

## RESEARCH ARTICLE

# General rules for environmental management to prioritise social ecological systems research based on a value of information approach

Katrina J. Davis<sup>1,2</sup>  | Iadine Chadès<sup>1,3</sup>  | Jonathan R. Rhodes<sup>1,4</sup>  | Michael Bode<sup>1,5</sup> 

<sup>1</sup>Centre of Excellence for Environmental Decisions, The University of Queensland, St Lucia, Queensland, Australia

<sup>2</sup>Land, Environment, Economics and Policy Institute, University of Exeter Business School, Exeter, England

<sup>3</sup>CSIRO, Ecosciences Precinct, Dutton Park, Queensland, Australia

<sup>4</sup>School of Earth and Environmental Sciences, The University of Queensland, St Lucia, Queensland, Australia

<sup>5</sup>School of Mathematical Sciences, Queensland University of Technology, Brisbane City, Queensland, Australia

## Correspondence

Katrina J. Davis  
Email: k.davis2@exeter.ac.uk

## Funding information

Centre of Excellence for Environmental Decisions, Australian Research Council, Grant/Award Number: CE11001000104

Handling Editor: Silvia Carvalho

## Abstract

1. Globally, billions of dollars are invested each year to help understand the dynamics of social ecological systems (SES) in bettering both social and environmental outcomes. However, there is no scientific consensus on which aspect of an SES is most important and urgent to understand; particularly given the realities of limited time and money.
2. Here we use a simulation-based “value of information” approach to examine where research will deliver the most important information for environmental management in four SESs representing a range of real-life environmental issues.
3. We find that neither social nor ecological information is consistently the most important: instead, researchers should focus on understanding the primary effects of their management actions.
4. Thus, when managers are undertaking social actions the highest research priority should be understanding the dynamics of social groups. Alternatively, when manipulating ecological systems it will be most important to quantify ecological population dynamics.
5. *Synthesis and applications.* Our results provide a standard assessment to determine the uncertain social ecological systems (SES) component with the highest expected impact for management outcomes. First, managers should determine the structure of their SES by identifying social and ecological nodes. Second, managers should identify the qualitative nature of the network, by determining which nodes are linked, but not the strength of those interactions. Finally, managers should identify the actions available to them to intervene in the SES. From these steps, managers will be able to identify the SES components that are closest to the management action(s), and it is these nodes and interactions that should receive priority research attention to achieve effective environmental decision making.

## KEYWORDS

adaptive management, complexity, environmental management, learning, research priorities, social network analysis, social ecological systems, value of information

## 1 | INTRODUCTION

Between 2001 and 2008, annual global spending on environmental management was close to US\$20 billion (Waldron et al., 2013). Traditionally, the focus of this spending has been on developing an understanding of ecosystems or single species (McRae, Dickson, Keitt, & Shah, 2008; Simberloff, 2003). This narrow research approach has delivered mixed benefits because it omits relevant wider system dynamics (Liu et al., 2007). For example, the Convention on International Trade in Endangered Species of Wild Fauna and Flora (CITES) has often neglected the social motivations and pressures that drive the endangered species trade, and this has contributed to its failure to protect many species (Lenzen et al., 2012; Wolch & Emel, 1998). Equally, many marine protected area networks are designed on purely biological grounds despite their long-term success being heavily affected by social factors such as social acceptability and financial capacity (Christie, 2004; Gill et al., 2017; Mascia et al., 2003).

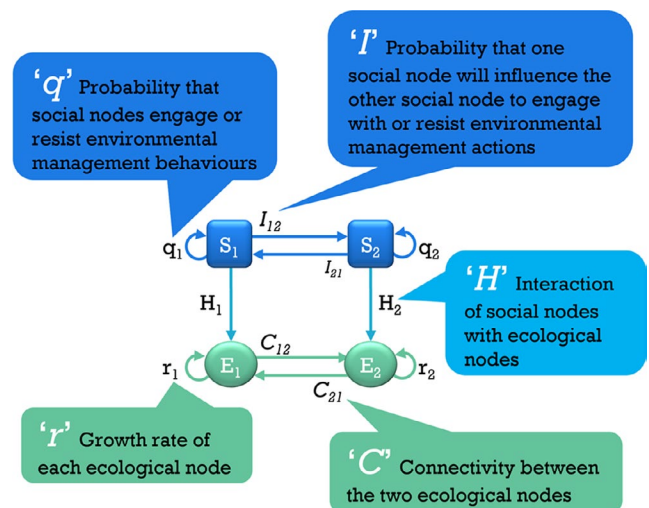
To improve management outcomes, the characteristics and dynamics of the wider social ecological system (SES) are receiving increasing research attention (Bodin, 2017). However, the dynamics of these coupled SES systems—how social actors interact over time, and the connections between and within social and ecological processes—create additional dimensions of uncertainty for environmental managers (Ostrom, Burger, Field, Norgaard, & Policansky, 1999). Research can improve managers' understanding of these more complex SES models, but this requires funding, and can delay management that is often urgently needed. For example, next to nothing was known about the "extinct" Australian night parrot *Pezoporus occidentalis*, which was rediscovered in 2013 (Pyke & Ehrlich, 2014). Five years later, and despite numerous programs of research, managers are still far from understanding how to protect it (Leseberg, nd; Pyke & Ehrlich, 2014). Furthermore, under economic constraints, increasing investment in ecological research may come at the cost of reduced investment in social research and vice versa. Therefore, knowledge acquisition must be prioritised based on an evaluation of its expected benefits and costs (Canessa et al., 2015; Grantham et al., 2008; Grantham, Wilson, Moilanen, Rebelo, & Possingham, 2009; Li et al., 2017; Runge, Converse, & Lyons, 2011).

To improve environmental management outcomes, a crucial research question is—what is the value of knowing more about each component (hereafter "uncertain system component") of coupled SES? We apply a simulation-based version of formal "value of information" theory (Raiffa & Schlaifer, 1961) to calculate the expected value of perfect information regarding each uncertain SES component (EVPXI, where X is each uncertain SES component) (sensu Yokota & Thompson, 2004). We then calculate which information—social or ecological—will deliver the greatest improvement in management outcomes.

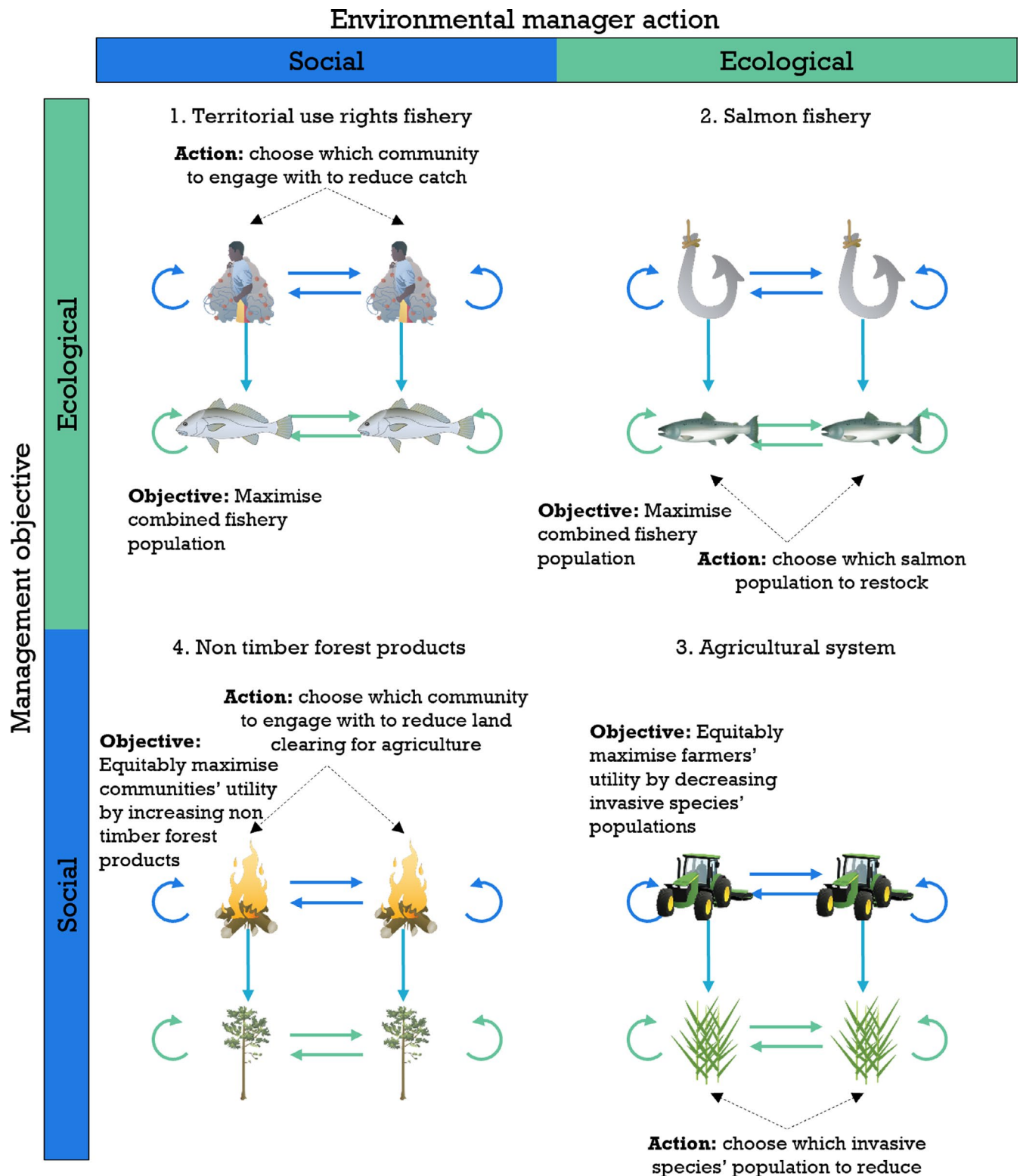
Within the broad field of environmental management, different disciplines have argued for research effort to be concentrated on different system elements. For example, environmental research has traditionally focused on understanding uncertain ecological system

components (Chadès et al., 2011). Meanwhile, both environmental and social fields of research have debated whether research effort should focus on understanding the dynamics of either nodes (e.g. the management functions of social actors; Marín & Berkes, 2010) or interactions (e.g. ecological processes such as connectivity; Pulliam, 1988; Urban & Keitt, 2001), with few studies contrasting the two (Sanchirico & Wilen, 1999). Other approaches, such as structured decision making (e.g. Martin, Runge, Nichols, Lubow, & Kendall, 2009), highlight the importance of understanding and clearly defining management objectives; as opposed to system dynamics. Our contribution in this research compares each of these options, and particularly focuses on the relative value of gathering ecological versus social information. We also assess whether it is more important to research the system components that managers are aiming to change (i.e., their objectives), or the system components that they plan to act upon.

We construct a general model of an SES that is simple enough to be analytically tractable, while also containing all the fundamental elements of an SES (Bodin & Tengö, 2012) (see Figure 1). Our system construction builds on recent research proposing network 'motifs'—simplified, but non-trivial patterns of interconnections (Bodin & Tengö, 2012), which can be described as the basic building blocks of most networks (Milo et al., 2002). To discover which information is most valuable, we consider four different management problems—two from fisheries and two from sustainable agriculture (Figure 2). We designed our four problems to investigate the influence of all permutations of action and management objectives on research priorities (Figure 2). To give two



**FIGURE 1** Stylised representation of our social ecological system (SES) network structure. This structure has two social groups (nodes  $S_1$  &  $S_2$ ) who interact with two ecological populations (nodes  $E_1$  &  $E_2$ ). Arrows indicate the direction of potential interactions between social groups and ecological populations. These dynamics are determined by the behaviour of both the nodes and interactions, including the social ecological interactions that couple the social and ecological systems



**FIGURE 2** Four different environmental management problems with different management actions and objectives (see Figure 1 for description of each uncertain social ecological system component). Image credits: Saxby, T.; Mulloway, D.T.; Nastase, E.; Hawkey, J.; Integration and Application Network, University of Maryland Center for Environmental Science ([ian.umces.edu/imagelibrary](http://ian.umces.edu/imagelibrary))

examples of these permutations: 'what is the most important element of an SES to understand when managers are intervening in a social system to achieve an ecological outcome?' And: 'what is the

most important element of an SES to understand when managers are intervening in an ecological system to achieve an ecological outcome?'

## 2 | MATERIALS AND METHODS

### 2.1 | Overview of analyses

Our aim is to determine the relative expected value of different types of information in socio-ecological systems (SESs), to guide research to inform management actions. We explore this question using four SESs with different management objectives and actions (see Figure 2). We frame these questions using network theory (note, however, that we do not perform any network analysis). Below, we provide a brief overview of value of information theory before describing our SESs in more detail and then providing details of the modelling approach.

### 2.2 | Value of information

Before commencing a management project, managers must decide whether to reduce uncertainty in a given aspect of the system (i.e., to learn about  $I_{xy}$ ,  $q_x$ ,  $H_x$ ,  $C_{xy}$  or  $r_x$ ). We measure the expected value of information as the improvement in an outcome when particular information is known with certainty, compared to when that information is unknown (Canessa et al., 2015; Runge et al., 2011). We define the value of information following Raiffa and Schlaifer (1961) and Yet, Constantinou, Fenton, and Neil (2018). Our SES model consists of a set of possible management actions  $\mathbf{A}$  and a set of uncertain SES parameters  $\theta$  with joint probability distribution  $P(\theta)$ . For each management action  $a \in \mathbf{A}$  the model aims to predict the utility of  $a$  denoted by  $U(a, \theta)$ . The expected utility of each management action  $a$  is

$$E_{\theta} \{U(a, \theta)\} = \sum_{\theta} U(a, \theta) P(\theta) \quad (1)$$

If the value of the SES parameters is unknown, we can calculate the expected utility of each management action and identify which action  $a$  yields the highest expected utility (Yokota & Thompson, 2004), that is:

$$\max_a [E_{\theta} \{U(a, \theta)\}] \quad (2)$$

Alternatively, if it were possible to gather perfect information about all uncertain SES parameters, then managers could select the action that would maximise the value of the management outcome. Expected utility under this 'perfect information' setting is given by:

$$E_{\theta} \left( \max_a [U(a, \theta)] \right) = \sum_{\theta} P(\theta) \max_a [U(a, \theta)] \quad (3)$$

The difference between maximum expected utility with perfect information (Equation 3) and maximum expected utility (Equation 2) is the expected value of perfect information (EVPI):

$$\text{EVPI}(\theta) = E_{\theta} \left( \max_a [U(a, \theta)] \right) - \max_a [E_{\theta} \{U(a, \theta)\}] \quad (4)$$

In our research setting, we are interested in understanding the value of information for individual SES parameters to improve management outcomes. We therefore calculate the expected value of perfect information on 'X' (EVPXI). EVPXI is the difference in expected utility of an optimal action taken when the exact value of an uncertain model input ( $\theta^x$ ) is known (Equation 5) compared to one taken

knowing only prior information (Equation 2) (Yokota & Thompson, 2004). We illustrate this case with the following example. Consider a division of our uncertain SES parameters into parameter of interest  $\theta^x$ , and the rest of the parameters  $\theta^{-x}$ . The expected benefit if we have perfect information about  $\theta^x$  is:

$$E_{\theta^x} \left\{ \max_a [E_{\theta^{-x}|\theta^x} \{U(a, \theta)\}] \right\} \quad (5)$$

That is, we are only calculating the expectation over the unknown parameter values of  $\theta^{-x}$ , given the value of  $\theta^x$ . This formulation allows us to define EVPXI as follows:

$$\text{EVPXI}(\theta^x) = E_{\theta^x} \left( \max_a [E_{\theta^{-x}|\theta^x} \{U(a, \theta)\}] \right) - \max_a [E_{\theta} \{U(a, \theta)\}] \quad (6)$$

Essentially, EVPXI measures the relative benefits of resolving uncertainty in any one particular uncertain parameter, e.g. ecological or social nodes.

### 2.3 | Systems overview

Our four SESs exhaustively describe potential management actions and objectives for a very simple SES network motif. We replicate the finite set of motifs described in Bodin and Tengö (2012) by replicating the basic network structure (two social and two ecological nodes), and assuming uncertain priors—which allows us to assess the expected value of information (described above) across all parameters. We intend for our results and conclusions to be as generalizable as possible; hence, the system models we employ are as generic as possible (see Appendix S1 for a detailed description of objectives). Managers engage with nodes as this is the most commonly observed management intervention, e.g. payments for environmental services (Ferraro & Kiss, 2002), or restocking wild populations (Aprohmanian, Martin Smith, McGinnity, McKelvey, & Taylor, 2003). This means that we are not considering systems where managers act on interactions. Thus, for example, a manager might revegetate an ecological habitat patch, but they would not revegetate linear habitat to improve dispersal (Jellinek, Parris, McCarthy, Wintle, & Driscoll, 2014). The fundamental components of each system model are (a) a discrete-time, continuous-state model of the ecological dynamics; (b) a management objective function; and (c) a discrete-time, discrete-state model of the social dynamics, based on the influence of the management action. Below, we outline these components for each of the four systems we consider. The range of uncertainty considered in each parameter is described in Table 1.

### 2.4 | System 1

Management problem 1 is based on a territorial use rights fishery (Wilén, Cancino, & Uchida, 2012). There are two fishing groups ( $S_1$  and  $S_2$ ) and two fishery populations ( $E_1$  and  $E_2$ ). Each fishing group harvests their own fishery ( $0 \leq H_1$  &  $H_2 \leq 0.4$ , see Table 1).

**TABLE 1** Description of social ecological parameter assessed in the value of information analysis

Parameter	Range	Description	Network	Node or interaction
$r$	$0.2 \leq r \leq 2$	Growth rate of ecological population	Ecological	Node
$C$	$0 \leq C \leq 1$	Connectivity between ecological populations	Ecological	Interaction
$H$	$0 \leq H \leq 0.4$	Harvest of ecological population by social nodes	Social ecological	Interaction
$q$	$0 \leq q \leq 1$	Willingness to engage with management	Social	Node
$I$	$0 \leq I \leq 1$	Influence of one social node on another	Social	Interaction
Other parameters				
$D$	0.25	Management intervention impact		
$M$	0.25	Management addition or removal of ecological population		

The fishery populations grow logistically with growth rates  $r_1$  and  $r_2$ , and there is dispersal between the populations that is likely asymmetric ( $0 \leq C_{12}$  &  $C_{21} \leq 1$ ). An environmental manager is acting in the system, and their goal is to *maximise* the equilibrium size of the harvested fishery, even if this reduces yields. They might associate a higher stock abundance with superior ecosystem functioning or believe that it makes the stock better-equipped to deal with environmental change. To achieve their objective, managers intervene in one of the two social groups to encourage or incentivise a permanent harvest reduction of  $D = 0.25$ . Variations on this management setting have been observed around the globe. For example, in Chile, a co-management program was instituted to stimulate the recovery of shellfish populations. As in our example, fishers in Chile voluntarily participate in observing catch limits (Castilla & Defeo, 2001). Community based fisheries management also features in Japan, where fishing rights apply to the entire sea area adjacent to a given fishing village (Yamamoto, 1995).

### 2.4.1 | Ecological dynamics

The abundance of the fishery population at patch  $j$  at time  $t$  is denoted  $E_{j,t}$  and changes through time as:

$$E_{j(t+1)} = E_{j(t)} + r_j E_{j(t)} (1 - E_{j(t)}) - C_{jg} E_{j(t)} - (1 - Du_{p,k}) H_i E_{j(t)} + C_{gi} E_{g(t)} \quad (7)$$

Since we are interested in long-term outcomes, we calculate and use the system equilibrium: the vector of  $E_j^*$  values where all  $E_{j,t+1} = E_{j,t} = E_j^*$ .

The growth rates  $r_j$  drive increases in abundance. The stocks are demographically linked by the dispersal parameters ( $C_{jg}$ ), which denote the proportional exchange of individuals. For example,  $C_{12}$  describes the proportion of adult fish who move from ecological population 1 to ecological population 2. The harvest terms ( $H_i$ ) indicate the proportion of the adult population removed from each population by social group  $i$  each time step. We constrained the value of  $H_i$  between 0 and 0.4 to limit catches below the maximum sustainable yield (Punt, Smith, Smith, Tuck, & Klaer, 2014) (see Table 1), as the system would otherwise not

contain a persistent population. These harvest parameters connect the social groups with the ecological populations, and therefore encapsulate the social ecological interactions. The binary variable  $u_{p,k} = \{0,1\}$  describes the influence of management, as described below.

### 2.4.2 | Management objective

In system 1, managers aim to engage the social system to achieve an ecological objective—*maximise* the equilibrium size of the ecological metapopulation:

$$\max_{A=\{0,1\}} B = E_1^* + E_2^* \quad (8)$$

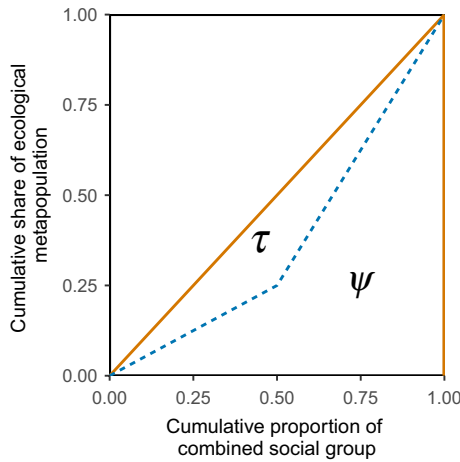
To do so, managers must choose to intervene with social group one ( $a = 1$ ), or group two ( $a = 0$ ). The time and resources required for the managers to intervene mean that only one group can be targeted. As we outline below, the dynamics of the SES are probabilistic, depending on the response of the social groups to the management intervention. Managers are therefore actually attempting to maximise the expected value.

### 2.4.3 | Social dynamics in response to management

The state of the social system is described by the vector  $\mathbf{u}_p$ , where  $p = \{1, 2, 3, 4\}$ , whose binary elements  $u_k = \{0,1\}$  describe whether group  $k$  engages in the environmental action. The values of  $\mathbf{u}_p$  are determined by the management action  $\mathbf{A}$ , which (as described above) denotes whether the managers engage with group one ( $a = 1$ ) or group two ( $a = 0$ ).

We model engagement as a random process, where each social group has a probability  $q_i$  of engaging with a management intervention targeted at that group. For example, in this SES, if the managers choose to engage with social group one by choosing  $a = 1$ , then that group will undertake the desired action (reducing their harvest rate) with probability  $q_1$ . Once the group makes its decision, it may influence group two to similarly engage, with probability  $I_{12}$ . This influence network is characterised by the matrix  $I$ :





**FIGURE 3** Illustration of the calculation of the Gini Coefficient, which assesses the proportion of the total ecological population which occurs in ecological node 1 relative to ecological node 2. Red line describes the Lorenz curve, blue line describes the line of equality. In this example, ecological node 1 (50% of population) has 25% of the total ecological metapopulation

$$I = \begin{bmatrix} 0 & I_{12} \\ I_{21} & 0 \end{bmatrix} \quad (9)$$

The willingness of each group to engage ( $q_i$ ), therefore defines the dynamics of the social nodes, and the inter-group influence  $I_{ij}$  defines the dynamics of the network.

Given a particular management action  $a \in \mathbf{A}$ , the response of the communities is defined by a discrete probability distribution over  $\mathbf{u}_p$ :

$$\Pr(\mathbf{u}_1 = [1,1]) = \mathbf{A}q_1 I_{12}q_2 + (1-\mathbf{A})q_2 I_{21}q_1 \quad (10)$$

$$\Pr(\mathbf{u}_2 = [0,1]) = (1-\mathbf{A})q_2(1-I_{21}q_1) \quad (11)$$

$$\Pr(\mathbf{u}_3 = [1,0]) = \mathbf{A}q_1(1-I_{12}q_2) \quad (12)$$

$$\Pr(\mathbf{u}_4 = [0,0]) = \mathbf{A}(1-q_1) + (1-\mathbf{A})(1-q_2) \quad (13)$$

Thus, to calculate the expected performance of the SES given a particular management action  $a$ , we calculate  $B$  as a function of all  $\mathbf{u}_p$ , weighted probabilistically using Equations 10–13:

$$\begin{aligned} \langle B(\mathbf{A}) \rangle = & [E_1^*(\mathbf{u}_1 = [1,1]) + E_2^*(\mathbf{u}_1 = [1,1])] \cdot \Pr(\mathbf{u}_1 = [1,1]) \\ & + [E_1^*(\mathbf{u}_2 = [0,1]) + E_2^*(\mathbf{u}_2 = [0,1])] \cdot \Pr(\mathbf{u}_2 = [0,1]) \\ & + [E_1^*(\mathbf{u}_3 = [1,0]) + E_2^*(\mathbf{u}_3 = [1,0])] \cdot \Pr(\mathbf{u}_3 = [1,0]) \\ & + [E_1^*(\mathbf{u}_4 = [0,0]) + E_2^*(\mathbf{u}_4 = [0,0])] \cdot \Pr(\mathbf{u}_4 = [0,0]) \end{aligned} \quad (14)$$

We assume that the management action carries either no net cost for the group (either has no cost, or is subsidised by the manager), or generates positive benefits, but that the groups will not instigate this action without management intervention. This could be because the groups are unaware of the benefits (assuming they exist), are reluctant to instigate the action, or lack the capacity to begin implementation (Pannell et al., 2006).

## 2.5 | System 2

The management setting for system 2 is a recreational fishery, where managers are planning on restocking a salmon population. In practice, this can occur because managers want to (a) facilitate colonization of new habitats; (b) restore spawning biomass in severely depleted populations, (c) compensate for major environmental disturbances such as hydroelectric development, or (d) augment an existing fishery to enable larger catches (Ritter, 1997; Ward, 2006). For example, in Florida in the USA, saltwater recreational fishing is a multi-billion dollar (US) industry, and fish stocking is used to restore depleted stocks (Tringali et al., 2008). In our system example there are two salmon populations ( $E_1$  &  $E_2$ ) and two recreational fisher groups ( $S_1$  &  $S_2$ ). Each recreational fisher group fishes in their own salmon fishery ( $H_1$  &  $H_2$ ). The management action is to intervene in the ecological system by restocking salmon by  $M = 0.25$  in one of the populations. Note that, once again, this is a permanent intervention and implies managers will commit to an annual restocking rate of 0.25. As with the previous system, the management objective is ecological: *maximise* the equilibrium salmon metapopulation (Equation 15). Due to resource constraints, managers can only choose one population to restock. In response to the management action, the recreational fisher groups may choose (with probability  $q_1$  &  $q_2$ ) to *increase* their salmon harvest by  $D$ ; undermining the management objective. If managers restock their salmon population, that fisher group may encourage the other fisher group to also increase their salmon harvest with probability  $I_{ij}$ . The structure of the SES in system 2 is the same as in system 1, however, instead of a social intervention, the managers intervene in the system through the ecological populations. The differences in the dynamics of system 2 relative to system 1 are outlined below.

$$\begin{aligned} E_{j(t+1)} = & E_{j(t)} + r_j E_{j(t)}(1-E_{j(t)}) - C_{jg} E_{j(t)} \\ & - (1 + Du_{p,k}) H_i E_{j(t)} + C_{gj} E_{g(t)} + \mathbf{A} M E_{j(t)} \end{aligned} \quad (15)$$

The ecological dynamics in system 2 account for the restocking of the ecological population by managers. If managers restock ecological population  $E_j$ , then group  $S_i$  will respond by *increasing* their harvest with probability  $q_i$ , rather than decreasing it. The discrete probability distribution for action vector  $\mathbf{u}_p$ ,  $p = \{1, 2, \dots, 6\}$  whose binary elements  $u_k = \{0, 1\}$  describe whether group  $k$  engages in the environmental action and depends on the management action are as follows:

$$\Pr(\mathbf{u}_1 = [1,1,0,1]) = \mathbf{A}q_1 I_{12}q_2 \quad (16)$$

$$\Pr(\mathbf{u}_2 = [1,1,0,0]) = \mathbf{A}q_1(I_{12}(1-q_2) + 1 - I_{12}) \quad (17)$$

$$\Pr(\mathbf{u}_3 = [1,0,0,0]) = \mathbf{A}(1-q_1) \quad (18)$$

$$\Pr(\mathbf{u}_4 = [0,1,1,1]) = (1-\mathbf{A})q_2 I_{21}q_1 \quad (19)$$

$$\Pr(\mathbf{u}_5 = [0,0,1,1]) = (1-\mathbf{A})q_2(I_{21}(1-q_1) + 1 - I_{21}) \quad (20)$$

$$\Pr(\mathbf{u}_6 = [0,0,1,0]) = (1-\mathbf{A})(1-q_2) \quad (21)$$

## 2.6 | System 3

System 3 is an agricultural production system where a biological pest ( $E_1$  &  $E_2$ ) negatively affects the utilities of two farmers ( $S_1$  &  $S_2$ ) (Silverstein, 1981). Previous studies have estimated that pests and diseases lower crop production by 30%–40% (Thomas, 1999). To control agricultural pests, managers often try to encourage farmers to adopt integrated pest management practices, for example, biopesticides or resistant cultivars (Parsa et al., 2014). In our system, social ecological interactions occur when farmers manage (remove) the pest population located on their farm ( $H_1$  &  $H_2$ ). The objective of managers is to equitably *maximise* the utility of farmers; they intervene in the system by reducing one of the biological pest populations by  $M = 0.25$ . Farmers respond (with probability  $q_1$  &  $q_2$ ) to that action by *decreasing* (by  $D$ ) their own efforts to remove the pest population. Similar to a study by Baggio and Hillis (2018), we assume that farmers will make their management decision based on information they acquire from their social network. This influence of one farmer to encourage a reduction in removal effort by the other is controlled by  $I$ . The social objective is assessed by how much the pest populations are minimised, modified by the difference between the outcomes for the two farmers; it reflects both the negative impact of the pest populations on the farmers' productivity, and a preference for equitable engagement in environmental management.

The structure of the SES in system 3 is largely the same as in systems 1 and 2. In system 3, however, there is a social objective, and managers intervene in the ecological system by removing a proportion  $M$  of the ecological population in node  $E_1$  or  $E_2$ . If managers reduce the biological pest population  $E_j$ , then group  $S_i$  will respond by *decreasing* their own removal with probability  $q_j$ , rather than increasing it

$$E_{j(t+1)} = E_{j(t)} + r_j E_{j(t)} (1 - E_{j(t)}) - C_{jg} E_{j(t)} - (1 - Du_{p,k}) H_i E_{j(t)} + C_{ji} E_{g(t)} - AM E_{j(t)} \quad (22)$$

Farmers' utility is measured as a composite of the inverse size of the pest metapopulation (assessed at equilibrium,  $E_j^*$ ), and a Gini coefficient (Dorfman, 1979) which indicates how equally the two populations are reduced. To maximise social utility the pest populations would need to be removed completely on both farms. The system was assessed as in Equation 23.

$$\max_{A=\{0,1\}} B = (E_1^* + E_2^*) (1 - G) \quad (23)$$

The Gini coefficient ( $G$ ) (Dorfman, 1979) (see Equation 24 and Figure 3) was calculated by assessing the proportion of the total ecological population ( $\tau + \psi$ ) which occurred in ecological node 1 ( $\tau$ ) relative to ecological node 2 ( $\psi$ ).

$$G = \frac{\tau}{(\tau + \psi)} \quad (24)$$

The discrete probability distribution for management vector  $u_p$  is as described in system 2.

## 2.7 | System 4

System 4 is based on a non-timber forestry products (NTFP) extraction system. NTFP harvest has been shown to affect ecological processes (Ticktin, 2004), including forest structure and composition (Ndangalasi, Bitariho, & Dovie, 2007). However, commercial NTFP harvest has been promoted as a conservation strategy because it offers local rural people with economic alternatives to destructive land uses such as logging and cattle ranching (Ticktin, 2004). This is the management setting in which we base system 4. In this system, two social groups ( $S_1$  &  $S_2$ ) can extract NTFP from their local forest ( $E_1$  &  $E_2$ ) or convert the land to agriculture by clearing the forest ( $H_1$  &  $H_2$ ) (Chopra, 1993). The management action is social—managers offer incentives to social groups to *decrease* land clearing for agriculture (by  $D$ ), and the objective is social—to equitably *maximise* the communities' utility by increasing non-timber forest products (through increasing the size of the forest patches). Groups will engage with managers—decreasing their land clearing—with probability  $q_p$ , and influence the other social group to similarly engage with probability  $I_{if}$ . Note that in this system, social interactions can amplify the benefits of intervention, while in the pest management system social interactions could reduce the benefits of an intervention.

The ecological dynamics are the same as specified in system 1. The social objective was assessed as specified in system 3 (Equation 23), except that these managers seek to equitably increase the equilibrium forest metapopulation, while the managers in system 3 sought to equitably reduce the pest population. The discrete probability distribution for this action vector  $u_p$  is the same as in system 1.

$$\max_{A=\{0,1\}} B = (E_1^* + E_2^*) (1 - G) \quad (25)$$

## 2.8 | Model discretisation

We conducted two EVPXI analyses (described in Section 2.2) in each of our four SES. In the first analysis we individually assessed the EVPXI of each of the individual five uncertain model inputs  $I_{xy}$ ,  $q_x$ ,  $r_x$ ,  $C_{xy}$  and  $H_x$ . In the second analysis we assessed the EVPXI of pairs of uncertain model parameters, grouped according to their character: the social inputs ( $I_{xy}$  and  $q_x$ ), the ecological inputs ( $C_{xy}$  and  $r_x$ ), and the socio-ecological inputs ( $H_x$ ). The parameterisation of these inputs is described in Table 1.

To individually assess the relative expected value of each of our five uncertain model inputs, we defined each uncertain model input of interest  $\theta^x$ ,  $x = \{1, 2, \dots, 5\}$ . Each  $\theta^x$  input comprises two parameters (because there are two values for each uncertain input,

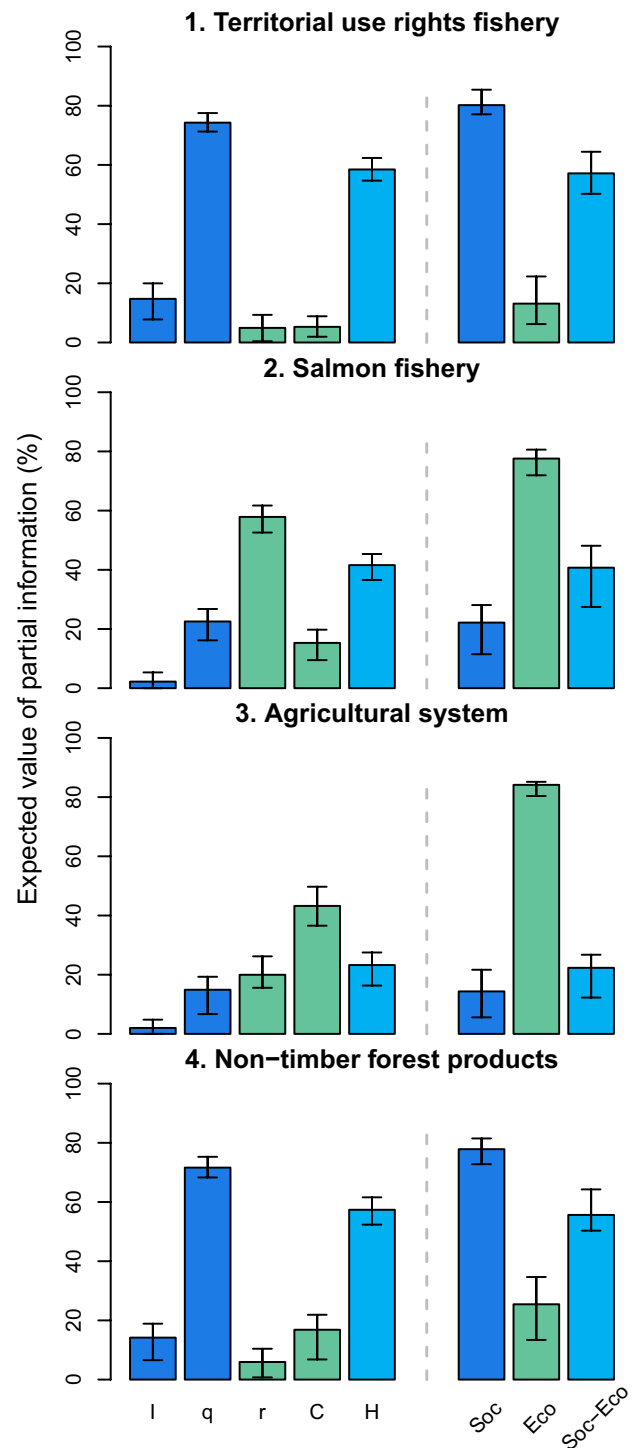
e.g.  $I_{12}$  and  $I_{21}$ ; or  $q_1$  and  $q_2$ ). Each input has a discrete, uniform distribution, which samples the full range of possible input values at  $n$  equally spaced intervals. This creates  $n^2$  discrete combinations (e.g. combinations of  $n$  values of  $I_{12}$  and  $I_{21}$ ). We then specified  $b$  replications of the other uncertain model inputs,  $\theta^{-x}$ ,  $-x \in \{1, 2, \dots, 10\}$ . Using random number setting “twister” in Matlab, we generated a  $b \times \theta^{-x}$  matrix of all other parameter values. We then created a  $b \times \theta^{-x}$  matrix for each of the  $n^2$  combinations to give a matrix of dimensions  $n^2 \times b \times \theta^{-x}$ . Each row vector of this replicated matrix provides a unique value for each  $\theta^{-x}$  (other uncertain model input) for each combination of  $\theta^x$  (the values for the uncertain model input of interest). The two specifications,  $n$  and  $b$ , define the computational intensity of our analysis. We were able to run the analyses for  $n = 15$  and  $b = 75$ , replicated 20 times.

The ecological model was run to equilibrium for each combination of  $\theta^x$  and  $\theta^{-x}$  ( $1, \dots, bn^2$ ), each management intervention  $a$ , where  $a \in A = \{1, 0\}$  depending on whether managers intervene at social or ecological node 1 or 2 respectively, and each possible state of the social system. The state of the social system is described by action vector  $u_p$  and as previously described, is partially determined by the initial management decision ( $A$ ), and partially by the dynamics of the social system. For example, in system 1, if both groups are persuaded to take action (the first through direct engagement, the second through the adoption and influence of the first), the action vector will be  $u = [1, 1]$ . The size of the ecological metapopulation at equilibrium under each model discretisation and possible state of the social system  $u_p$  was used to calculate EVPXI as described previously. The characteristics of each of our four SESs will determine the potential for management actions to affect expected utility—as the characteristics of each system are different, the magnitude by which expected utility can improve is not constant across our systems. To be able to compare the value of information across our systems, we standardised EVPXI by the maximum observed metapopulation across all discretisations ( $n$ ) and replications ( $b$ ) for each system.

### 3 | RESULTS

We evaluated the EVPXI of each type of social ecological information in four SES with different management actions and objectives (Figure 2). Systems 1 and 2 are fisheries examples; in both cases managers have an ecological objective, but in system 1 managers influence the network through the social group while in system 2 managers influence the network through the ecological population. Systems 3 and 4 are sustainable agriculture examples. Managers pursue social (primarily economic) objectives—in system 3 they undertake a social action, while in system 4 they undertake an ecological action.

Our EVPXI analyses showed that neither ecological nor social information is inherently more valuable for management: social information is most valuable in systems 1 and 4 (Figure 4), and ecological information is most valuable in systems 2 and 3. Regardless of the SES model, action or management objective, the highest



**FIGURE 4** Expected value of partial information, or perfect information regarding X (EVPXI, where X is an uncertain social ecological system model component), in four social ecological systems (see Figure 2). Social uncertain components:  $q$  is willingness of a social group to participate in management,  $I$  is the influence of one social group on the other; Ecological uncertain components:  $r$  is the ecological population growth rate;  $C$  is ecological connectivity; Social ecological uncertain components:  $H$  is the interaction of social groups with ecological populations. Error bars describe upper and lower quartiles. When interpreting the relative value of information, note that the ranking past the first EVPXI is uninformative. Subsequent rankings would require the re-evaluation of subsequent EVPXIs once the first EVPXI has been addressed



value of information was consistently associated with the uncertain component that was most directly affected by the management action (Figure 4). For example, managers intervene in the social nodes in problems 1 and 4 (Figure 2, left column), and it is therefore most important to understand each group's willingness to engage with managers (social node component  $q$ ). In problems 2 and 3, where managers engage the SES through the ecological nodes, the highest EVPXI concerns the growth rate of the salmon populations (ecological node component  $r$ ), and the connectivity between the two invasive species' populations (ecological interaction component  $C$ ). A sensitivity analysis of fixed parameters  $M$  and  $D$  confirmed that results are robust to changes in these parameter values (see Appendix S2).

## 4 | DISCUSSION

This is the first evaluation of the value of information in a dynamic SES network. Our results can be summarised as: 'learn about the system-lever that you plan to pull'. Although intuitive, our results are at odds with current, widespread research practices: not to consider management actions (or even, necessarily, objectives) when deciding where to prioritise research effort. For example, research effort into the aforementioned night parrot first concentrated on improving understanding of the bird's biology (Pyke & Ehrlich, 2014), without reference to specific management actions that might make use of such information.

Neither the social nor ecological components in our analysis consistently displayed a higher value of information. Their relative importance depended on which was being targeted by management actions. This result can be explained by the conditional nature of information. For example, in our first fishery problem (System 1), the management action involves engaging with a fishing group to reduce harvests. Only if engagement is successful (with probability  $q_x$ ), can the effects spread to the non-engaged fishing group (with probability  $I_{xy}$ ). This latter process of social influence ( $I_{xy}$ ) will only ever be relevant if the initial group engages with the managers ( $q_x$ ), and  $I_{xy}$  is therefore only conditionally important. By a similar argument, the socio-ecological connection ( $H_x$ ) is also irrelevant if the intervention fails. The highest EVPXI is therefore associated with  $q_x$ , not  $I_{xy}$  or  $H_x$ . If the initial action fails, then the process by which interventions propagate through the social network (its secondary impact) is not important. The more distant the parameter from the point of intervention, the lower its EVPXI. In general, this means that when management actions are social, then the highest EVPXI will be social; when management actions are ecological, the highest EVPXI will be ecological.

Unlike previous analyses that focused on the value of information in social or ecological systems in isolation from each other (Barnes, Lynham, Kalberg, & Leung, 2016; Chadès et al., 2011), our approach considers research priorities in a coupled SES. This explicit comparison allows us to conclude that neither social nor ecological information is more important than the other per se. Thus, contrary to a historical focus on environmental information (Clarke, 1995;

Fahrig & Merriam, 1994; Noss, 1990), and a more recent push to consider social information (Dickman, 2010; Mascia et al., 2003); environmental managers need to understand the actions available to them before they can identify which information to prioritise.

Surprisingly, system components closest to the management objective were not as important as system components closest to the management action. This result suggests that, while management objectives may change, the relative value of information remains intrinsic to the management action. The fact that EVPXI is not highest for those components close to management objectives contrasts with the focus of structured decision-making, which places primary emphasis on determining management objectives, e.g. the goals of stakeholders (Martin et al., 2009). We do not see this as a disagreement, since the goals of structured decision-making are much broader than simply evaluating the value of particular forms of information. Moreover, our conditional-importance interpretation presumably means that highest EVPXI will be associated with those parameters that link management actions with management objectives, and that parameters which are only indirectly linked should have low (or zero) EVPXI. Our analyses are not sufficient to observe such a phenomenon, since the networks are very small and most parameters directly link actions with objectives.

Our results can also be framed in terms of the primary versus secondary impacts of policy—we find that the primary effects of policy should be given first research priority. This finding is at odds with recent research in the field of economics, which has focused on the secondary impacts of policies, for example, the 'rebound effect' in energy markets and 'equilibrium sorting' models in housing markets (Herring & Roy, 2007; Kuminoff, Smith, & Timmins, 2013). Our result has further relevance for policy decisions, as technological and logistical constraints will limit managers' ability to change their actions in the short term (Cundiff, Fike, Parrish, & Alwang, 2009) whereas policy priorities (objectives) are often subject to greater short-term variability (Rodríguez et al., 2006).

On average, we find that the interactions in SES networks are relatively unimportant because they represent secondary processes. Our findings are at odds with the perceived importance of 'influence' in social network analysis, as a specific component of 'social capital' (Lin, 1999). In our analysis, influence (social interaction,  $I$ ) is always secondary in importance to  $q$ , which determines how likely a social group is to engage in environmental management. Although our model captures the essential elements of a connected SES, it is possible that the simple four-node geometry undervalues the importance of connections. In particular, large interaction networks can exhibit highly nonlinear dynamics that our model may not capture, such as the percolation threshold observed in complex networks (Newman & Watts, 1999). Such dynamics could dramatically increase the value of information associated with interactions, or with specific parts of the interaction network. However, our results suggest that, on average, information on interactions would still be less important than information on nodes. The value of information reflects its ability to alter management decisions. Because management will generally alter the characteristics of the nodes, rather than interactions,

events at the first node will still have to occur for the large number of interactions to matter. Moreover, unless we assume interactions are all the same strength (a strong assumption), each must be learned about separately. Therefore, while collectively interactions may be important, individually they may remain of secondary importance—even in complex networks.

The lessons from our results can be generalised to other managed and uncertain SES. We summarise these lessons as a standard assessment for managers to follow to determine the uncertain SES component with the highest expected impact for management outcomes. First, managers should determine the structure of their SES, by identifying social and ecological nodes. Second, they should identify the qualitative nature of the network, by determining which nodes are linked, but not the strength of those interactions. Third, they should identify the actions available to them (the managers) to intervene in the SES. From these steps, managers will be able to identify the SES components that are closest to the management action(s), and it is these nodes and interactions that should receive priority research attention. This standardised assessment will be most relevant in cases with 'simple' SES structures, e.g. systems with limited nodes and interactions. We limited our analysis to a tractably small SES because multi-dimensional value of information analysis is computationally intensive; our current analysis is already five-dimensional. However, the general interpretation of our results can be extrapolated to inform EVPXI in larger systems without the need for a formal value of information analysis—if managers can determine their available management actions and key system nodes. In the case of more complex SES, inferences about the EVPXI of system components may still be possible using motifs (Milo et al., 2002). If managers can identify dominant motifs in their SES, these motifs could form the basis of an EVPXI assessment.

In our analysis we estimated EVPXI. As with previous analyses (Costello et al., 2010; Johnson, Jensen, Madsen, & Williams, 2014; Runge et al., 2011), we focus on the benefits of additional information, rather than the costs of acquiring that information (but see Essington, Sanchirico, & Baskett, 2018). However, for environmental managers to make an informed decision regarding which uncertain component to investigate further, the relative costs of acquiring different types of information must be considered. These costs may include financial or time costs associated with gathering sample data. Other relevant factors that may increase overall cost include sampling feasibility, the level of expertise required to sample, and the reliability or reproducibility of sampling. These costs can be easily incorporated into the existing analysis by proportionally diminishing the EVPXI of information that is more expensive to collect. Alternatively, it is possible to calculate the expected value of partial sample information, which calculates the benefits of acquiring imperfect information on each model component.

In our EVPXI analysis, we assume a uniform prior distribution for all uncertain system components. This assumption implies managers know nothing about the components or structure of the system and allows us to imitate complete uncertainty. However, this approach may overstate the amount of uncertainty typically present in an

SES, as decision makers may have more information about some SES elements and less about others. It is also possible that uncertainty may be endogenous with respect to SES structure (i.e. the motif). For example, if managers are intervening in the social system, they may have more information about social system elements: reducing the EVPXI for social parameters. This indicates that the more that is known about a given SES, the more nuance is required when assessing EVPXI. Future efforts should test the impact on management outcomes of uncertain SES components in situations where informative priors are available. Priors could be elicited in a workshop context to capture expert's knowledge. Coupled with a sensitivity analysis, this approach would allow analysts to study the influence of prior information on the expected value of information. Alternatively, informative priors could be incorporated through the use of motifs (Bodin & Tengö, 2012; Milo et al., 2002). As described previously, motifs can be considered the basic building blocks of a network. However, it is worth noting that the relevance of any single motif may be limited, since its contribution to the overall dynamics will be moderated by its interactions with the broader SES network.

We show that to improve environmental management, research should systematically focus on improving understanding of the uncertain SES component that is most directly affected by management actions. Contrary to the assumptions of different subfields of environmental management, the value of information is not intrinsic to the character (social or ecological) of system nodes or interactions. Similarly, in contrast with the orthodoxy of structured decision-making, value of information is not related to management objectives. Thus, our results show that when managers are undertaking social actions (e.g., engaging with fishers to increase stock levels in a fishery) their highest research priority should be understanding the dynamics of social groups. Alternatively, when manipulating ecological systems (e.g., controlling invasive species), it will be most important to understand the dynamics of ecological populations. Our insights provide fundamental and practical decision support for addressing ever-present uncertainty that impedes effective environmental decision making worldwide.

## ACKNOWLEDGEMENTS

This research was conducted by the Australian Research Council Centre of Excellence for Environmental Decisions (CEED) (CE11001000104) and funded by the Australian Government. The authors would like to acknowledge the Commonwealth Scientific and Industrial Research Organisation (CSIRO); participants of the Australian Research Council CEED Social Network Analysis workshop; and a CSIRO Julius Career Award (IC).

## AUTHORS' CONTRIBUTIONS

All authors conceived the ideas for the study. M.B., K.J.D. and I.C., developed the model; K.J.D. carried out all analyses and wrote the paper. All authors contributed to the interpretation of results and writing and gave final approval for publication.

## DATA AVAILABILITY STATEMENT

Model code available via the Dryad Digital Repository <https://doi.org/10.5061/dryad.9nq5c8d> (Davis, Chadès, Rhodes, & Bode, 2019).

## ORCID

Katrina J. Davis  <https://orcid.org/0000-0002-6982-9381>

Iadine Chadès  <https://orcid.org/0000-0002-7442-2850>

Jonathan R. Rhodes  <https://orcid.org/0000-0001-6746-7412>

Michael Bode  <https://orcid.org/0000-0002-5886-4421>

## REFERENCES

- Aprahamian, M. W., Martin Smith, K., McGinnity, P., McKelvey, S., & Taylor, J. (2003). Restocking of salmonids—opportunities and limitations. *Fisheries Research*, 62, 211–227. [https://doi.org/10.1016/S0165-7836\(02\)00163-7](https://doi.org/10.1016/S0165-7836(02)00163-7)
- Baggio, J. A., & Hillis, V. (2018). Managing ecological disturbances: Learning and the structure of social-ecological networks. *Environmental Modelling & Software*, 109, 32–40. <https://doi.org/10.1016/j.envsoft.2018.08.002>
- Barnes, M. L., Lynham, J., Kalberg, K., & Leung, P. (2016). Social networks and environmental outcomes. *Proceedings of the National Academy of Sciences of the United States of America*, 113, 6466–6471. <https://doi.org/10.1073/pnas.1523245113>
- Bodin, Ö. (2017). Collaborative environmental governance: Achieving collective action in social-ecological systems. *Science*, 357(6352), eaan1114. <https://doi.org/10.1126/science.aan1114>
- Bodin, Ö., & Tengö, M. (2012). Disentangling intangible social-ecological systems. *Global Environmental Change*, 22, 430–439. <https://doi.org/10.1016/j.gloenvcha.2012.01.005>
- Canessa, S., Guillera-Aroita, G., Lahoz-Monfort, J. J., Southwell, D. M., Armstrong, D. P., Chadès, I., ... Converse, S. J. (2015). When do we need more data? A primer on calculating the value of information for applied ecologists. *Methods in Ecology and Evolution*, 6, 1219–1228. <https://doi.org/10.1111/2041-210X.12423>
- Castilla, J. C., & Defeo, O. (2001). Latin American benthic shellfisheries: Emphasis on co-management and experimental practices. *Reviews in Fish Biology and Fisheries*, 11, 1–30.
- Chadès, I., Martin, T. G., Nicol, S., Burgman, M. A., Possingham, H. P., & Buckley, Y. M. (2011). General rules for managing and surveying networks of pests, diseases, and endangered species. *Proceedings of the National Academy of Sciences of the United States of America*, 108, 8323–8328. <https://doi.org/10.1073/pnas.1016846108>
- Chopra, K. (1993). The value of non-timber forest products: An estimation for tropical deciduous forests in India. *Economic Botany*, 47, 251–257. <https://doi.org/10.1007/BF02862291>
- Christie, P. (2004). Marine protected areas as biological successes and social failures in Southeast Asia. *American Fisheries Society Symposium*, 42, 155–164.
- Clarke, G. M. (1995). Relationships between developmental stability and fitness: Application for conservation biology. *Conservation Biology*, 9, 18–24. <https://doi.org/10.1046/j.1523-1739.1995.09010018.x>
- Costello, C., Rassweiler, A., Siegel, D., De Leo, G., Micheli, F., & Rosenberg, A. (2010). The value of spatial information in MPA network design. *Proceedings of the National Academy of Sciences of the United States of America*, 107, 18294–18299. <https://doi.org/10.1073/pnas.0908057107>
- Cundiff, J. S., Fike, J. H., Parrish, D. J., & Alwang, J. (2009). Logistic constraints in developing dedicated large-scale bioenergy systems in the southeastern United States. *Journal of Environmental Engineering*, 135, 1086–1096. [https://doi.org/10.1061/\(ASCE\)EE.1943-7870.0000123](https://doi.org/10.1061/(ASCE)EE.1943-7870.0000123)
- Davis, K. J., Chadès, I., Rhodes, J. R., & Bode, M. (2019). Data from: General rules for environmental management to prioritise social-ecological systems research based on a value of information approach. *Dryad Digital Repository*, <https://doi.org/10.5061/dryad.9nq5c8d>
- Dickman, A. J. (2010). Complexities of conflict: The importance of considering social factors for effectively resolving human-wildlife conflict. *Animal Conservation*, 13, 458–466. <https://doi.org/10.1111/j.1469-1795.2010.00368.x>
- Dorfman, R. (1979). A formula for the Gini coefficient. *The Review of Economics and Statistics*, 61, 146–149. <https://doi.org/10.2307/1924845>
- Essington, T. E., Sanchirico, J. N., & Baskett, M. L. (2018). Economic value of ecological information in ecosystem-based natural resource management depends on exploitation history. *Proceedings of the National Academy of Sciences of the United States of America*, 115(7), 1658–1663. <https://doi.org/10.1073/pnas.1716858115>
- Fahrig, L., & Merriam, G. (1994). Conservation of fragmented populations. *Conservation Biology*, 8, 50–59. <https://doi.org/10.1046/j.1523-1739.1994.08010050.x>
- Ferraro, P. J., & Kiss, A. (2002). Direct payments to conserve biodiversity. *Science*, 298, 1718–1719.
- Gill, D. A., Mascia, M. B., Ahmadi, G. N., Glew, L., Lester, S. E., Barnes, M., ... Fox, H. E. (2017). Capacity shortfalls hinder the performance of marine protected areas globally. *Nature*, 543, 665–669. <https://doi.org/10.1038/nature21708>
- Grantham, H. S., Moilanen, A., Wilson, K. A., Pressey, R. L., Rebelo, T. G., & Possingham, H. P. (2008). Diminishing return on investment for biodiversity data in conservation planning. *Conservation Letters*, 1, 190–198. <https://doi.org/10.1111/j.1755-263X.2008.00029.x>
- Grantham, H. S., Wilson, K. A., Moilanen, A., Rebelo, T., & Possingham, H. P. (2009). Delaying conservation actions for improved knowledge: How long should we wait? *Ecology Letters*, 12, 293–301. <https://doi.org/10.1111/j.1461-0248.2009.01287.x>
- Herring, H., & Roy, R. (2007). Technological innovation, energy efficient design and the rebound effect. *Technovation*, 27, 194–203. <https://doi.org/10.1016/j.technovation.2006.11.004>
- Jellinek, S., Parris, K. M., McCarthy, M., Wintle, B., & Driscoll, D. (2014). Reptiles in restored agricultural landscapes: The value of linear strips, patches and habitat condition. *Animal Conservation*, 17, 544–554. <https://doi.org/10.1111/acv.12121>
- Johnson, F. A., Jensen, G. H., Madsen, J., & Williams, B. K. (2014). Uncertainty, robustness, and the value of information in managing an expanding Arctic goose population. *Ecological Modelling*, 273, 186–199. <https://doi.org/10.1016/j.ecolmodel.2013.10.031>
- Kuminoff, N. V., Smith, V. K., & Timmins, C. (2013). The new economics of equilibrium sorting and policy evaluation using housing markets. *Journal of Economic Literature*, 51, 1007–1062. <https://doi.org/10.1257/jel.51.4.1007>
- Lenzen, M., Moran, D., Kanemoto, K., Foran, B., Lobefaro, L., & Geschke, A. (2012). International trade drives biodiversity threats in developing nations. *Nature*, 486, 109–112. <https://doi.org/10.1038/nature11145>
- Leseberg, N. (nd). Conservation of the Night Parrot. (ed. Threatened Species Recovery Hub). National Environmental Science Program.
- Li, S.-L., Bjørnstad, O. N., Ferrari, M. J., Mummah, R., Runge, M. C., Fonnesbeck, C. J., ... Shea, K. (2017). Essential information: Uncertainty and optimal control of Ebola outbreaks. *Proceedings of the National Academy of Sciences of the United States of America*, 144, 5659–5664. <https://doi.org/10.1073/pnas.1617482114>
- Lin, N. (1999). Building a network theory of social capital. *Connections*, 22, 28–51.
- Liu, J., Dietz, T., Carpenter, S. R., Alberti, M., Folke, C., Moran, E., ... Taylor, W. W. (2007). Complexity of coupled human and natural systems. *Science*, 317, 1513–1516. <https://doi.org/10.1126/science.1144004>

- Marín, A., & Berkes, F. (2010). Network approach for understanding small-scale fisheries governance: The case of the Chilean coastal co-management system. *Marine Policy*, 34, 851–858. <https://doi.org/10.1016/j.marpol.2010.01.007>
- Martin, J., Runge, M. C., Nichols, J. D., Lubow, B. C., & Kendall, W. L. (2009). Structured decision making as a conceptual framework to identify thresholds for conservation and management. *Ecological Applications*, 19, 1079–1090. <https://doi.org/10.1890/08-0255.1>
- Mascia, M. B., Brosius, J. P., Dobson, T. A., Forbes, B. C., Horowitz, L., McKean, M. A., & Turner, N. J. (2003). Conservation and the social sciences. *Conservation Biology*, 17, 649–650. <https://doi.org/10.1046/j.1523-1739.2003.01738.x>
- McRae, B. H., Dickson, B. G., Keitt, T. H., & Shah, V. B. (2008). Using circuit theory to model connectivity in ecology, evolution, and conservation. *Ecology*, 89, 2712–2724. <https://doi.org/10.1890/07-1861.1>
- Milo, R., Shen-Orr, S., Itzkovitz, S., Kashtan, N., Chklovskii, D., & Alon, U. (2002). Network motifs: Simple building blocks of complex networks. *Science*, 298, 824–827. <https://doi.org/10.1126/science.298.5594.824>
- Ndangalasi, H. J., Bitariho, R., & Dovie, D. B. K. (2007). Harvesting of non-timber forest products and implications for conservation in two montane forests of East Africa. *Biological Conservation*, 134, 242–250. <https://doi.org/10.1016/j.biocon.2006.06.020>
- Newman, M. E. J., & Watts, D. J. (1999). Scaling and percolation in the small-world network model. *Physical Review E*, 60, 7332–7342. <https://doi.org/10.1103/PhysRevE.60.7332>
- Noss, R. F. (1990). Indicators for monitoring biodiversity: A hierarchical approach. *Conservation Biology*, 4, 355–364. <https://doi.org/10.1111/j.1523-1739.1990.tb00309.x>
- Ostrom, E., Burger, J., Field, C. B., Norgaard, R. B., & Policansky, D. (1999). Revisiting the commons: Local lessons, global challenges. *Science*, 284, 278–282. <https://doi.org/10.1126/science.284.5412.278>
- Pannell, D. J., Marshall, G. R., Barr, N., Curtis, A., Vanclay, F., & Wilkinson, R. (2006). Understanding and promoting adoption of conservation practices by rural landholders. *Australian Journal of Experimental Agriculture*, 46, 1407–1424. <https://doi.org/10.1071/EA05037>
- Parsa, S., Morse, S., Bonifacio, A., Chancellor, T. C. B., Condori, B., Crespo-Pérez, V., ... Dangles, O. (2014). Obstacles to integrated pest management adoption in developing countries. *Proceedings of the National Academy of Sciences of the United States of America*, 111, 3889–3894. <https://doi.org/10.1073/pnas.1312693111>
- Pulliam, H. R. (1988). Sources, sinks, and population regulation. *The American Naturalist*, 132, 652–661. <https://doi.org/10.1086/284880>
- Punt, A. E., Smith, A. D. M., Smith, D. C., Tuck, G. N., & Klaer, N. L. (2014). Selecting relative abundance proxies for BMSY and BMEY. *ICES Journal of Marine Science*, 71, 469–483. <https://doi.org/10.1093/icesjms/fst162>
- Pyke, G. H., & Ehrlich, P. R. (2014). Conservation and the Holy Grail: The story of the night parrot. *Pacific Conservation Biology*, 20, 221–226. <https://doi.org/10.1071/PC140221>
- Raiffa, H., & Schlaifer, R. (1961). *Applied statistical decision theory*. Boston, MA: Division of Research, Graduate School of Business Administration, Harvard University.
- Ritter, J. A. (1997). The contribution of Atlantic salmon (*Salmo salar* L.) enhancement to a sustainable resource. *ICES Journal of Marine Science*, 54, 1177–1187. [https://doi.org/10.1016/S1054-3139\(97\)80025-2](https://doi.org/10.1016/S1054-3139(97)80025-2)
- Rodríguez, J., Beard, T. D. Jr, Bennett, E., Cumming, G., Cork, S., Agard, J., ... Peterson, G. (2006). Trade-offs across space, time, and ecosystem services. *Ecology and Society*, 11(1), 28. <https://doi.org/10.5751/ES-01667-110128>
- Runge, M. C., Converse, S. J., & Lyons, J. E. (2011). Which uncertainty? Using expert elicitation and expected value of information to design an adaptive program. *Biological Conservation*, 144, 1214–1223. <https://doi.org/10.1016/j.biocon.2010.12.020>
- Sanchirico, J. N., & Wilen, J. E. (1999). Bioeconomics of spatial exploitation in a patchy environment. *Journal of Environmental Economics and Management*, 37, 129–150. <https://doi.org/10.1006/jeem.1998.1060>
- Silverstein, R. M. (1981). Pheromones: Background and potential for use in insect pest control. *Science*, 213, 1326–1332. <https://doi.org/10.1126/science.213.4514.1326>
- Simberloff, D. (2003). How much information on population biology is needed to manage introduced species? *Conservation Biology*, 17, 83–92. <https://doi.org/10.1046/j.1523-1739.2003.02028.x>
- Thomas, M. B. (1999). Ecological approaches and the development of “truly integrated” pest management. *Proceedings of the National Academy of Sciences of the United States of America*, 96, 5944–5951. <https://doi.org/10.1073/pnas.96.11.5944>
- Ticktin, T. (2004). The ecological implications of harvesting non-timber forest products. *Journal of Applied Ecology*, 41, 11–21. <https://doi.org/10.1111/j.1365-2664.2004.00859.x>
- Tringali, M. D., Leber, K. M., Halstead, W. G., McMichael, R., O'Hop, J., Winner, B., ... Barbieri, L. (2008). Marine stock enhancement in Florida: A multi-disciplinary, stakeholder-supported, accountability-based approach. *Reviews in Fisheries Science*, 16, 51–57. <https://doi.org/10.1080/10641260701776902>
- Urban, D., & Keitt, T. (2001). Landscape connectivity: A graph-theoretic perspective. *Ecology*, 82, 1205–1218. [https://doi.org/10.1890/0012-9658\(2001\)082\[1205:LCAGTP\]2.0.CO;2](https://doi.org/10.1890/0012-9658(2001)082[1205:LCAGTP]2.0.CO;2)
- Waldron, A., Mooers, A. O., Miller, D. C., Nibbelink, N., Redding, D., Kuhn, T. S., ... Gittleman, J. L. (2013). Targeting global conservation funding to limit immediate biodiversity declines. *Proceedings of the National Academy of Sciences of the United States of America*, 110, 12144–12148. <https://doi.org/10.1073/pnas.1221370110>
- Ward, R. D. (2006). The importance of identifying spatial population structure in restocking and stock enhancement programmes. *Fisheries Research*, 80, 9–18. <https://doi.org/10.1016/j.fishres.2006.03.009>
- Wilen, J. E., Cancino, J., & Uchida, H. (2012). The economics of territorial use rights fisheries, or TURFs. *Review of Environmental Economics and Policy*, 6, 237–257. <https://doi.org/10.1093/reep/res012>
- Wolch, J. R., & Emel, J. (1998). *Animal geographies: Place, politics, and identity in the nature-culture borderlands*. London: Verso.
- Yamamoto, T. (1995). Development of a community-based fishery management system in Japan. *Marine Resource Economics*, 10, 21–34. <https://doi.org/10.1086/mre.10.1.42629097>
- Yet, B., Constantinou, A., Fenton, N., & Neil, M. (2018). Expected value of partial perfect information in hybrid models using dynamic discretization. *IEEE Access*, 6, 7802–7817. <https://doi.org/10.1109/ACCESS.2018.2799527>
- Yokota, F., & Thompson, K. M. (2004). Value of information literature analysis: A review of applications in health risk management. *Medical Decision Making*, 24, 287–298. <https://doi.org/10.1177/0272989X04263157>

## SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

**How to cite this article:** Davis KJ, Chadès I, Rhodes JR, Bode M. General rules for environmental management to prioritise social ecological systems research based on a value of information approach. *J Appl Ecol*. 2019;56:2079–2090. <https://doi.org/10.1111/1365-2664.13425>