Fuzzy Models to Inform Social and Environmental Indicator Selection for Conservation Impact Monitoring

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Abstract
Conservation projects increasingly aim to deliver both environmental and social benefits. To monitor the success of these projects, it is important to pick indicators for which there is a reasonable expectation of change as a result of the project, and which resonate with project stakeholders. Results chains are widely used in conservation to describe the hypothesized pathways of causal linkages between conservation interventions and desired outcomes. We illustrate how, with limited additional information, results chains can be turned into fuzzy models of social-ecological systems, and how these models can be used to explore the predicted social and environmental impacts of conservation actions. These predictions can then be compared with the interests of stakeholders in order to identify good indicators of project success. We illustrate this approach by using it to select indicators for a water fund, an increasingly popular and multiobjective conservation strategy.

Introduction
Demonstrating the results of conservation interventions is a basic expectation of funders and stakeholders, and is required to attract ongoing investment in conservation projects. Although there are a range of reasons for monitoring the outcomes of interventions (McDonald-Madden et al. 2010), demonstrating impact is a significant one that motivates much monitoring effort. Conservation projects are increasingly complex with multiple objectives, often spanning ecological and human well-being outcomes, and many potential indicators of achievement (Game et al. 2014; Baylis et al. 2016). Deciding on which indicators are good measures of project success and suitable candidates for monitoring has become one of the principal, and often most challenging, tasks of applied conservation science. There is a growing body of literature on the selection of indicators for conservation and sustainable development projects (e.g., Santana-Medina et al. 2013; Asbjornsen et al. 2015; Hicks et al. 2016). Lessons include the importance of choosing indicators for which a detectable change can be expected over the life of a project (Tulloch et al. 2011), and the importance of selecting indicators that resonate with the intended audience (Higgins & Zimmerling 2013; Biedenweg et al. 2014). Alignment between these two aspects of indicator relevancy is not guaranteed. The diversity of macroalgae, for example, may provide a sensitive and timely indication of the outcomes of a coastal conservation project, but if the audience for that information does
not find it compelling, its utility as an indicator is greatly diminished. This lesson is particularly pertinent for community-based conservation projects where success is dependent on support from communities involved.

Outcome monitoring should obviously focus on attributes of social-ecological systems for which the program desires to influence change. Results chains are commonly used to represent the perceived causal linkages between a conservation intervention and the desired outcomes (Conservation Measures Partnership 2013; Margoluis et al. 2013; e.g., Figure 1). Results chains provide a useful framework within which to select indicators for monitoring because they allow context-specific evidence to be assembled in support of the hypothesized pathway of change (Richards & Panfil 2011). However, a results chain is likely to contain many more attributes than could realistically be monitored. This means that some prioritization of attributes is required.

The ability to detect project impacts through monitoring will depend on available resources and monitoring techniques, but in general, will be easier when an indicator experiences either a big change or a change significant relative to the background variability in the indicator (Tulloch et al. 2011). Typically, results chains identify a set of causally connected attributes but not the extent to which these different attributes are likely to change as a result of an intervention.

Because the proximate impacts of a conservation project are often somewhat removed from the fundamental outcomes stakeholders care most about (Murcia et al. 2016), predicting how attributes of a social-ecological system are likely to change as a result of a project can be challenging. Making this prediction requires a model. This may be an explicit model formalized using mathematical equations, or a mental model (Nichols 2001; Biggs et al. 2011). For the vast majority of environmental projects, there is unlikely to be sufficient information, time, or expertise to develop a thorough mathematical model. Results chains are, in effect, mental models (Doyle & Ford 1998; Biggs et al. 2011); they represent a set of beliefs about the network of causal relationships between variables that describe how a system operates once a management intervention is applied. As in Figure 1, the variables that compose this network can range from physical properties like “sediment load in a stream,” to intangible attributes like “pride in the landscape.” A common term for graphically represented mental models is cognitive maps (Axelrod et al. 1976; Özesmi & Özesmi 2004).

Here, we propose that results chains can be viewed as cognitive maps that model how a system is perceived to change in response to a management intervention. Through a rapid participatory process, a fuzzy modeling approach can be used to explore the dynamics of the system when a conservation intervention (management action or treatment) is applied to the social-ecological system. This approach is based on the concept of a fuzzy cognitive map (FCM). FCMs have been used in conservation and environmental planning to explore social-ecological systems linked to issues like the bush meat trade (Nyaki et al. 2014), estuary management (Vasslides & Jensen 2016), and ground water use (Giordano et al. 2013).

We illustrate this approach to indicator selection with the design of a monitoring program for a water fund in Colombia, Fondo Agua por La Vida y por la Sostenibilidad (FAVS). Water funds have increased rapidly in popularity as a conservation strategy around the globe, particularly in Latin America (Bremer et al. 2016). Water Funds are characterized by multiple watershed stakeholders investing in a collective action fund to finance watershed conservation. While water funds always target water quality and/or regulation, they also provide a good example of a complex conservation project because they typically aim to deliver multiple benefits, including improving local livelihoods and protecting biodiversity (Goldman-Benner et al. 2012; Bremer et al. 2016). Water funds are also a relatively recent strategy so there is not yet a detailed body of evidence about their social and environmental impacts, and it is therefore particularly important to complement their implementation with appropriate monitoring.

We demonstrate how information gained from a fuzzy model of water fund activities can be combined with information about those attributes of the system most important to stakeholders, in order to select attributes that will be monitored as indicators of water fund outcomes. This information also provided a chance to look at alignment between expected impacts of the water fund and those elements of the system that are of greatest interest to stakeholders.

**Methods**

**Study site**

FAVS promotes watershed protection and sustainable development in 16 watersheds in the Cauca Valley of Colombia, which include páramo (highland grasslands), Andean forest, and small-scale agricultural and ranching lands. Supporters of the fund include the Colombian sugar sector (ASOCANA, PROCAÑA, and CENICANA), the regional environmental authority, The Nature Conservancy, and grassroots organizations (river users associations). FAVS’ objectives focus on water supply for the sugar sector, rural livelihoods, and biodiversity conservation. The fund works through local river associations in each watershed to implement conservation.
Figure 1 Results chain describing the anticipated ecological and social impacts of fencing riparian forests on farms in the Cauca Valley of Colombia. Riparian fencing is one of a number of activities (or treatments) supported by the water fund, FAVS. Lines between nodes characterize the strength of influence of a parent node on the observed value of the child nodes it is linked to, relative to all the other, specified or unspecified influences on each node. A high influence inferred the parent node being causally responsible for most of the expected change in the child node. Medium influence was interpreted as the parent node being causally linked to change in the child node but where other nodes were similarly important. Low influence was interpreted as a case where many other parent nodes influenced the value of a child node or the influence of the parent node was low compared to another node. Signs on each node indicate the expected direction of change, and lighter colored nodes represent impacts that are considered undesirable.

and sustainable development activities including riparian restoration and agroforestry systems.

Results chains

We started by linking FAVS activities to anticipated ecological and social impacts through results chains developed with participation of local and technical experts (8 people total), including community river association (AsoBolo) representatives (3), the water fund manager, a local hydrologist, and staff and scientists from The Nature Conservancy and The Natural Capital Project (3). This group collectively developed results chains for each of the four main water fund activities; fencing of riparian vegetation, fencing of springs, farm-scale agroforestry systems, and development of silvopastoral systems for cattle production. We developed results chains by starting with a particular water fund activity and tracing all the expected outcomes of that activity. The four results chains were then refined through focus groups with landowners participating in water fund activities (3 groups with 6–9 participants in each group) to ensure they reflected landowner perceptions of social-ecological dynamics. In the case of water funds, thorough results chains require input of both local and technical knowledge and are therefore reflective of hybrid knowledge and coproduction of this knowledge (Bessette 2006).

Fuzzy cognitive maps

Using results chains as the framework, we constructed FCMs to explore the relative impact of program activities on social and ecological attributes. Cognitive maps are directed graphs where each node represents a management action or social-ecological response variable, and the links between nodes represent a causal relationship in a specified direction (i.e., a positive change in a node is expected to produce either a positive or negative change in the node to which it is immediately linked to). We treated the results chains as means-ends cognitive maps (Giordano et al. 2013), rather than comprehensive models of the social-ecological system. In contrast to results chains, conceptual or situation models are more comprehensive in that they attempt to characterize all major factors influencing the social-ecological variables of interest (Margoluis et al. 2009). As such, each node in the...
cognitive map will likely be influenced by a range of factors not represented in the cognitive map. Each of the water fund activities represented an input node in the cognitive map (i.e., a node with no incoming causal links thus lacking a parent node), subsequently referred to as treatments. The remaining nodes represent important social-ecological or geophysical attributes expected to change in response to the treatments, subsequently referred to as variables. The local and technical experts were asked to characterize the strength of influence of a parent node on the observed value of the child nodes it is linked to, relative to all the other, specified or unspecified influences on each node. The strength assigned to a link was determined by informal consensus following discussion by the group.

The strength of each link was characterized as “high,” “medium,” and “low.” A high weight inferred the parent node was causally responsible for most of the expected change in the child node. Medium weight was interpreted as the parent node being causally linked to change in the child node but where other nodes were similarly important. Low weight was interpreted as a case where many other parent nodes influenced the value of a child node or the influence of the parent node was low compared to another node. The cognitive map and associated connection strengths for each treatment (water fund activity) were subsequently transcribed using the software Mental Modeler (Gray et al. 2013). Because there were numerous nodes in common between each cognitive map, Mental Modeler was used to combine the four separate cognitive maps into a single map, and to export the matrix of relationships between all nodes in the combined cognitive map. This matrix of qualitative relationships was then translated into fuzzy quantitative values from -1 to +1, to give the matrix W. A high weight link between nodes received a value of 1, a medium weight link 0.5, and a low link 0.2. Where there was a negative link between nodes, these same values were coded as negatives.

Impact simulation

The FCM described above can be used to qualitatively explore which variables are likely to experience the greatest change as a result of the treatments. First, steady state values for the FCM need to be calculated. Following Kosko (1987) and Xirogiannis et al. (2004), we used the operation

\[ A^{t+1} = f(WA^t) \] (1)

where \( A^t \) is a vector containing all treatment and variable values at time step \( t \), \( W \) is the matrix of weights between all treatments and variables in the FCM, and \( f \) is the logistic function \( 1/(1 + e^{-1x}) \). All values in the initial vector were equal to 1 (Özesmi & Özesmi 2004). Equation (1) is then repeated, with vector \( A^{t+1} \) replacing \( A^t \) at each repetition until the system converges on a fixed point. This is considered the steady state and provides a baseline from which to explore system dynamics when a treatment is applied. As described by Özesmi & Özesmi (2004), the impact of a treatment (in this case, the water fund activities) can be simulated by repeating the steady state calculation above but with the value of each of our treatment variables fixed at 1 (i.e., these values do not change from time step to time step). We can then look at the relative change for each variable between the steady state value and “what if” treatment scenario (Gray et al. 2015). We did this for a total of five scenarios, one for each of the four treatments on their own, and one for all four water fund treatments together.

Stakeholder importance

To assess which attributes of the social-ecological system were perceived as most important by water fund stakeholders, we compiled a list of social-ecological variables in the FCM. Stakeholders were then asked to assign values of 1–100 to each of these variables according to how much they value the variable and therefore how important they thought this variable was to monitor. A variable considered absolutely important to measure was given a 100, while 1 would be a variable considered of almost no importance. Everything else was assigned a value relative to this. Each stakeholder did this individually and anonymously. A total of 16 stakeholders from two general groups were surveyed; landowners participating in water fund activities 9 in the Bolo watershed for which the results chains were developed and representatives from the organizational stakeholders, AsoBolo, FAVS, Cenicaña, TNC, and the environmental authorities (7, identified by each organization). As these two groups may be interested in different outcomes, stakeholder importance was averaged within these two groups.

Results

Results chains, FCM, and predicted impacts

Results chains revealed a diverse set of perceived linked social-ecological outcomes of water fund treatments (Figures 1, and S1–S3). The cognitive map compiled from the four results chains contained a total of four treatments and 29 unique social-ecological or geophysical variables (Figure S4). Using the cognitive map to simulate the combined impact of undertaking all four treatments, we see that vegetation cover and water quality (with
Variable importance and indicator selection

Overall, there was a moderate degree of concordance between the variables identified as most important by each of the stakeholder groups, with 6 of the 10 most important variables (defined by mean importance score) in common between participating landowners and organizational stakeholders (Table 1). The variables perceived as being most valued and therefore important to monitor covered a range of domains including health (nutrition and water quality), agricultural production and income (production of avocado and bananas), and ecology (biodiversity, vegetation cover, and soil conservation). Of the 6 important variables common to both stakeholder groups, 4 of them were among the variables predicted...
Table 1 The 10 most important social-ecological variables for the water fund to measure impact on, as perceived by participant stakeholders (9) and organizational stakeholders (7)

| Variable                        | Importance score | SD  |
|---------------------------------|------------------|-----|
| Soil conservation               | 98.6             | 7.9 |
| Cattle entering stream          | 94.3             | 7.9 |
| Ecological connectivity         | 94.3             | 11.1|
| Biodiversity                    | 91.4             | 12.1|
| Nutrition (quantity)            | 91.4             | 11.7|
| Farm water availability         | 90.0             | 20.4|
| Water quality (bacteria)        | 88.6             | 19.9|
| Vegetation cover                | 85.7             | 19.8|
| Household income                | 82.9             | 19.8|
| Production of avocado & bananas | 82.9             | 22.7|
| Water quality (bacteria)        | 100.0            | 0   |
| Participation in water fund activities | 100.0     | 0   |
| Pride in landscape              | 100.0            | 0   |
| Soil conservation               | 100.0            | 0   |
| Cattle health                   | 96.7             | 1   |
| Nutrition (quantity)            | 93.3             | 14.1|
| Vegetation cover                | 92.2             | 17.1|
| Production of avocado & bananas | 90.0             | 17.3|
| Biodiversity                    | 90.0             | 30  |
| Entertainment & recreation      | 90.0             | 30  |

Note: Gray shading denotes variables that are among the most important for both groups of stakeholders. Importance score refers to the mean score across that stakeholder group. Stakeholders were instructed to give a score of 100 to the variable they perceived as most important to monitor. SD denotes standard deviation.

by the fuzzy modeling to experience a moderate to large relative response to the four water fund treatments combined. These are, vegetation cover, water quality (bacteria), production of avocado and bananas, and soil conservation. As variables that are valued by stakeholders and predicted to change as a result of the treatments being implemented, these are identified as priority variables for monitoring the impact of the water fund project.

Discussion

Water funds, and other programs targeting joint social and ecological benefits, are rapidly growing around the world (e.g., Benett & Carroll 2014). The methodology described in this article fills a significant gap by providing a rapid and participatory indicator selection methodology for such projects.

A major strength of the fuzzy qualitative modeling methodology used here is the ability to structure knowledge in a participatory fashion that can draw on both local and technical expert knowledge, particularly in data-scarce systems (Biggs et al. 2011). We believe that this ability means that the methodology described here is both widely applicable and accessible to the majority of conservation projects globally. We recognize that the mathematical expertise required to use FCMs to simulate the impact of different treatments will not always be available, however, software that can automate this process is freely available (Gray et al. 2013) such that analytical skills need not be a barrier to its application. Although results chains are an increasingly familiar construct in conservation, perhaps the most challenging aspect of applying the method described here is developing sets of consistent results chains that thoroughly characterize how social-ecological systems are perceived function among local and technical stakeholders.

Indicator selection frameworks often include consideration of the costs of monitoring different indicators (e.g., Tulloch et al. 2011). We did not include this consideration in our methodology for a number of reasons. First, there will almost always be multiple ways to monitor any particular variable (de Lange et al. 2016). Different monitoring methods will typically involve a trade-off between cost and rigor or robustness; trade-offs that require a thorough understanding of an audience’s risk tolerance and the existing evidence base in order to resolve. Second, monitoring costs change rapidly as technology changes, such as the ability to use mobile phones to perform household surveys, or UAVs to look at vegetation changes, meaning that indicator selection could rapidly be based on incorrect costs data and therefore less valid. Instead, we suggest seeking creative and cost-effective ways to monitor the set of indicators that resonate with the intended audience and are expected to be firmly linked to project outcomes.

Despite growing recognition of the interconnection of human and natural systems, social and ecological monitoring of conservation projects most often occurs separately (Asbjornsen et al. 2015), and social monitoring is particularly scarce (Hicks et al. 2016; McKinnon et al. 2016). The methodology described here helps address a major challenge of indicator selection outlined earlier; the need to predict which system attributes are likely to be most impacted by a management intervention, but also...
provides a practical way to integrate social and ecological monitoring. Because the results chains used here are explicit hypotheses about how social-ecological systems will respond to management interventions, observations of change in the system consistent with the predictions from the fuzzy models would provide support for the hypotheses as specified in the results chains. By describing the pathway by which change in a social-ecological system is hypothesized to happen, results chains articulate a set of outcomes intermediate to the fundamental objectives of the management actions. Where time lags are expected before changes in fundamental objectives (e.g., household nutrition) are realized, tracking intermediate outcomes (e.g., avocado production) can be a practical way to assess progress over shorter time periods. Usefully, in the case study here, having predictions regarding which attributes of the social-ecological system were likely to experience the most change and where changes may be more modest, helped guide expectations of the outcomes among stakeholders, hopefully better aligning them with the future outcomes of the project.

The FAVS water fund case study also demonstrates the importance of linking indicators to the interests of intended audiences. While we were able to identify a set of indicators important to organizational and participant stakeholder groups, nearly half the indicators prioritized by either group, were not in the set considered most important by the other group. For example, 3 of the top 5 indicators identified by landowner stakeholders were not present in the top 10 from the organizational stakeholders (extent of community participation in water fund activities, pride in the landscape, and cattle health). These differences reflect varied stakeholder views on project success, and underscore the importance of monitoring variables that resonate with each stakeholder group in order to foster ongoing project support among participants (Bennett 2016).

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**Supporting Information**

Additional Supporting Information may be found in the online version of this article at the publisher’s web site:

**Figure S1.** Results chain describing the anticipated ecological and social impacts of fencing the area around natural springs on farms in the Cauca Valley of Colombia.

**Figure S2.** Results chain describing the anticipated ecological and social impacts of agroforestry practices on farms in the Cauca Valley of Colombia.

**Figure S3.** Results chain describing the anticipated ecological and social impacts of silvopastoral practices on farms in the Cauca Valley of Colombia.

**Figure S4.** Cognitive map derived by combing the results chains for all four management activities (or treatments) supported by the water fund, FAVS (Figures 1, S1–S3).

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