale of the study area. Kernel density mapping is a technique that fits a smoothly curved surface or kernel over each observation based on a specified bandwidth or search radius (Alessa et al., 2008). In our analysis, we used standardized kernel densities to reduce the effect of density calculations derived from variable quantities of mapped points. Standardized kernel densities were calculated by subtracting the mean grid density from each grid cell value and dividing by the standard deviation of the grid density. This process generated raster maps (hotspot maps) of social values for the two modelling scenarios (biological only and multiple-value).

2.6. Local hotspots (Getis–Ord Gi*)

The Getis–Ord Gi* method identifies whether a particular location is surrounded by lower or higher point densities than expected relative to the mean distribution. Specifically, the Gi* statistic measures the degree of association that results from the concentration of all points within a radius of a certain distance from the original point (Getis & Ord, 1992). The result is a raster map that identifies local hotspots (areas with significantly more points than expected at given distance) and coldspots (areas with significantly fewer points than expected at a given distance). This analysis was performed on both social value scenarios (biological only and multiple-value) using 95% confidence levels to determine the areas of spatial significance.

2.7. Modelling alternatives for measuring coupled social-ecological space

We considered multiple scenarios to measure social–ecological hotspots. Because social-ecological hotspots are the intersection of two spatial data layers representing important social and ecological areas, the degree of spatial overlap will be influenced by the size of the social and ecological data layers that are intersected. Larger hotspot areas will result in greater probability of spatial overlap in the study region and potentially larger social-ecological space, while smaller hotspot areas have lower probability of spatial intersection and potentially smaller social-ecological space. In modelling social-ecological space, decisions must be made about the quantitative importance threshold to apply which determines the size of the component hotspots. For global measures of point distributions, a critical density value (threshold or cut-off) is typically applied to determine the spatial areas of hotspots. This threshold (cut-off value) represents a subjective judgement. Lower threshold values produce larger hotspot areas, while larger threshold values produce smaller hotspot areas. Given that even standardized densities can produce variable-sized hotspots based on the number of point observations, and given that multiple data layers will be intersected to identify social-ecological space, an argument can be made that the input hotspot data layers for social and ecological importance should be standardized by area rather than using a subjective density threshold value. Thus, social and ecological hotspot maps can be generated based on density threshold values and then spatially intersected, or social and ecological hotspot maps can be generated based on an equalized areas and then spatially intersected. In our analyses, we examined both options—(1) defining importance density thresholds for the input data layers followed by spatial intersection, and (2) applying an equal-area criterion for the input data layers followed by spatial intersection.

What is an appropriate density threshold to determine hotspots? Selecting the top 30% of density values as a cut-off for identifying hotspots has been used in multiple studies (Alessa et al., 2008; Whitehead et al., 2014) and we selected this value as our baseline for comparison. To be comprehensive, we selected two additional density cut-off values (top 10% and 50% of density values) in addition to the 30% value to understand the potential effects of the cut-off value on social-ecological space. The frequency distributions of cell densities were used to determine which specific cells satisfied the density threshold criteria.

In the equal-area model, the component hotspot layers (social and ecological) were equalized by area before spatial intersection. If the social and ecological hotspot data layers are unequal in area based on the importance threshold or cut-off, the smaller of the two component hotspot layers is increased based on importance to match (equalize) the larger hotspot component. In theory, either the social or ecological hotspot data layer could comprise a larger proportion of the study area. In practice, the top 10, 30, and 50% of the most important ecological areas identified with *Zonation* software equates to 10, 30, and 50% of the study area respectively and was the larger of the two component hotspot data layers. Standardized social value densities were equalized in area with the most ecologically important areas based on the top 10, 30, and 50% importance thresholds.

2.8. Operationalizing social-ecological hotspot spatial concurrence

The combination of different model configurations (biological only versus multiple social values), using kernel density and simple density with three density thresholds (10, 30, and 50%), the Getis–Ord Gi* local hotspot method, and application of the equal-area criterion, provides 30 pairwise combinations of social value hotspots for spatial intersection with the ecological importance data generated from the *Zonation* output.

We used two methods to examine the spatial concurrence (overlap) between social and ecological hotspots in the region. We calculated the phi correlation coefficient (φ) using a 2×2 contingency table where grid cell values represent the presence or absence of the social or ecological hotspot in the same study location (grid cell). The phi coefficient is a variation of the Pearson correlation coefficient that is used for binary data and is related to the chi-square statistic ($\chi2$), where $\chi2 = n\ \varphi2$ (Chedzoy, 2006; Zhu, Pfueller, Whitelaw, & Winter, 2010). The phi coefficient measures the strength of the relationship on a scale from 0 to 1 where larger values for phi indicate greater spatial overlap between the social and ecological hotspot areas.

The Jaccard coefficient (Van Jaarsveld et al., 1998) directly measures the degree of spatial overlap between social-ecological hotspots in each scenario and can range from 0 to 100 percent. A larger Jaccard coefficient indicates greater spatial concurrence between each pair of social and ecological hotspot data layers. The Jaccard coefficient (J) was calculated as follows:

$$J = \frac{\text{Number of grid cells shared by social and ecological hotspot layers}}{\sum \text{Number of additional grid cells for both layers}} \times 100$$

The degree of spatial concurrence for each of the social-ecological hotspot scenarios was calculated and plotted using line graphs to show how spatial overlap changes under alternative definitions of social hotspots (biological value only and multi-value), with alternative hotspot density thresholds (10, 30, 50%), and by applying the equal-area criterion.

2.9. Relationship of social-ecological hotspots to protected areas

To understand the potential implications of SES hotspot methods for regional conservation planning, SES hotspots were overlayed on a map of existing protected areas within the study area. This type of analyses identifies whether SES hotspots fall within or outside existing protected areas. Protected areas were identified based on their designation under the Nature Conservation Act 1992 (QLD) and downloaded from the Queensland Government website (Queensland Government, 2015). These areas include national and conservation parks with relatively high legal protection from future development and comprise 612.3 km^2 (14.9%) of Baffle Basin region. These protected areas were merged to create a single protected areas spatial layer. We then overlayed SES hotspots that were generated using biological social values with hotspot density thresholds (10, 30, 50%) using density values (unequal areas) and followed by overlay of equalized area hotspot components. We calculated the area and percentage of the ecological and social hotspot components and the SES hotspots that were inside/outside of the protected areas. For purposes of visualization, we generated maps showing the spatial overlay of both density value-based SES and equal-area generated SES.

3. Results

3.1. Survey results and respondent characteristics

A total of 1835 households in the Baffle Basin were sampled and invited to participate in the study. The response rates for the web-based and hardcopy PPGIS surveys were 11.7% and 44.6% respectively and provided 264 responses for analysis. The total number of spatial attributes identified by respondents was 9190 (72% via web-based and 28% via hardcopy surveys). The number of key informants and volunteers who participated in the survey was 24 and 45, respectively. The distributions of landscape values mapped by the key informant and volunteer sampling groups were compared to the household sampling group and found to be similar. Therefore, we combined the data from the different sampling groups for spatial analyses.

A non-response bias check was performed by sending postcards to non-participants, asking their reason(s) for non-participation. The dominant reason (38.2%) given by non-participants was lack of knowledge of the region. Other frequent reasons for non-participation included living outside the Baffle region (12%), not having enough time (10%), and being retired and no longer living in the area (5.3%).

The majority of respondents (58%) were male. The age of all respondents ranged from 19 to 90, with an average age of 59. Study respondents expressed a reasonably high level of self-assessed knowledge and familiarity with the study region, with 60% of internet respondents indicating their knowledge about the places in the Baffle region was excellent or good, and 37% assessing their knowledge as average or below average. About 52% of hardcopy survey participants self-assessed their region knowledge as excellent or good.

A large proportion of internet respondents (83%) had visited all or almost all of the locations that they identified on the map compared with 58% of hardcopy participants. Given the similarity in point distributions between the internet and hardcopy respondents, we integrated the data from these two groups for spatial analyses.

3.2. Social and ecological system mapping results

We used kernel density, simple point density, and Getis–Ord GI* methods to measure the spatial distribution of social values (Fig. 3a, b, and c). The ecological hotspots were generated from spatial prioritization analysis undertaken based on the range maps of 162 species in the region (Fig. 3d). These spatial distributions were used for measuring and comparing multiple social-ecological hotspots scenarios.

3.3. Evaluation of social-ecological hotspot methods

We quantified the spatial overlap between each pair of social and ecological hotspots for biological and multiple-value scenarios using the phi and Jaccard coefficients. The results of the two methods are presented in Table 2a and b. In both social value scenarios using equal-area measurement and alternative density cut-offs, the Jaccard coefficients were larger relative to the phi correlations between the same social and ecological hotspot scenarios. The largest spatial overlap (about 50% with Jaccard) was observed between social and ecological values when we equalized the area of importance in both social and ecological hotspots using the top 50% as a cut-off. Using phi, there was little practical difference in the spatial overlap (about 30%) using either biological or multiple-value social hotspots, a 50% density cut-off, and the standardized kernel or point density methods.

The social hotspots in both biological and multiple-value scenarios had larger spatial concurrence with ecological hotspots when applying equal-area measurement to the density cut-offs. There was also a notable trend in increasing spatial overlap (both phi and Jaccard) with larger density cut-offs, regardless of the global methods used to generate the social hotspots (see Fig. 4a and c). For example, using phi, the spatial overlap increased from about 5% (at 10% importance) to about 20% (at 30% importance), to about 30% (at 50% importance). When using density value cut-offs without applying the equal-area criterion, there was relatively little spatial overlap between social and ecological hotspot areas. The degree of spatial concurrence using Jaccard increased slightly with larger density cut-off values, but spatial concurrence did not reveal any significant trend across the different scenarios (see Fig. 4b and d). Without applying the equal-area criterion, there was little difference in spatial concurrence when increasing the cut-off threshold from 30% to 50%.

When using Getis–Ord Gi* analysis as a localised method for both biological and multiple-value scenarios, there was significantly less spatial concurrence than with equal-area global density methods at 50% cut-off thresholds (according to phi coefficient) (Fig. 4a and c). When global density areas were not equalized, spatial overlap using Getis–Ord Gi* was considerably larger in both social scenarios (Fig. 4b and d). The largest spatial concurrence was observed with Getis–Ord Gi* analysis at the 30% cut-off level.

3.4. Relationship between social-ecological hotspot methods and protected areas

The spatial overlap of SES with existing protected areas was calculated for hotspot importance thresholds (10, 30, 50%) with the equal-area criterion. The results appear in Table 3. The smallest area, but largest percentage of spatial overlap occurred using the 10% importance threshold. As would be expected, the *area* of SES spatial overlap with protected areas increased at 30% and 50% importance thresholds, while the *percent* of total SES area contained within protected areas declined. The SES spatial overlap with protected areas was influenced more by the location ecological hotspots than the location of social hotspots as evidenced by the significantly larger percentages of ecological hotspots contained with protected area boundaries. Thus, the most important SES hotspot areas (e.g. 10% threshold) are more likely to be located within existing protected areas, while less important SES areas are likely to fall outside existing protected areas. Further, ecologically important locations derived from species distributions shows stronger spatial concurrence with protected area designation than mapped social perceptions of biological importance. These spatial overlay results are presented in Fig. 5b. For purposes of contrast, we also mapped density value-based SES hotspots (Fig. 5a). Without equalizing the social and ecological hotspot areas before spatial intersection, the result was a relatively small SES area located near the mouth of Baffle Creek, with most of the terrestrial area of the SES located within an existing protected area (i.e., Mouth of Baffle Creek Conservation Park).

4. Discussion

The primary objective of this research was to measure and evaluate social-ecological hotspots under variable conditions that included alternative social value definitions, multiple importance thresholds, local versus global hotspot identification methods, and two different metrics for calculating spatial concurrence. The determination of social-ecological space (SES) was sensitive to both the methods and the parameters chosen. In particular, the greatest difference in SES calculation resulted when an equal-area hotspot criteria was applied (or not) to the social importance thresholds. The sensitivity of SES measurements to unequal-area social and ecological hotspots was reflected in the results of the two measures of spatial concurrence, phi and Jaccard. Under conditions that equalize social and ecological hotspot areas before spatial overlay, the Jaccard coefficient performed better in capturing and describing SES. When the use of importance thresholds produced highly unequal social and ecological areas for overlay, the phi method performed better in identifying SES.

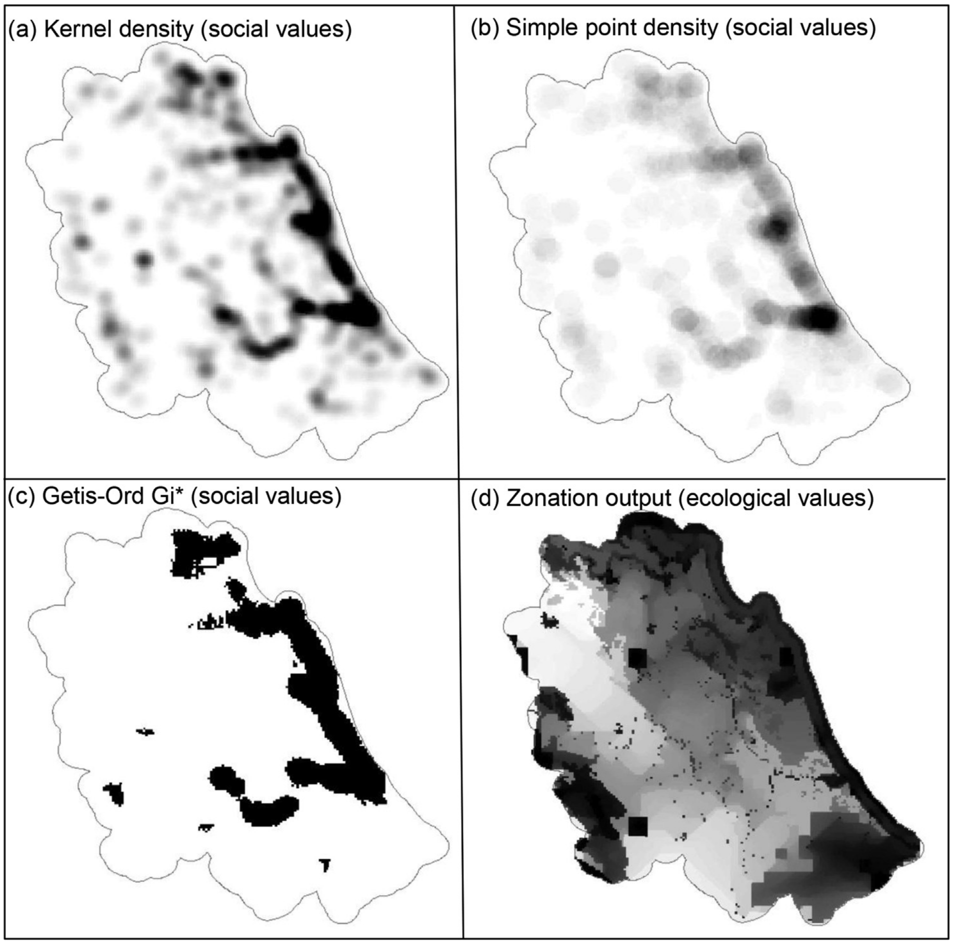

Fig. 3. Maps showing the spatial distribution of social and ecological values in the Baffle Basin region. Darker areas indicate higher densities of social values or higher priorities of ecological values. Social value distributions were generated from multiple-value point data using: (a) kernel density, (b) simple point density, or (c) Getis–Ord Gi* methods. Ecological importance was generated by a Zonation model (d) based on species distributions.

In this study, using *Zonation* had the effect of equating ecological importance (i.e., top 10, 30, 50%) with the proportion of the study area. This outcome would not occur if alternative methods were used to determine ecological importance. For example, if ecological importance were determined from point data similar to the social data used in this study, or if ecological importance were determined by aggregating polygon areas, the ecological importance criterion (e.g., top 30%) may not encompass the same proportion (i.e., 30%) of the study area. Applying the equal-area criteria requires equalizing the importance areas based on the larger of the social or ecological component hotspots. The key point is that the method of determining importance (e.g., density value cut-off, grid

Table 2
Spatial concurrence (overlap) results from social-ecological hotspots generated using alternative social value definitions (biological only vs. multiple-value) and importance thresholds (top 10, 30, 50%). Phi and Jaccard (in parenthesis) coefficients are presented as percentages from: (a) spatial concurrence using biological values only, and (b) spatial concurrence using multiple-values.

		Phi coefficient (Jaccard coefficient)%				
		Method				
		Local	Global			
		Getis–Ord Gi*	Standardized kernel density		Simple point density	
a						
Biological value			**Similar-sized**	**Value-based**	**Similar-sized**	**Value-based**
Hotspot threshold	50%	16.3(15.9)	31.2(48.8)	5.5(0.63)	31.8(50.8)	3.6(0.97)
	30%	19(17.9)	19.9(28.2)	5.5(0.45)	20.7(26.9)	7.2(1)
	10%	4.8(8.2)	5(7.9)	6.3(0.44)	5.9(7.4)	5.3(0.62)
b						
Multiple-value			**Similar-sized**	**Value-based**	**Similar-sized**	**Value-based**
Hotspot threshold	50%	18.3(19.7)	30.1(48.2)	6(1.1)	28.8(46)	5.2(1.3)
	30%	22(21.8)	22.5(29.7)	5.8(0.5)	23.3(28.6)	7.2(0.9)
	10%	5.8(9.2)	5.2(7.9)	5.9(0.43)	4.9(7.7)	5.4(0.6)

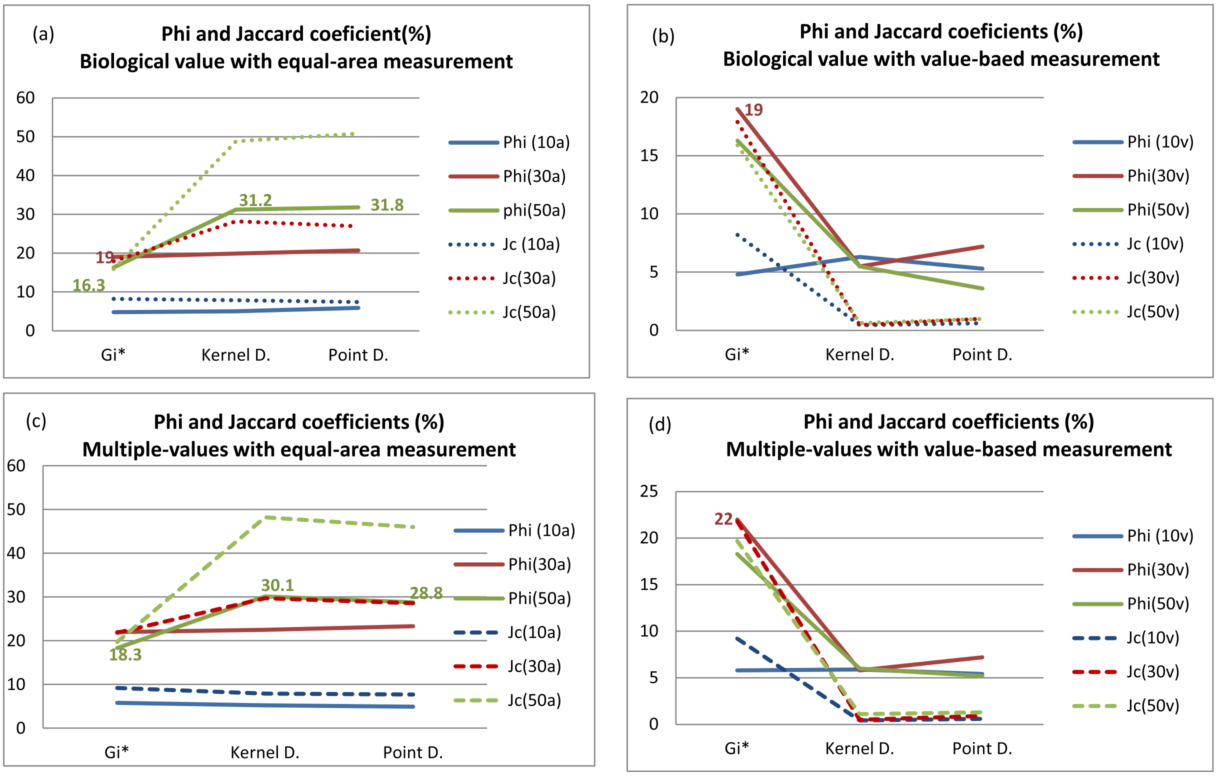

Fig. 4. Line graphs showing phi and Jaccard (Jc) coefficients under alternative social value definitions (biological only vs. multiple-value) and importance thresholds (top 10, 30, 50%). The four panels show: (a) biological value with equal-area measurement, (b) biological value with value-based measurement, (c) multiple-values with equal-area measurement, and (d) multiple-values with value-based measurement.

cell ranking, or simple heuristic judgment) determines the area of importance which has implications for using SES hotspots for land use planning analysis.

Some additional context is important to help interpret the SES spatial concurrence findings. Using the phi coefficient, the degree of SES spatial concurrence ranged from 5% to a maximum of about 32% under conditions that equalized social and ecological hotspot areas at 50% importance thresholds (Table 2a). Although one would not expect SES spatial concurrence to approach 100% under the best of conditions, an important question concerns the level of SES spatial concurrence that would be considered "normal" (or baseline) for the SES variable being measured (in this case, biological importance). Although this study was the first to quantify spatial concurrence under variable conditions, a previous study by Brown, Smith, Alessa, and Kliskey (2004) collected spatially-explicit public perceptions of biological importance using PPGIS and compared the results with biologically important areas identified by a panel of biological "experts". That study reported spatial concurrence of about 30% between the PPGIS and expert assessments. Although the previous study used a different method to assess biological importance (expert polygon delineation vs. *Zonation* modelling), the studies appear similar enough to suggest that the SES spatial concurrence findings in this study fall within the range of expectations, reaching a maximum near 30% spatial concurrence. Thus, the evaluation of SES hotspot methods for biological importance suggests that the expected range of SES spatial concurrence is not 0–100% but rather has maximum spatial concurrence near 50%. The question is why?

The assessment of biological importance from an ecological perspective differs from the assessment of biological importance from a social perspective. In this study, biological importance was determined through the ranking of spatial locations based on species range maps. The social assessment of biological importance was much broader and included perceptions based on personal experience with nature, socialization processes, or information received through social networks or media. When individual perceptions of biological importance are aggregated, they become measures of collective social importance, albeit with a high degree of spatial variability. The fact that ecological and social hotspots for biological importance exhibit low to moderate spatial concurrence may be viewed as a positive outcome because different importance systems are being combined to identify multi-criteria important areas.

An important question is whether the findings of this study can provide guidance for assessing social-ecological space in other settings and conditions. This study was situated in a specific

Table 3
Social-ecological hotspot area (% of area) located inside and outside of designated terrestrial protected areas in the Baffle Basin study area under alternative importance thresholds.

	10% Threshold	30% Threshold	50% Threshold
Ecological hotspot (from zonation)	108 km^2 (45.1%) 132 km^2	331 km^2 (37.2%) 558 km^2	510 km^2 (29.5%) 1219 km^2
Social hotspot (biological only values)	99 km^2 (25.2%) 294 km^2	353 km^2 (27.6%) 926 km^2	2043 (24.4%) 1584 km^2
SES hotspot (equal area criterion applied)	20 km^2 (47.4%) 23 km^2	834 (46.4%) 241 km^2	1743 (35.1%) 806 km^2

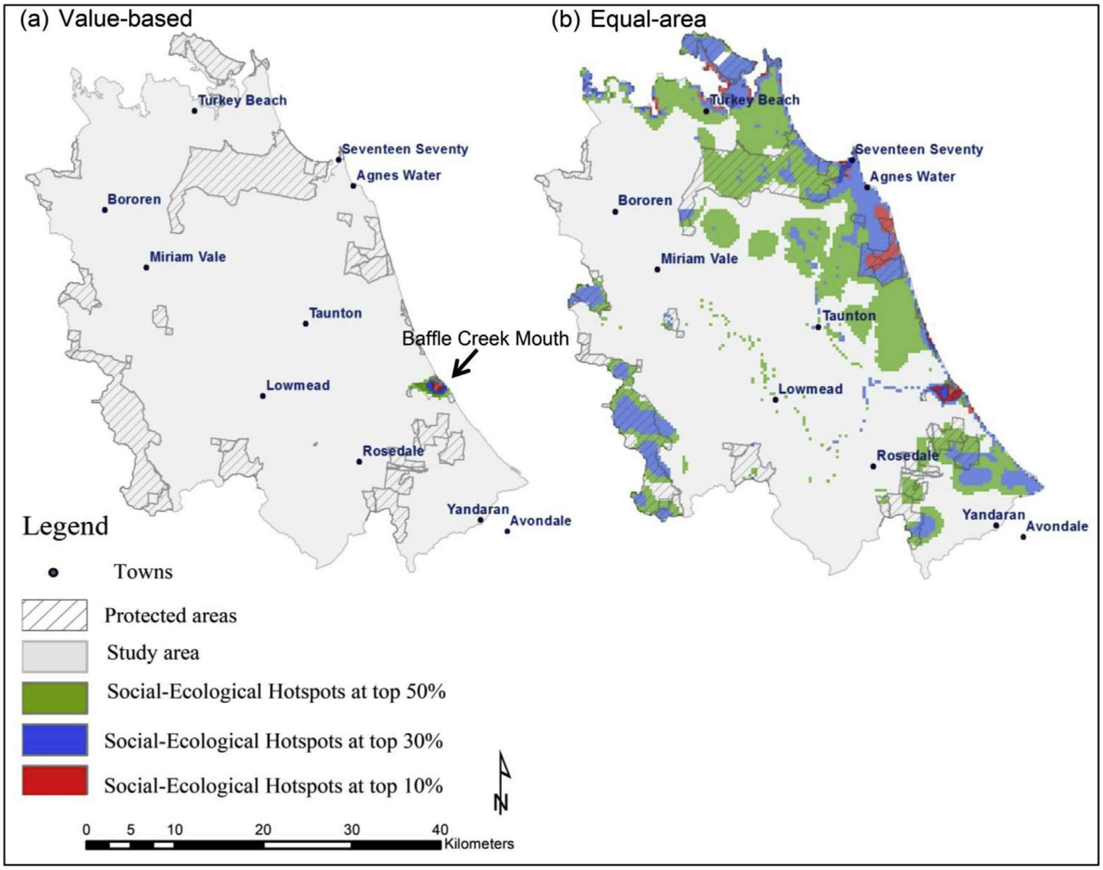

Fig. 5. Comparisons of social-ecological hotspots generated with 10%, 30%, and 50% importance thresholds and their distributions in the study area with existing protected areas using: (a) density value-based thresholds, and (b) equal-area criterion applied to importance thresholds.

geographic and social context (Baffle Basin region, Australia), used participatory mapping methods with residents to identify important social values and species range maps to identify important ecological values, and evaluated a diverse, but not exhaustive, list of methods for measuring social-ecological space. The social importance data was based on an adequate, but not exceptionally large sample of regional residents while the ecological importance data was modelled from species range maps, each of which has its own limitations in accuracy and validity. Under these circumstances, the identification of SES must necessarily be tentative, but as the first research effort to examine alternative methods for measuring social-ecological hotspots, we developed some decision rules in Table 4 derived from the combination of parameters examined in this study.

If SES are to be determined using hotspot thresholds that measure the highest social and ecological importance (e.g., top 10% criterion), the use of either global (kernel or simple density) or local hotspot methods (Getis–Ord Gi*) provide comparable results. But arguably, the choice of a 10% hotspot threshold for SES analysis has limited utility for regional conservation planning because future proposed land uses do not generally involve the most ecologically important areas because these areas have already received some form of legal, protected status. Indeed, almost half of the top 10% most ecologically important areas identified in the Baffle region are located within existing national parks and protected areas. Following this logic, the most relevant areas for land use planning analysis would be SES hotspots, but not necessarily the most important SES areas in the region. Proposed changes in land use (e.g., new residential development or new mining activity) often occur “on the margin” in areas that are biologically important, but perhaps not identified as *most* important. This would suggest selecting more liberal hotspot importance thresholds (for example top 30–50%) to identify SES hotspots outside of protected areas. The SES hotspots could be used to identify and rank areas for protection occurring outside of designated protected areas. Given that some of these areas may be privately owned, these lands could be further classified according to level of protection as identified by Brown et al., (2015). Thus, conservation planning would consist of a

Table 4
Suggested guidelines for identifying social-ecological hotspots under different scenarios.

		Large differential between social and ecological hotspots area (value-based)		Similar-sized areas	
		Biological value	Multiple- value	Biological value	Multiple- value
Smaller Cut-off	10%	No difference in methods	No difference in methods	No difference in methods	No difference in methods
Larger cut-off	30%	Getis–Ord Gi*	Getis–Ord Gi*	Global methods	Global methods
	50%	Getis–Ord Gi*	Getis–Ord Gi*	Global methods	Global methods

two-step process that involves regional assessment of SES hotspots (described herein), followed by more specific assessment of the areas that comprise SES hotspots outside of designated protected areas.

Larger SES importance thresholds appear more relevant to regional conservation planning analysis and decision support as they identify larger areas outside of protected areas that merit further conservation consideration. More specifically, we would recommend applying equal-area criterion using global methods with larger importance thresholds (e.g., 30–50%). As a general principle, we recommend applying the equal-area criterion to whatever importance threshold is chosen. If density value-based methods are used, there is a higher probability of generating unequal area social and ecological hotspots as input to SES hotspot determination, resulting in smaller SES hotspots. These value-based methods also introduce a type of implicit weighting wherein the larger of the two component hotspots (either social or ecological) exerts greater influence in SES identification. Under these conditions, we recommend using Getis–Ord Gi* to identify SES hotspots at 30%–50% because this method generates larger SES areas than kernel or simple density methods (see Table 3).

The validity of social-ecological hotspots depends on the quality of spatial data used to generate the social and ecological importance maps. Both the social and ecological maps have important limitations. We attempted to obtain a large, representative sample of PPGIS study participants in the study region, but were only marginally effective in our recruitment efforts. Survey response rates have been declining over the past decade, increasing the challenge for researchers to collect representative social data. Our PPGIS household sampling response rates (12% internet, 44% hardcopy) were typical of response rates reported in other PPGIS studies in developed countries (see Brown & Kytta, 2014), but would have benefited from a larger sample size because the quantity of point data available for density analysis is directly related to the number of study participants. The ecological importance spatial data layer was limited to consideration of species ranges within the region. Additional ecological variables could have been included in the Zonation model and weightings could have been applied to different species.

If the social-ecological systems conceptual framework is to support and guide conservation and other land use planning, additional applied research will be needed in other study contexts. Case study research is inherently limited to the set of conditions in which the research is undertaken. Different ecoregions in other countries would have differences in the distribution of species and habitats, as well as potentially different social values for biological importance, both of which would influence the spatial distribution of the component social and ecological hotspots that determine SES hotspots. For example, some societies might emphasize the utilitarian, consumptive use of biological resources as a measure of biological importance while other societies might express appreciative, non-consumptive values that drive biological importance. In the determination of ecological importance, other ecological variables such as vegetation communities, climate, and soil types could be used to determine ecological importance. Regardless of the methods used to measure social and ecological importance within a given social and biophysical context, we suggest the spatial integration guidelines provided herein are robust enough to accommodate these differences to identify SES hotspots.

Further, there is a need to better integrate SES concepts into existing spatial decision support tools. One recent and innovative approach has been to directly include spatially-explicit social values from PPGIS into conservation assessment models such as *Zonation* to identify conservation prioritizations (Whitehead et al., 2014). The approach presented herein differs in that it prioritizes social and ecological importance data independently and then integrates the spatial data layers using simple spatial overlay techniques. There is merit in both approaches. Our preference is to keep social and ecological importance data layers separate and outside the complexity of a model for simplicity and transparency. SES hotspot maps allow one to easily visually determine whether ecological or social importance (or both) will be significant factors in future decisions.

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