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1 Integration of social and ecological sciences for natural resource decision making: challenges  
2 and opportunities

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4 Kelly F. Robinson<sup>1, \*</sup>, Angela K. Fuller<sup>2</sup>, Richard C. Stedman<sup>3</sup>, William F. Siemer<sup>3</sup>, Daniel J.  
5 Decker<sup>3</sup>

6

7 <sup>1</sup> New York Cooperative Fish and Wildlife Research Unit, Department of Natural Resources,  
8 Cornell University, Ithaca, NY 14853, USA

9 <sup>2</sup>U.S. Geological Survey, New York Cooperative Fish and Wildlife Research Unit, Department  
10 of Natural Resources, Cornell University, Ithaca, NY 14853, USA, ORCID 0000-0002-9247-  
11 7468

12 <sup>3</sup>Cornell Center for Conservation Social Sciences, Department of Natural Resources, Cornell  
13 University, Ithaca, NY 14853, USA

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\* Corresponding author; present address: Quantitative Fisheries Center, Department of Fisheries and Wildlife, Michigan State University, East Lansing, MI 48842, USA, kfrobins@msu.edu, 517-884-8872, ORCID 0000-0001-8109-9492

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25 **Abstract**

26 The last 25 years have witnessed growing recognition that natural resource management  
27 decisions depend as much on understanding humans and their social interactions as on  
28 understanding the interactions between non-human organisms and their environment. Decision  
29 science provides a framework for integrating ecological and social factors into a decision, but  
30 challenges to integration remain. The decision-analytic framework elicits values and preferences  
31 to help articulate objectives, and then evaluates the outcomes of alternative management actions  
32 to achieve these objectives. Integrating social science into these steps can be hindered by failing  
33 to include social scientists as more than stakeholder-process facilitators, assuming that specific  
34 decision-analytic skills are commonplace for social scientists, misperceptions of social data as  
35 inherently qualitative, timescale mismatches for iterating through decision analysis and  
36 collecting relevant social data, difficulties in predicting human behavior, and failures of  
37 institutions to recognize the importance of this integration. We engage these challenges, and  
38 suggest solutions to them, helping move forward the integration of social and  
39 biological/ecological knowledge and considerations in decision-making.

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41 Key words: adaptive management; multi-objective decision analysis; decision science; natural  
42 resources; social science; structured decision making

43 **Introduction**

44           Decision making for natural resource management requires understanding both the  
45 ecological and social aspects of a decision (Bennett et al. 2017). Despite the recognition that  
46 effective natural resource management must integrate the social and ecological sciences (Decker  
47 et al. 1992), such integration in practice is relatively rare. The increasing use of decision science,  
48 including decision analysis (i.e., “structured decision making” and “adaptive management”;  
49 Gregory and Keeney 2002, Gregory et al. 2012), in natural resource management offers  
50 possibilities for integrating social and ecological sciences into decision making. Despite this,  
51 challenges remain. In decision analysis, values (i.e., preferences) are elicited to articulate  
52 objectives of the decision maker(s), and the outcomes of alternative management actions are  
53 evaluated relative to each other based on their predicted ability to achieve objectives.  
54 Stakeholder values guide the process (Keeney 1992, 1996) and help clarify how decision maker  
55 priorities relate to stakeholder preferences. Thus, an accurate, detailed understanding of  
56 stakeholder values is vital to the integrity of the entire decision process; all the ecological and  
57 biological data one can amass to feed the process will not make up for poor understanding of  
58 stakeholder values. This means data from *social science* research—not anecdote, intuition,  
59 facilitator, or special interest preferences—specific to the decision context are needed to support  
60 decision analysis. Lacking that, the process could go off track, seemingly supporting decisions  
61 that ultimately are unlikely to be socially accepted, potentially hindering conservation. With  
62 such consequences in mind, we describe the use of multi-objective decision analysis in natural  
63 resource management, outline several challenges related to incorporating social science into  
64 decision analysis, provide suggestions for overcoming these challenges, and identify avenues for  
65 future research.

66 **Use of Decision Science in Natural Resource Management**

67           Decision analysis is a quantitative method used in decision science, first developed for  
68 incorporating economic uncertainty into business decision making (Raiffa 1968), and is a  
69 framework for quantitatively evaluating decision options (Peterman and Peters 1998). The  
70 process of iterating through the steps of a decision can be applied to decisions that include  
71 ecological and social dimensions common in natural resource management (Peterman and Peters  
72 1998). The steps of structured decision making include defining the problem, identifying relevant  
73 objectives, describing management actions that could achieve the objectives, predicting the  
74 consequences of each action on each objective, and evaluating tradeoffs among objectives  
75 (Figure 1; Hammond et al. 1999). We then refer to adaptive management, in the decision  
76 theoretic sense (McFadden et al. 2011), as a special case of structured decision making, in which  
77 repeated decisions are made to reduce uncertainty through learning by doing. Applications of  
78 decision analysis largely have focused on predicting the effects of management actions on  
79 ecological objectives (e.g., population size or harvest rates; Williams and Johnson 1995), often  
80 failing to consider, or only giving perfunctory thought to, social objectives.

81           Despite recent growth, the use of quantitative, structured approaches to inform fish and  
82 wildlife management decisions is still relatively uncommon (Runge et al. 2013, McGowan et al.  
83 2015, Sells et al. 2016). Examples include using adaptive harvest management to manage  
84 waterfowl hunting pressure (Williams and Johnson 1995, Johnson et al. 2015), considering  
85 tradeoffs between salmon abundance and revenues from hydropower production (Failing et al.  
86 2013), and managing bighorn sheep pneumonia epizootics (Sells et al. 2016). Substantive  
87 incorporation of social science theory and methods into these decisions is even less common. It  
88 is conceivable that not all decision science problems require integrating social considerations,

89 but given the social context underlying natural resource management (Bennett et al. 2017) and  
90 the inherently political nature of fish and wildlife management, social considerations will always  
91 be a key component of a successful decision. That being said, decision analytic techniques can  
92 be useful for focusing on a single objective of a larger decision problem or on problems that are  
93 simply plagued by ecological uncertainty (e.g., adaptive management applications such as  
94 Gannon et al. 2013). However, care must be taken to ensure that social objectives are not being  
95 ignored. Here we focus on multi-objective decision problems that are common in natural  
96 resources management, in which ecological, economic, and social values are often at play  
97 (McDaniels et al. 2006).

98         Each step in the decision-analytic framework offers opportunities for social science to  
99 inform management decisions, including defining values, preferences, and objectives of  
100 stakeholders, quantifying those objectives, and making tradeoffs among them (Figure 1). We  
101 first explore a number of challenges associated with the integration of ecological and social  
102 sciences in multi-objective decision analysis and then discuss potential solutions.

### 103 **Challenges for Integrating Social Science into Decision Analysis**

104 1)       Ecologists often lack familiarity and experience with social science

105         In fisheries and wildlife management, most examples of decision analysis that we are  
106 aware of have been led by ecologists rather than social scientists. Decision analysis in fish and  
107 wildlife management is in its infancy, and the ecological scientists who have attempted to  
108 incorporate social science into analyses are to be lauded for their efforts to pioneer decision  
109 analysis in this field. But lack of social science expertise in these early examples can become a  
110 research limitation. Ecologists may view social science as "common sense" compared to the  
111 technical complexity of ecology (Gregory and Keeney 2002). Ecologists—quite reasonably—

112 usually lack formal training in theories and methods of social science inquiry, yet without access  
113 to social scientists on their decision analysis teams, some ecological scientists elect to design  
114 survey instruments on their own, without the benefit of expertise in accepted social science  
115 theory and/or research methods (Pooley et al. 2014). Alternatively, decision analysis teams might  
116 choose to focus specifically on biological objectives and values, rather than including social  
117 values in the decision analysis, because they are either more comfortable with predicting  
118 ecological consequences (Johnson et al. 2015) or recognize that they do not have the expertise  
119 for the social component. To date, social scientists who have been asked to participate in a  
120 decision-analytic process have often played one of two roles. They have either been incorrectly  
121 perceived as “people managers,” or “communicators,” brought on as meeting facilitators to  
122 manage conflicts among stakeholders (Endter-Wada et al. 1998), or they have been sought as an  
123 afterthought to translate research results to the general public or stakeholders. Neither of these  
124 roles take full advantage of the contributions social science can make to decision analysis (Fox et  
125 al. 2006).

126 2) Decision analysis requires specialized skills

127 Decision analysis in natural resource applications has tended to focus on predicting  
128 ecological consequences of management actions and has generally stopped short of paying due  
129 diligence to the skill set that social scientists can bring to the analysis. Perhaps decision analysis  
130 teams assume that social scientists, by nature, are good communicators (see Challenge 1) and  
131 therefore can be called on to apply techniques that, in reality, require formal training in decision  
132 analysis. Decision analysis requires specialized skills, including predictive modeling, stakeholder  
133 feedback facilitation, and quantification of stakeholder values. Skills like eliciting values  
134 information from stakeholders in small group interviews or elucidating the range of value

135 considerations across multiple groups (e.g., technical and lay audiences, interest groups; Gregory  
136 2017), are unique to decision analysis and therefore common for neither ecologists *nor* social  
137 scientists.

138 3) (Mis)perceptions of social data

139 Decision analysts sometimes struggle to integrate social science into natural resource  
140 decision making because they are not aware that, or misunderstand how, core social science  
141 constructs (e.g., "social values") can be measured systematically and quantified (and hence, more  
142 easily integrated into decision making). This assumption that social values cannot be quantified  
143 has been invoked, for example, as a reason for difficulties in optimizing tropical finfish  
144 management decisions (Andalecio 2010). Moving towards systematic assessments of preferences  
145 can facilitate integration with ecological information in support of management thinking (see  
146 Stedman 2003). An unscientific approach to the social dimensions of a management problem  
147 (Challenge 1) can lead to poorly informed measures of stakeholder values: simply put, if  
148 decision analysis teams don't believe that social values can be measured, they are probably less  
149 likely to try to integrate them into decision-making processes.

150 4) Scale mismatches

151 Mismatches may exist between spatial and temporal scales required for decision analysis  
152 and social science. Many researchers have discussed potential resolutions for issues of scale in  
153 decision making for social-ecological contexts (see Holling 2001, Wilson et al. 2016). These  
154 authors described problems related to mismatches in human expectations for the timescale of  
155 ecological outcomes versus reality, as well as time required to observe the effect of technological  
156 and behavioral solutions. We suggest that timescale mismatches also occur because the time  
157 necessary to gather relevant social science, as well as biological, data can be at odds with the

158 iterative nature of decision analysis. In decision analysis, the stakeholder group often iterates  
159 among the objectives-setting, alternative actions, and consequences steps of the process, as new  
160 information becomes available or discussions spur revisions (Hammond et al. 1999). For  
161 example, in the decision process for managing outbreaks of pneumonia in bighorn sheep (*Ovis*  
162 *canadensis*), four fundamental objectives were described in the first iteration of the decision  
163 analytic process (Mitchell et al. 2013). The working group refined the set of objectives to include  
164 a total of six fundamental objectives in the final version of the process (Sells et al. 2016),  
165 exemplifying the time that is often necessary to iterate through a decision analysis and finalize  
166 all components. While this iteration is a natural and useful part of the decision-making process, it  
167 can be problematic for predicting consequences of the actions on all objectives (ecological and  
168 social). In particular, social science tools like survey questions used to elicit stakeholder values  
169 and preferences require time for design, construction, dissemination, and analysis. When  
170 objectives change, revisions to the survey instrument might not be possible, or, at minimum,  
171 require additional time and money. Changes to surveys often require that the instrument be  
172 subjected to additional rounds of review by an institutional review board or subjected to other  
173 lengthy review processes from governments (e.g., the Paperwork Reduction Act in the USA) or  
174 universities, which can take time and require additional scrutiny. These temporal mismatches in  
175 the implementation of decision analysis can be frustrating for all parties involved, as groups  
176 struggle to reconcile the desire to define and analyze the problem as accurately as possible with  
177 the desire to make a decision as quickly as possible.

178 5) Human behaviors are difficult to predict

179 Even with the best models and data, human behavior is notoriously difficult to predict  
180 (Heberlein 2012), as multiple constraints prevent people from behaving in accordance with their

181 beliefs and attitudes (Stern 2000). Accordingly, many of the most-used models (e.g., the Theory  
182 of Planned Behavior [Ajzen 1991]) have focused instead on understanding behavioral intention  
183 rather than actual behavior. This adds another crucial level of uncertainty to including human  
184 preferences in decision analysis—an uncertainty that is often misunderstood or overlooked by  
185 decision analysis teams. Values and basic beliefs do not directly predict specific behaviors  
186 (Vaske and Manfreda 2012), leading to uncertainty in the links among values, objectives, and  
187 predictive models of human behavior. Uncertainty in behavioral intention manifests as partial  
188 controllability—the difference between the intended and realized implementation of a  
189 management action, which can affect achievement of the objectives (Williams et al. 2002).  
190 Failure to account for partial controllability could lead to the choice of a suboptimal management  
191 action.

192 6) Failure of institutions to recognize the importance of social science

193         The integration of social and ecological science in decision analytic processes requires  
194 funding to support this work, including potentially increased funds for additional staff, survey  
195 instruments, and workshops. The typical funding sources for fish and wildlife management do  
196 not necessarily recognize the importance of this integration, and therefore might decline to fund  
197 more expensive projects that include social science. In addition, management and research  
198 institutions commonly fail to reward interdisciplinary work, and at times actively discourage  
199 ecologists from working on projects with substantial social components if such efforts are not  
200 seen as central to natural resource management. As long as funders and institutions fail to  
201 recognize the importance of social science in making management decisions, multi-objective  
202 decision making will likely not reach its full potential for aiding the resolution of difficult  
203 management problems.

204 **Solutions and Suggestions for Integrating Social Science into Decision Analysis**

205 Many of the challenges described above can be alleviated by adapting current practices or  
206 ways of thinking. We offer solutions for these challenges, as well as examples from the literature  
207 of how groups have overcome these challenges and integrated ecological and social sciences into  
208 their decision analyses.

209 1) Include social scientists at the beginning of the decision analysis

210 Decision analysis is a collaborative process that benefits from understanding and  
211 considering multiple perspectives about the problem being considered. Forming an effective  
212 team of collaborators with the necessary skills takes time, strategic thought, and effort. Thus,  
213 including social scientists fully at the beginning of a project is the first and most important step  
214 toward overcoming challenges to integration (Challenges 1–6, Figure 1; Endter-Wada et al.  
215 1998). Establishing a multi-disciplinary team early in the process ensures that social scientists  
216 have the opportunity to participate in framing the problem and objectives and the time to collect  
217 needed data (Endter-Wada et al. 1998, Pooley et al. 2014). Often, a combination of small-group  
218 interactions among stakeholders and large-scale techniques, like surveys, is required to integrate  
219 social data fully into a decision analysis. The social data collected should directly relate to the  
220 objectives, which drive the rest of the decision analysis; inclusion at the outset provides  
221 opportunity for stakeholder input early in the decision process (Gregory and Keeney 1994). For  
222 example, biologists and anthropologists together led landowners through a series of workshops  
223 to make decisions for land use planning in western North Carolina, incorporating stakeholders’  
224 concerns at each step (Ferguson et al. 2015). This case demonstrates that when social scientists  
225 are included at the inception of a decision analysis, social values and ecological knowledge can

226 each be considered thoroughly, potentially leading to fewer changes in the objectives as the  
227 process progresses, and partially alleviating timescale mismatches (Challenge 4).

228 Including social scientists at the beginning of a decision problem can be useful in an  
229 adaptive management context, as well. Uncertainty in natural resources management is not  
230 limited to ecological objectives, as human behavior is difficult to predict (Challenge 5), and  
231 uncertainties related to human values could affect the ultimate decision choice. As such, social  
232 scientists can first provide insight into the objectives setting process, ensuring that all sources of  
233 uncertainty are accounted for in the decision analytic framework. Second, social scientists can  
234 then provide the appropriate techniques for monitoring stakeholder values and behaviors in an  
235 adaptive management framework, providing data to update predictions of the achievement of  
236 social objectives like hunter satisfaction (Johnson et al. 2015) or behavioral changes associated  
237 with action implementation (Dhanjal-Adams et al. 2016).

238 2) Methods exist to quantify complex social values

239 Realizing that well-established, valid, and reliable protocols exist for measuring  
240 seemingly abstract social constructs, rather than assuming otherwise, can save decision analysts a  
241 great deal of time trying to create their own measures (Challenge 3). First, care must be taken to  
242 create a well-thought out set of objectives to ensure that the preferences expressed do not  
243 represent multiple meanings (Stedman 2003). We feel that it is all too common for an ecologist  
244 to attempt to characterize stakeholder satisfaction with a simple question, such as, “on a scale of  
245 1–5 rate your satisfaction associated with white-tailed deer hunting.” However, “hunter  
246 satisfaction” may be based on values of hunters who prefer to harvest different ages, sexes, and  
247 sizes of deer, each of which must be quantified separately, rather than including a general and  
248 overarching “hunter satisfaction” value, which would improperly lump diverse—or even

249 competing—specific preferences (Robinson et al. 2016). Parsing social values as described  
250 above is an initial step in appropriately characterizing the social elements of a decision problem.

251         Constructed scales can provide a method to measure preferences or values that do not  
252 have a direct natural scale (Keeney 1992). A constructed scale is developed with the stakeholder  
253 group specifically for the stated objective. For example, members of the St’at’imc First Nations  
254 in British Columbia, Canada, created an objective for the “Cultural and Spiritual Quality of the  
255 River,” including the smell, sound, sight, and feel of the river (Failing et al. 2013). By working  
256 with elders and community members, a quantitative, multidimensional scale was created to  
257 measure how specific water management techniques would affect this objective. Similarly, in  
258 considering non-native fish removal at the Glen Canyon Dam, USA, Native American tribes  
259 involved in the adaptive management process helped create scales for objectives of avoiding  
260 taking of life, respecting non-human life, respecting relationships between humans and non-  
261 humans, and protecting sacred sites (Runge et al. 2011a). Proxy attributes, indirect measures of  
262 an objective (Keeney 1992), can be used in the absence of a reasonable constructed scale. The  
263 Millennium Ecosystem Assessment used proxy attributes (or “indicators”) to give a quantitative  
264 scale to some difficult-to-measure objectives (Alcamo et al. 2003). For example, they assessed  
265 human well-being by measuring rates of malnutrition. Through careful facilitation and elicitation  
266 of values, and by explicitly working with social scientists to measure them, these difficult-to-  
267 measure values can be integrated into the decision analysis.

268 3)       Preferences and tradeoffs: combine the tools of decision analysis and social science

269         Making tradeoffs among competing objectives is one of the most important aspects of  
270 decision analysis (Hammond et al. 1999). The issues and objectives that are important to  
271 stakeholders in natural resource management problems require techniques that take into account

272 the complexity, uncertainty, and potential controversy inherent in these decisions (Gregory et al.  
273 1997). Decision-analytic tools like direct rating (Goodwin and Wright 2009) and swing  
274 weighting (Edwards and Barron 1994) are useful for eliciting objective tradeoffs in individual  
275 and small-group settings (Challenge 2). Analyses like downside weighting (Gregory et al. 2012)  
276 and value of information (Runge et al. 2011b) can demonstrate how uncertainties like partial  
277 controllability can affect the choice of management action (Challenge 5).

278 Engaging large groups of stakeholders to elicit preferences and tradeoffs requires a  
279 survey that can address the multiple value dimensions of stakeholders and identify their stance  
280 regarding key tradeoffs (Challenges 1, 2, 5; Gregory 2000). Attitude surveys that include not  
281 only a series of rating questions about preference (e.g., a Likert scale), but also a set of questions  
282 for ranking the objectives for the decision problem, can provide important information about  
283 how stakeholders value the complex set of objectives (Siemer et al. 2015, Robinson et al. 2016,  
284 2017). This method still requires making inferences about how relative ranks translate into  
285 weighted objectives (see Robinson et al. 2016 for full description), but that process is much  
286 better informed if supported by good social data.

287 Stated-choice surveys are another good option for gathering necessary information from a  
288 large stakeholder group to make tradeoffs among objectives. These surveys ask respondents to  
289 choose from a hypothetical set of management actions that are described as ranges of objective  
290 measures (e.g., aspects of season choice for turkey hunting; Adamowicz et al. 1994, Schroeder et  
291 al. 2017). The range of predicted outcomes for each objective can be used to create a set of  
292 hypothetical actions. By asking respondents to state preferences for these hypothetical actions,  
293 social scientists can estimate the relative strength of options not actually presented to the  
294 respondents (i.e., the actual set of management actions under consideration; Louviere et al. 2000,

295 Fieberg et al. 2010). In this way, stakeholders state their preference for a range of predicted  
296 outcomes for their objectives, rather than choosing an action directly, eliminating (potentially  
297 incorrect) inferences on the part of the stakeholder (Hunt et al. 2010). These preferences then can  
298 be incorporated directly into the analysis of tradeoffs (Schroeder et al. 2017). Although stated-  
299 choice surveys effectively gather social science data needed to make tradeoffs, they are complex  
300 to construct and analyze (Fieburg et al. 2010), underscoring the necessity of engaging social  
301 scientists at the beginning of the decision-analytic process (Challenge 1).

302 4) Methodological promise for future integration of ecological and social data

303 We believe that Social Values Mapping (Brown et al. 2004, Alessa et al. 2008) has great  
304 promise for decision analysis (Challenge 3). This approach explicitly maps environmental values  
305 (e.g., a metric of biological productivity) that are spatially coincident with human perceptions of  
306 the value of these locations. Mapping social values can be performed by participants manually  
307 with paper maps, or through more sophisticated computer-mapping systems. The resulting data  
308 can be analyzed using a variety of statistics, including the Getis-Ord  $GI^*$  statistic (Getis and Ord  
309 1992) that identifies clusters of points where social values are concentrated. Spatial  
310 representation of social values is particularly important for predicting consequences of  
311 management actions in a spatial context, given that social values often vary across geographic  
312 extent (Enck and Brown 2008, Leong et al. 2012). Indeed, local values are place-specific (Brown  
313 et al. 2002); identifying areas on the landscape that have high social values (e.g., biological,  
314 cultural, spiritual, aesthetic; see Alessa et al. 2008) allows for identifying “social-ecological  
315 hotspots” (areas where high social values and ecological values overlap). Additionally,  
316 researchers can identify “warmspots” (areas of low social values and high ecological values, or  
317 vice versa) and “coldspots” (areas of low social value and low ecological value), which may

318 have even more relevance in certain decision contexts. For example, areas on the landscape  
319 represented as coldspots may be areas where management actions would be least detrimental,  
320 both socially and ecologically. Social values mapping would allow multiple ecological values to  
321 be included, provided there are spatial representations of the objective in question.

322 5) Publication and education

323 Full case studies of the use of decision analysis (either structured decision making or  
324 adaptive management) for natural resources management are still quite rare in the published  
325 literature (Runge et al. 2013, McGowan et al. 2015, Sells et al. 2016). As such, there are few  
326 examples of the use of this framework for management, and even fewer examples of the full  
327 integration of social science into decision analysis. In addition, finding appropriate outlets for  
328 publication of these case studies can be a challenge, as the paper can span ecology, social  
329 science, policy, and decision science, and may not fit in specialized journals. Publication of these  
330 case studies would be beneficial on multiple levels. By publishing these case studies more  
331 frequently, practitioners (both ecologists and social scientists) would be able to draw from the  
332 successes of and challenges faced by others in the field when implementing decision analysis  
333 projects (McGowan et al. 2015). Equally important, ecologists and managers would have a larger  
334 set of examples to draw from when crafting funding proposals that include social scientists and  
335 when funding, academic, or management institutions question the necessity of social science in  
336 management. Although the results of many decision analysis problems exist as reports on agency  
337 or university websites, the publication of these examples in the appropriate journals would  
338 extend the reach of these efforts to the broader community of practice.

339 In addition to publication, enhancing the community of practice for decision analysis in  
340 social-ecological systems requires enhanced education in ecological and social science programs.

341 For example, training ecologists about the importance of not only decision analysis, but the need  
342 to integrate social and ecological values into this framework, is necessary (Challenge 2). A basic  
343 understanding of social science techniques and theory, and how it can be integrated into decision  
344 making, would prepare this new generation of ecologists to seek out interdisciplinary avenues for  
345 decision analysis and eliminate the misunderstandings associated with the role of social science  
346 (Challenge 1) and how it can be used in a quantitative decision framework (Challenge 3).

### 347 **Discussion**

348         Decision analysis provides a framework to decompose a decision into a series of steps,  
349 including eliciting the values structure of stakeholders and using science, both ecological and  
350 social, to predict how management actions influence those values (Keeney 1992, 1996).

351 Historically, however, applications of decision analysis to natural resource problems have  
352 focused heavily on ecological science, typically not applying social science in the process, and  
353 instead making assumptions or using unscientific information about social values.

354         In this paper, we have used “decision analysis” as a description for both structured  
355 decision making and adaptive management. We view adaptive management through the lens of  
356 the Decision-Theoretic school (McFadden et al. 2011), in which adaptive management is a  
357 special case of structured decision making for recurrent decisions with uncertainty. Therefore,  
358 social science can still be integrated into adaptive management, even when modeling strategies,  
359 such as dynamic programming, might preclude practitioners from incorporating multiple  
360 objectives in a utility function. Decision analysis, at its core, is a decision aiding technique  
361 (Gregory et al. 2001, Robinson and Fuller 2017), and as such, social science can be incorporated  
362 in the discussion of objectives, alternatives, and tradeoffs. In addition, social science can enable  
363 practitioners and decision makers to see when uncertainty in social objectives might affect the

364 ultimate decision. Overall, we do not believe that integrating social science more fully into  
365 adaptive management frameworks is necessarily more difficult or impossible, but we do suggest  
366 that it will require careful planning and extra consideration.

367         Decision analysis offers an opportunity for expanding and improving integration of social  
368 science, but it will take effort and discipline to overcome persistent challenges. Among the  
369 challenges is the tendency of decision analysis teams (often led by ecologists) to attempt to fill  
370 all roles in a decision-analytic process, including social scientist, facilitator, communicator and,  
371 sometimes, proxy stakeholder representative and proxy decision maker. Other challenges are  
372 technical—the framework for decision analysis and the methods of social science do not always  
373 align in scale or timing, but these challenges can be addressed if they are recognized. In addition,  
374 technical challenges exist in social science, especially how to predict human behavior and how to  
375 quantify values in a way necessary for evaluating management actions. Finally, some challenges  
376 are institutional, such as the degree to which funders and other institutions (e.g., agencies and  
377 universities) emphasize the need for integration of social science into decision analysis.

378         Although this list of challenges is daunting, they can be overcome. We suggest that many  
379 operational challenges, in particular, can be remedied simply by including social scientists at the  
380 beginning of the decision-analysis process. Purposefully integrating ecological and social  
381 disciplines can also lead to overcoming other challenges. For example, by including social  
382 scientists in the process, the tools of both decision analysis and social science can be combined  
383 creatively to determine ways to quantify values, measure preferences, and make tradeoffs among  
384 management actions. In addition, practitioners can make use of other tools that are available to  
385 improve decision analysis, such as social values mapping. Finally, we suggest that publication of  
386 formal case studies of decision analysis for natural resources management, as well as more

387 pointed integration of the benefits of interdisciplinary decision analysis in educational materials  
388 for the next generation of ecologists and social scientists, would provide tangible evidence of the  
389 benefits of including social science in decision analysis problems. Most importantly, integrating  
390 social science into decision analysis requires willingness of all parties to work together, in a  
391 collaborative, trusting fashion that is respectful and mutually reinforcing. We hope that by  
392 highlighting challenges and offering potential solutions, ecological and social scientists can work  
393 together more effectively to tackle complex natural resource management problems.

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536 49

537 **Fig. 1** Integration of social science into decision analysis occurs at all steps in the process

538 (adapted from Runge et al. 2013)

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