Uncertainty and the Management of Multi-state Ecosystems: An Apparently Rational Route to Collapse

Running Head: rational route to collapse

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Abstract. We use a simple model of ecosystem management to demonstrate that apparently rational management approaches can lead to ecological collapse. Our model of the ecosystem management of lake eutrophication integrates lake dynamics, management decision-making, and learning in a framework that is deliberately simplified to highlight the role of model uncertainty. The simulated lake can switch between alternate eutrophic and oligotrophic states. Managers consider two management models of the lake, one for an oligotrophic lake and the other for a eutrophic lake. As managers observe the lake varying from year to year, they estimate how well each of the two management models is supported by the observed data. Management policies maximize the expected net present value of the lake. Even under optimistic assumptions about environmental variation, learning ability, and management control, conventional decision theory and optimal control approaches fail to stabilize ecological dynamics. Rather, these methods drive ecosystems into cycles of collapse and recovery. We suggest how scientists could help prevent ecosystem management from driving ecosystems towards collapse.

Ecosystem management has a long and diverse history. It has sometimes been successful (Berkes and Folke 1998), and sometimes not. For example, historical societies, such as the Maya (Hodell et al. 2001), and modern scientifically managed resource extraction systems, such as the Northern cod (Walters and Maguire 1996), have appeared to succeed at ecosystem management until an abrupt and surprising collapse. Researchers have tried to explain these collapses. Some researchers attribute ecological collapse to ignorance of gradual ecological change (Martin 1973, Alroy 2001), rational overexploitation (Clark 1973), or the difficulties of creating effective institutions to manage common pool resources (Hardin 1968). Others focus on the role of social inequality and greed (Blaikie and Brookfield 1987). Although few people would argue that resource collapses derive from single causes, we believe that downplaying the uncertainty of management models may be a neglected cause of ecological collapse.

A large portion of ecological management involves decision making under conditions of uncertainty. Current approaches to ecosystem management often cope with uncertainty by fitting models to data, or using data to compare competing models (Hilborn and Mangel 1997, Clark et al. 2001). In some ecological conflicts, the management of salmon in the Columbia River for example, ecological management has focused on expensive and sophisticated attempts to assess the credibility of a wide variety of alternate models of ecosystem functioning (Marmorek and Peters 2001). The aim is to discover which model or set of models appears to best forecast the future behavior of the ecosystem. Although such efforts are certainly worthwhile, there may be pressure for science to act as a dispassionate tool to assess the relative validity of a selected set of alternative models. Too often the consideration of uncertainty focuses only upon the prediction errors of a single model while the credibility of the model itself is not assessed (Clark et al. 2001). The credibility of a given model depends on the other models with which it is compared and on the data available for comparing models. If the data represent only a subset of the potential behavior of the ecosystem, then the model comparison may be biased, or the appropriate model may not even be discovered, because the behaviors of the ecosystem relevant to the appropriate model have not been observed. If an important model is omitted from the set of models under consideration, substantial errors can occur in assessing the credibility of models, making predictions, and choosing management actions. Thus, model uncertainty has critical implications for ecosystem management, but the assessment of model uncertainty is limited by the range of ecosystem behaviors observed in the data, and by the diversity of models created by the analyst.

In this paper, we show that when the family of models being considered does not adequately capture key dynamics, even sophisticated management approaches will function poorly. We model a management process that uses passive adaptive management to select policies. Passive adaptive management is thought to be the best management practice when active adaptive management experiments are not possible (Walters 1986). In this case, passive adaptive management chooses policies based on the posterior probabilities of two competing models given observed data. We focus on model misspecification by allowing the managers to know, with precision, the model parameters and the state of nature.

RATIONALE

Case studies and detailed simulation models provide insight into the diversity of ecosystem management approaches that have been applied in different situations. However, the complexity of the examples and the multiple interacting sources of variation in each situation make it difficult to isolate the role of uncertainty in a clear way. Therefore, we have created an exceptionally simple socio-ecological model of ecosystem management that isolates the role of model uncertainty.

Our model greatly simplifies the dynamics of the ecosystem, the information available to managers, and the impact of management interventions, in order to focus attention on model uncertainty, its interaction with decision making, and its implications for ecosystem dynamics. We use linear equations to describe lake dynamics, providing access to useful analytical simplifications. Ecologists have often introduced highly simplified models to isolate the role of particular processes, such as the logistic model to study density dependence. Although the logistic model exposes useful insights about density dependence, one would not use it to predict or manage a population with complex age and spatial structure, and subjected to multiple limiting factors. Similarly, our model would not be used to predict ecosystem management in situations where ecological dynamics contain multiple feedback loops and are driven by complex external events or when ecological policies are determined by the interplay of a diversity of interacting institutions. In our model, dynamics cannot be explained by such ecological or social complexities because they are omitted. Instead, the model allows us to focus specifically on the role of model uncertainty in the dynamics of a managed ecosystem. We will show that the dynamics of model choice from a limited set of alternatives lead to cycles of collapse and recovery.

To investigate the dynamics of ecosystem management we use the problem of lake eutrophication. Lakes can exist in either an oligotrophic or eutrophic state (Scheffer et al. 1993, Smith 1998). Oligotrophic lakes are characterized by low nutrient inputs, low to moderate levels of plant production, and relatively clear water. Eutrophic lakes have high nutrient inputs, high plant production, and murky water. They can also be anoxic and produce blooms of toxic algae. People usually find that oligotrophic lakes produce ecosystem services, such as water for human consumption, irrigation, or industrial use, resources such as fish or waterfowl, or recreation, that are more valuable than those produced by eutrophic lakes (Wilson and Carpenter 1999).

Eutrophication is usually caused by the excessive input of nutrients, primarily phosphorus (P) to a lake (Schindler 1977). Many types of human activities produce nutrients, but agricultural fertilizers are a chief source (Carpenter et al. 1998b). Phosphorus in fertilizer builds up in soil that erodes into water bodies and causes eutrophication (Bennett et al. 2001).

Agricultural production depends upon the use of fertilizer. Because fertilizer increases the value of agriculture while decreasing the value of ecosystem services, there is a tradeoff between the benefits from polluting activities and the costs these activities impose on ecosystem services. Phosphorus recycling within a lake can maintain a eutrophic state. Recycling exhibits threshold behavior that is related to the accumulation of P in sediments, wind mixing, and the oxygen content of deep water (Carpenter et al. 1998a). Experimental lake manipulations have shown that only a few years of high P levels can lead to the accumulation of enough P in the sediment to initiate P recycling (Schindler et al. 1987). In eutrophic lakes, the amount of P recycled from lake sediments may exceed annual inputs (Soranno et al. 1997). The ease with which a eutrophic lake can return to an oligotrophic state following a reduction of nutrient inputs depends upon properties of the lake such as area, depth, food web structure, submerged vegetation, and the concentration of P in lake sediments. Some eutrophic lakes quickly return to an oligotrophic state following the cessation of nutrient addition, while others do not (Scheffer et al. 1993, Carpenter et al. 1998a).

A MINIMAL MODEL

Our model of ecosystem management consists of a model of lake dynamics, a learning process, and a management decision making process (Fig. 1). Lake P dynamics can produce eutrophic or oligotrophic states. Managers have two competing management models of the lake. Their degree of belief in each of these models determines their expectation of the lake's response to management. Lake management is based upon maximizing the expected value of a tradeoff between lake pollution and lake ecosystem services. Each year, scientists collect data and update their beliefs about their management models. The details of the lake, learning, and management components of our ecosystem management model are presented below.

[Insert Fig. 1 Near Here]

<u>Lake dynamics</u>

We represent the state of a lake by the concentration of P. We assume that the dynamics of P within a lake depends upon the loading of P, P removal, and P recycling. The P dynamics in a lake are modeled by the difference equation

<1> $$X_{t+1} = B * X_t + b + l_t + S_t \quad \text{if } X_t < X_{crit} \text{ and}$$

$$X_{t+1} = B * X_t + r + b + l_t + S_t \quad \text{if } X_t \geq X_{crit}$$

$$S_t \sim N(0, \sigma^2)$$

Where X_t represents the concentration of P at time t, b is the baseline natural P loading into the lake, l_t is the additional anthropogenic P loading into the lake at time t, and r is the amount of P recycled and maintained in the lake. B represents the proportion of P that is retained in the lake after one year. X_{crit} is the critical P concentration at which P recycling begins. S_t is a random variation in P loading at time t drawn from a normal distribution with mean 0 and standard deviation σ.

The proportion of P retained by the lake (B) must be between 0 and 1. Both the base (b) and the anthropogenic loading (l_t) must be equal to or greater than zero. Furthermore, for cultural eutrophication to occur the value of X_{crit} must exceed b.

Over a wide range of parameters and P loadings, lake dynamics can exhibit two alternate equilibrium values of X. The following equilibrium points (X_1^*, X_2^*) are found by letting $X_{t+1} = X_t$:

<2> $$X_1^* = \frac{b+l}{1-B} \text{ if } X_1^* < X_{crit} \text{ and } X_2^* = \frac{r+b+l}{1-B} \text{ if } X_2^* > X_{crit}$$

If $X_1^* < X_{crit}$ an oligotrophic equilibrium exists, and if $X_2^* > X_{crit}$ a eutrophic equilibrium also exists. Because the equilibrium value of X depends upon the P loading, changes in P loading can cause equilibrium point to appear or disappear (Fig. 2). This response to changes in P loading can cause surprising changes in lake behavior.

[Insert Fig. 2 Near Here]

Learning:

Managers have two alternative models of the lake. Managers have some degree of belief that the lake is either oligotrophic <3> or eutrophic <4>, but management is uncertain about which of these management models is more accurate.

<3> Model 1: $$X_{t+1} = B * X_t + b + l_t + S_t$$

<4> Model 2: $$X_{t+1} = B * X_t + r + b + l_t + S_t$$

Model 1 corresponds to the belief that P loading drives lake P dynamics. Model 2 corresponds to the belief that P recycling and P loading drive lake P dynamics. For a given P loading, the eutrophic model (Model 2) predicts a higher observed concentration of P in the lake than the oligotrophic model. Each of these models accurately describes lake dynamics under a range of conditions (Model 1 is correct when $X < X_{crit}$, while Model 2 is correct when $X \geq X_{crit}$). However, managers are unaware that recycling is a function of P concentration.

To focus our analysis on model uncertainty, we allow managers to know correctly and precisely the rate of nutrient retention (B), natural P load (b), the amount of P recycling (r), and the probability distribution of shocks (S). This assumption provides the managers with more information than they would likely have in reality. This simplification places all management uncertainty on the choice between models <3> and <4>. Managers attempt to maximize the utility of the lake by controlling P loading to the lake. Using passive adaptive management, the managers attempt to improve their management by updating their relative belief in these competing models. Each simulated year managers test Model 1 and Model 2 against the lake's observed behavior. Because they are limited to two models they believe Model 1 with probability p_1 and Model 2 with probability p_2, where $p_1 + p_2 = 1$. This type of management action corresponds to management that compares existing models of nature rather than creating new models.

The likelihood kernel of a model given a single observation at time t can be calculated as

<5> $$L_{1,t} = \exp\left[-\frac{\left(X_{t,m1} - X_{t,obs}\right)^2}{\sigma^2}\right] \text{ and } L_{2,t} = \exp\left[-\frac{\left(X_{t,m2} - X_{t,obs}\right)^2}{\sigma^2}\right]$$

where $X_{t,m1}$ is the value of X at time t predicted by Model 1 at time $t-1$, and $X_{t,m2}$ is the same for Model 2. These likelihood kernels can be used to update the posterior probability of each model, using Bayes' rule (Walters and Ludwig 1994):

<6> $$p_{1,t} = \frac{p_{1,t-1}L_{1,t}}{p_{1,t-1}L_{1,t} + p_{2,t-1}L_{2,t}} \text{ and } p_{2,t} = \frac{p_{2,t-1}L_{2,t}}{p_{1,t-1}L_{1,t} + p_{2,t-1}L_{2,t}}.$$

At each time step equations <5> and <6> are recalculated to update the probability that managers assign to each model based upon their past observations.

<u>Management:</u>

The management aspect of the model assumes that managers value the lake as a source of ecosystem services (e.g. clean water) and as a sink of P pollution <7>.

<7> $U = U_b + U_c$

We assume that the value of the lake as a pollution sink increases linearly with the amount of P loaded into the lake <8>, and that the value of services produced by the lake declines as a quadratic function of lake P concentrations <9>.

<8> $U_b = k_1 l$

<9> $U_c = -k_2 X^2$

Therefore, net utility at time t be rewritten as <10>

<10> $U_t = k\, l_t - X_t^2$ where $k = k_1 / k_2$

This utility function is used for illustrative purposes. The assumption of this simple utility function for the management of an ecosystem ignores differences in values between the different people who have a stake in the lake. Rigorous economic analysis would address the heterogeneous values of different stakeholders as well as the difficult problem of producing a valid measure of aggregate welfare (Deaton and Muellbauer 1980).

The expected utility of a given P loading rate depends upon the management model is used to forecast the lake's P dynamics. Consequently the optimal loading is different for each management model (Fig. 3).

[Insert Fig. 3. Near Here]

Because the managers have two competing models of lake response, expected utility is

<11> $E[U_t] = p_{1,t} E[U_{1,t}] + p_{2,t} E[U_{2,t}]$.

The managers seek to maximize the expected net present value of the lake, which is the summation of future expected utilities discounted by the discount rate 1-δ.

<12> $E[V_t] = \sum_{s=t}^{\infty} \delta^s E[U_s]$.

The optimal loading, *l**, is the time series of P loadings that maximizes the expected net present value of the lake (Appendix A).

<13> $l^* = \frac{k(1-B\delta)}{2\delta} - BX_t - b - rp_{2,t}$

Substituting optimal loading <13> into <3> and <4> with p_2=0 and p_2=1, respectively, yields the expected optimal equilibrium value of X for management model 1 and model 2.

<14> $X^* = \frac{k(1-B\delta)}{2\delta}$

However if <13> is substituted into equation <1> with p_2=0 and p_2=1 there are four possible alternate equilibrium values. Two of these equilibria are the expected optimal value of X for each model <14>, and two are unexpected equilibria values of X. The highest equilibrium value occurs when the lake recycles P, but the managers do not believe that it does (i.e. strong belief in model 1). The lowest equilibrium value occurs when the lake does not recycle P, but managers believe that it probably does (i.e. strong belief in model 2). These unexpected equilibria are given by

<15> $X^*_{m1,r} = X^* + r$, and $X^*_{m2,nr} = X^* - r$

Because P recycling occurs if $X > X_{crit}$, $X^*_{m1,r}$ can only exist if there is P recycling; that is if $X^*_{m1,r} > X_{crit}$. Similarly, $X^*_{m1,r} > X_{crit} > X^*_{m2,nr}$ can only exist if there is no P recycling, which is true when $X^*_{m2,nr} < X_{crit}$. Consequently, there are two alternate stable states if $X^*_{m1,r} > X_{crit} > X^*_{m2,nr}$.

Implementation

Parameters of the model were chosen so that alternate stable states existed and natural P loading was less than X_{crit} (i.e. plausible P loading rates). Furthermore, for ease of presentation, the model was parameterized so that maximum values of X and net utility are less than 1. At a high discount rate (e.g. δ=0.5) the future is not highly valued and managers will sacrifice the future state of the lake for the benefits of disposing of P in the present. Such high discount rates are both uninteresting and atypical. To avoid illustrating the effects of discounting we choose a relatively low discount rate. Parameters chosen for an example model are b=0.02, B= 0.1, r=0.2, X_{crit}= 0.7, σ^2 = 0.02, k=1.5 and δ=0.99. The model was implemented in Microsoft Excel.

RESULTS

The optimal loading chosen by a manager depends upon the degree of belief in each management model. However, because each management model implies a single equilibrium, lake managers can be surprised by the switches between alternate equilibria that occur in the lake. When the lake is managed using Model 1, the expected equilibrium does not exist, and the system will be attracted towards an equilibrium that is higher than expected (Fig. 4a). Similarly, if the managers believe Model 2, a lower optimal loading will be chosen, producing a stable equilibrium, however in this case there is also another lower stable equilibrium (the oligotrophic state) to which a shock can move the ecosystem (Fig. 4b).

[Insert Fig. 4 Near Here]

While changes in belief and loading vary smoothly, changes in utility and lake P are occasionally abrupt providing both positive and negative surprises. This movement between one equilibrium and another results in an aperiodic cycling in belief in different models, lake P concentration, P loading and net utility (Fig. 5).

[Insert Fig. 5 Near Here]

Resilience can be used as an index of the potential for transitions between the oligotrophic and eutrophic states. Resilience can be defined as the amount of change required to shift the lake from one state to another (Holling 1973). Because X_{crit} separates oligotrophic and eutrophic states, the distance between the current state of the lake X_t and X_{crit} can be used as a measure of resilience. Managers are unaware of the resilience of the lake, because they are unaware that P recycling occurs when X_t exceeds X_{crit}. Examining how shifts in P loading and belief in management models alter resilience helps reveals why abrupt transitions between oligotrophic and eutrophic states occur.

Figure 6 shows two different perspectives on the dynamics of the same simulation. In Fig. 6a, as P loading increases, resilience gradually decreases, and then persists at a high utility and low resilience, until a shock causes the lake to shift to a eutrophic state. When the lake shifts to a eutrophic state, utility drops rapidly while the resilience of the eutrophic state increases. In response to the shift to a eutrophic state, managers reduce P loading, which gradually decreases the resilience of the eutrophic state until the lake abruptly reverts to an oligotrophic state and the cycle begins again.

The P loading that managers apply to a lake depends upon what probabilities managers assign to competing models. In Fig 6b, changes in belief in Model 2 (that the lake is eutrophic) are compared to resilience and how well management forecasts the future dynamics of the lake. As belief that the lake is oligotrophic declines, predictions become more accurate, but resilience declines. When the oligotrophic lake becomes eutrophic there is a surprising error in prediction and resilience increases. After several poor predictions, belief in the oligotrophic model declines and model predictions become more accurate. However, as belief in the eutrophic lake further increases, prediction becomes less accurate. This is because there is no stable eutrophic management equilibrium. When the lake switches back to a oligotrophic state its resilience increases. Belief in Model 2 increases temporarily because belief depends upon past observations rather than the current state of the lake. However, once entering the oligotrophic state, belief in the eutrophic model (Model 2) declines rapidly.

[Insert Fig. 6 Near Here]

DISCUSSION

Our model is a simple, transparent parable about rational, scientific management leading to cycles of collapse and renewal for a managed ecosystem. In our model, rational scientific management is represented by a passive adaptive management process in which no effort is made to enlarge the model space. Management actions are rational in the sense that data and competing models is used to make decisions that maximize expected utility. Cycles arise from the dynamics of the beliefs of managers as supported by actual lake behavior. As the weight of evidence builds for a particular management model, policies become fixed and belief in the model fossilizes as no contradictory evidence is gathered. Eventually, a surprise provides new evidence that supports the alternative model, increasing uncertainty, and resulting in changes in policy. Evidence accumulates in support of the alternative model, leading to the fixation of a different policy, until the system produces another surprise. Because management actions depend upon what managers know at a given time and the models that are available to them, even if a system has exhibited cycles in the past, managers will attribute these cycles to some low probability events. Breaking away from these cycles requires creating a new management model of the system that adequately captures the dynamics of the system.

In respect to its information dynamics, our model is related to work in economics that explores learning and its limits. Rational behavior can create chaos in markets (Brock and Hommes 1997) and cyclic behavior in economies (Nyarko 1991). Economists have also explored the adaptive management of simpler systems, in which the system being managed neither evolves dynamically (Easley and Kiefer 1988), nor exhibits alternative stable states (Beck and Wieland, 2002). Future research could be able to extend our work to examine active adaptive ecosystem management.

Our model is an abstraction of the general situation in which a manager must choose input rates to an ecosystem of a substance with unknown persistence, recycling, or transformations. Many ecological processes exhibit time-lagged dynamics, delays in response to intervention, or irreversible change. Examples include carbon dioxide enrichment of the atmosphere, persistent organic pollutants, and heavy metal pollution. Thus, in a general way, we expect that our findings about uncertainty, learning, and ecosystem dynamics would arise in more detailed and realistic models for managing inputs of a wide variety of substances to a wide variety of ecosystems.

The route to collapse shown here provides an alternative to other explanations of ecological collapse including inability to detect gradual change (Martin 1973, Alroy 2001), the tragedy of the commons (Hardin 1968), command and control management (Holling and Meffe 1996), social inequality (Blaikie and Brookfield 1987), or rational overexploitation (Clark 1973). The mechanism demonstrated here is one plausible cause of the cycles seen in more complex models of ecosystem management (Carpenter et al. 1998b, Janssen and Carpenter 1999, Janssen 2001).

The surprises that cause policy shifts in this model are analogous to those seen in many case studies of ecosystem management (Gunderson et al. 1995). For example, cultural eutrophication of lakes in North America, initially recognized following World War II, was a surprise (Hasler 1947), as was the emergence of dead zones and harmful algal blooms as serious environmental problems for coastal oceans (Downing et al. 1999). In these cases, long periods of stasis reinforced the notion that "dilution was the solution to pollution," however this belief was eventually made untenable by surprising and massive changes in receiving waters (Likens 1992). Similarly, surprising collapses in Northern cod (Walters and Maguire 1996) and Peruvian achoveta fisheries (Pitcher and Hart 1982) have been blamed, at least in part, on inadequate models of the fishery. Additionally, and unexpectedly, cod populations have not recovered despite a decade of severely limited fishing (Bundy 2001). The emergence of the ozone hole over Antarctica and of AIDS provide two strikingly different examples of how large-scale social-ecological systems can behave in surprising ways.

By definition, surprises are infrequent events. Most of the time, ecosystem behavior fluctuates around a repeated pattern - it remains within a regime that becomes familiar to scientists and policymakers. Thus, scientific evidence accumulates in support of models that explain ecosystem dynamics within that familiar regime. Policies ultimately become fixed at an apparent optimal point and ecosystem behavior is constrained within a small portion of its actual range. This biased sample of the ecosystem's potential behaviors increases belief in the prevailing model. The solidification of evidence and policy choices around this apparently best model sets the stage for surprise if, and when, ecosystem dynamics shift to a new regime.

There are many ways to avoid the rational route to collapse. They all involve expanding the range of models under consideration. Opening the decision making process to include a more diverse set of stakeholders can increase the set of information and models that can be developed and tested during ecosystem management. More specifically, scientists can contribute to broadening the worldview of ecosystem management in at least three ways. (1) Scientists can point out that uncertainty is a property of the set of models under consideration. This set of models is a mental construct (even if it depends in part on prior observation of the ecosystem). It therefore depends on attitudes and beliefs that are unrelated to putatively objective information about the ecosystem. Despite this discomforting aspect of uncertainty, it cannot be ignored. (2) Scientists can help to imagine novel models for how the system might change in the future. There will be cases where such novel models carry non-negligible weight in decision, for example when the costs of collapse are high. The consequences of candidate policies can be examined under models with very different implications for ecosystem behavior. Such explorations of the robustness of policies can be carried out when model uncertainty is quite high or even unknown, for example in scenario analysis (Wack 1985, van der Heijden

1996, Peterson et al. In Review). (3) Scientists can point out the value of safe, informative experiments to test models beyond the range of available data. In the model presented here, fossilization of beliefs follows from fixation on policies that do not reveal the full dynamic potential of the ecosystem, leading to the underestimation of model uncertainty. Experimentation at scales appropriate for testing alternative models for ecosystem behavior is one way out the trap. Of course, large-scale experiments on ecosystems that support human well-being must be approached with caution. Nevertheless, in situations where surprising and unfavorable ecosystem dynamics are possible, it may be valuable to experiment with innovative practices that could reinforce desirable ecosystem states.

The consideration of diverse models in decision making or in adaptive management is neither easy nor cost-free. In future work we plan to assess these issues by examining how model diversity and active adaptive management influence the success of simulated ecosystem management. However, the experiences of those who have attempted to apply adaptive management suggest that while technical challenges remain nontrivial, the social, economic and political complexities of organizing such schemes are far greater barriers to their implementation (Walters 1997, Marmorek and Peters, 2001). Thus the study of effective institutional designs for ecosystem management is a key area for future research.

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APPENDIX A:

CALCULATION OF THE OPTIMAL LOADING

The optimal loading, l^*, is the time series of P loadings that maximizes the net present value of expected utility

<A.1> $$V = \sum_t \delta^t E[U_t]$$

where the summation is over infinite time t, δ is the annual discount factor, and U_t is given by <10>. Therefore

<A.2> $$V = \sum_t \delta^t E\left[kl_t - X_t^2\right]$$

The expected discounted present value at time t is given by an expression of the form $V_t = k\, l_t - X_t^2 + \delta\, E_t[V_{t+1}]$. This expression will be defined precisely below, given a feedback policy that calculates l_t as a function of X_t and the parameters. This recursion is familiar to behavioral ecologists (Bellman 1957, Mangel and Clark 1988).

At each time step, we have belief probabilities for the two models, $p_{1,t}$ and $p_{2,t}$, where $1 = p_{1,t} + p_{2,t}$. Given these probabilities, we wish to compute the value functions $V_1(X_t)$ and $V_2(X_t)$, and then compute the loading that maximizes the net expected value weighted by belief probabilities for the two models. This loading maximizes the following expression over l_t:

<A.3> $$V_{1,2} = k\, l_t - X_t^2 + \delta\, [p_{1,t}\, V_1(X_{t+1}) + (1-p_{1,t})\, V_2(X_{t+1})]$$

In this paper, we do not address future dynamics of the belief probabilities. This represents passive adaptive management, in which current beliefs are used to choose policy without consideration of possible future changes in beliefs (Walters 1986). Also, we assume that loading can be negative. In a real lake, negative loading corresponds to an intervention that removes phosphorus, such as dredging (Cooke et al. 1993). The assumption that loading can be negative is consistent with our goal of minimizing the model's complexity in order to understand the implications of passive adaptive management. A calculation of optimal loading for a similar model in which loading must be non-negative is presented by Carpenter et al. (1999).

We will compute the optimal policy over the set of policies that jump to a fixed level y in one time step. In the deterministic case, the optimal policy will jump to the optimal level of X in one step (Clark 1990). Our case is stochastic. For a nonlinear stochastic lake model with two stable states, the policy computed by this method is close to optimal (Carpenter et al. 1999) and we assume that the method is adequate for the purposes of this paper.

In this paragraph, we show that y*, the optimal level of X, is the same under both models. The goal is to find y* that will maximize $V(X_t \mid \text{model } i)$. Under a given model i, we then compute the value of l_s that will cause $E_s[X_{s+1} \mid \text{model } i]$ to jump to y* in one step. We will derive y* under model 1 (where the unknown parameter is b), and then show that y* is the same under model 2 (where the unknown parameter is b+r). We begin with the value function, which satisfies the recursion

<A.4> $$V(X_s) = V(y + S_{s+1}) = k\, l_s - X_s^2 + \delta\, E_s[V(y + S_{s+1})]$$

What is l_s given y? In the next few steps, we will calculate the value of l_s that gets $E_s[X_s+1]$ to y in one step, and then compute $E_s[V(y + S_{s+1})]$, and then choose y* to maximize $V(y + S_s)$. From <3>

<A.5> $$X_{s+1} = B\, X_s + l_s + b + S_s$$

Recall that S_s is drawn after l_s is chosen. Take expectations of both sides of <A.5> to calculate l_s

<A.6.> $$l_s = y - B\, X_s - b$$

Define

<A.7> $$W(y) \equiv E_s[V(y + S_{s+1})]$$

Because S_s are identically and independently distributed (IID), W(y) depends only on y.

Because y is a constant target and S_s is IID,

<A.8> $$E_{s-1}[V(X_s)] = E_{s-1}[V(y + S_{s-1})] = W(y)$$

We use <A.8> to take E_{s-1} of both sides of <A.4>, and (using the fact that S is IID) obtain

<A.9> $$W(y) = E_{s-1}[k\, l_s - X_s^2] + \delta\, W(y)$$

By definition $E_{s-1}[S_{s-1}] = 0$ and $E_{s-1}[S_{s-1}^2] = \sigma^2$. Consequently

<A.10> $$E_{s-1}[k\, l_s - X_s^2] = E_{s-1}[k(y - B(y + S_{s-1}) - b) - (y + S_{s-1})^2)]$$

<A.11> $$E_{s-1}[k\, l_s - X_s^2] = k(y - B\, y - b) - (y^2 + \sigma^2)$$

Using <A.11> we get from <A.9>

<A.12> $$W(y) = k(y - B\, y - b) - (y^2 + \sigma^2) + \delta\, W(y)$$

<A.13> $$W(y) = [1 / (1 - \delta)]\, [\, k(y - B\, y - b) - (y^2 + \sigma^2)\,]$$

Now the optimal y is found by choosing y* to maximize

<A.14> $$V(X_s) = V(y + S_s) = k\, l_s - X_s^2 + [\delta / (1 - \delta)]\, [\, k(y - B\, y - b) - (y^2 + \sigma^2)\,]$$

with $l_t = y - B\, X_t - b$. Differentiate <A.14> with respect to y and solve for y* to find

<A.15> $$y^* = k\, (1 - B\, \delta) / 2\, \delta$$

Note that we get exactly the same expression for y* if we replace b with b+r in the preceding argument. Therefore the choice of the optimal target y* is the same under both models. Of course, the optimal load l^* is different under the two models, because under model 1 $l^*_t = y^* - B\, X_t - b$ and under model 2 $l^*_t = y^* - B\, X_t - (b + r)$. W(y) also depends on the choice of model (because under model 2, b in <A.13> is replaced by b+r).

Now we use the insights obtained above to compute the optimal load l^* in the case where we have nonzero belief probabilities about the two models. Under the first model

<A.16> $$V_1(X_t) = k(y^* - B\, X_t - b) + \delta\, W_1(y^*)$$

where W_1 denotes W calculated under model 1 (i.e. with r=0). Under the second model

<A.17> $$V_2(X_t) = k[y^* - B\, X_t - (b + r)] + \delta\, W_2(y^*)$$

Equations <A.16> and <A.17> are used in <A.3> to find the expression that will be maximized to find l_t. The value function is iterated one time step to find the terms that involve X_{t+1} and are impacted by l_t. Each value from time t+2 onward is computed by assuming that each successive l_s is chosen to move $E_s[X_{s+1}]$ to y*, and y* is the same under both models. Therefore, none of these terms at t+2 and beyond depends on l_t. When we take the expectations of terms involving X_{t+1}, discard terms that do not involve l_t, differentiate with respect to l_t, and solve for l_t we find

<A.18> $$l^*_t = y^* - [B\, X_t + b + r\, p_{2,t}]$$

Fig 1. Schematic diagram of the lake ecosystem management model.

Fig 2. An illustration of the P dynamics model. In example A) low P loading results in a single stable oligotrophic equilibrium. In B) at a higher P loading the same lake has two stable equilibrium values – one oligotrophic (the lower point) and one eutrophic (the higher point).

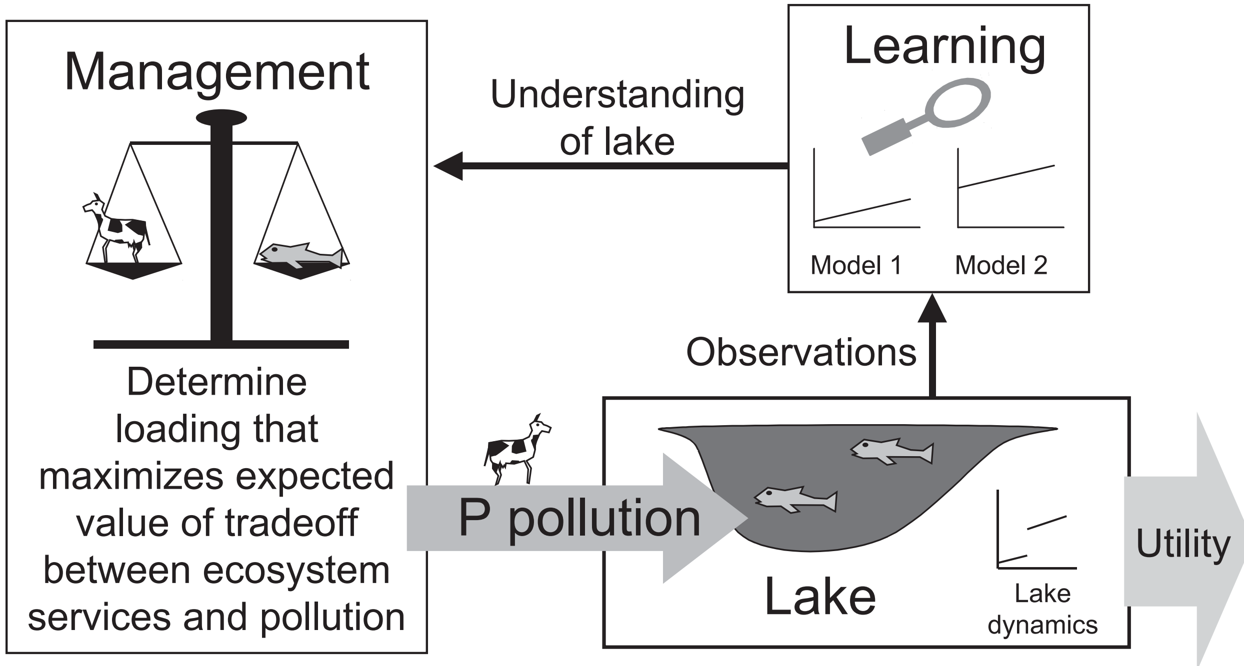
Fig 3. Expected utility of different amounts of loading for the oligotrophic and eutrophic management models.

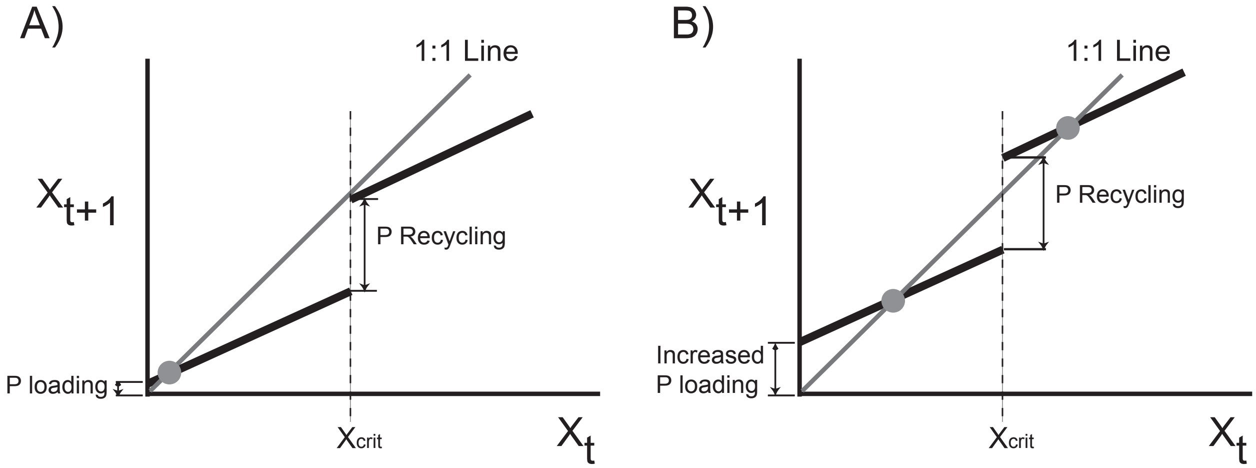
Fig 4. Expected and actual P equilibria values when A) lake is managed as if model 1 is true, and B) as if model 2 is true.

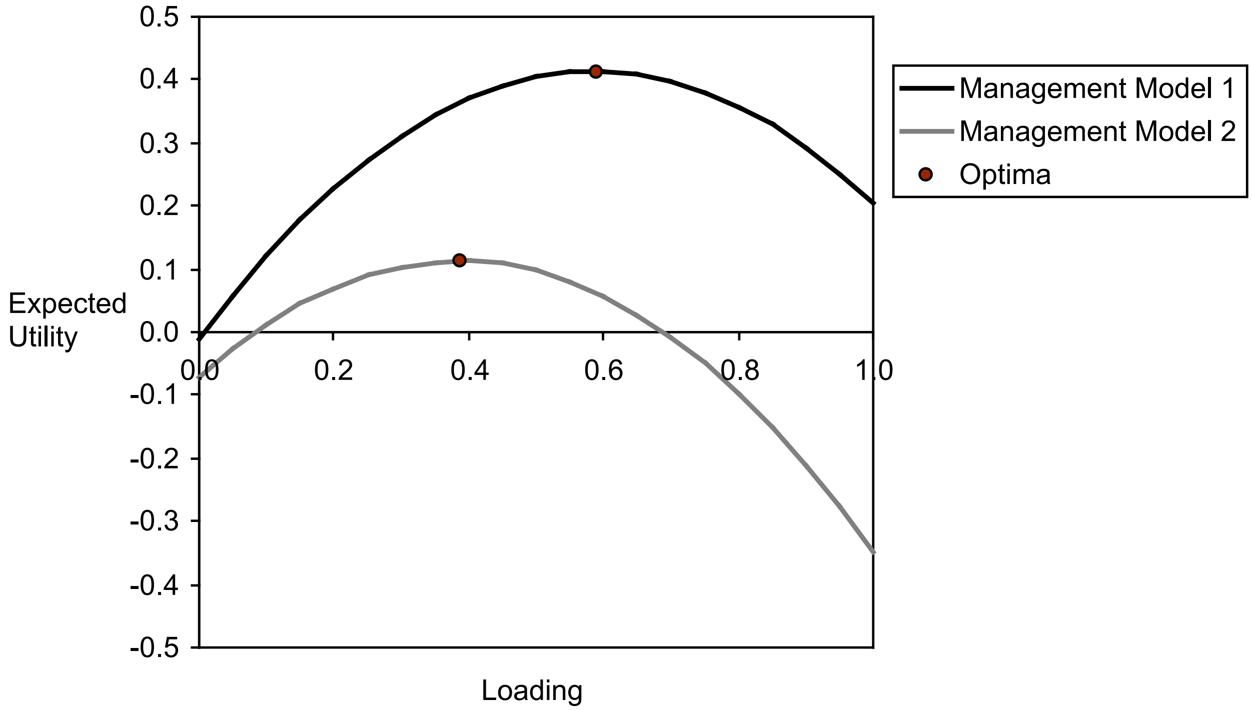
Fig 5. A single realization of the model time dynamics. A) P loading to the lake varies gradually while levels of P within the vary more dramatically. B) Changes in belief in the competing management models varies cyclically over time. C) Changes in utility produced by the lake vary abruptly, while expected utility varies slowly.

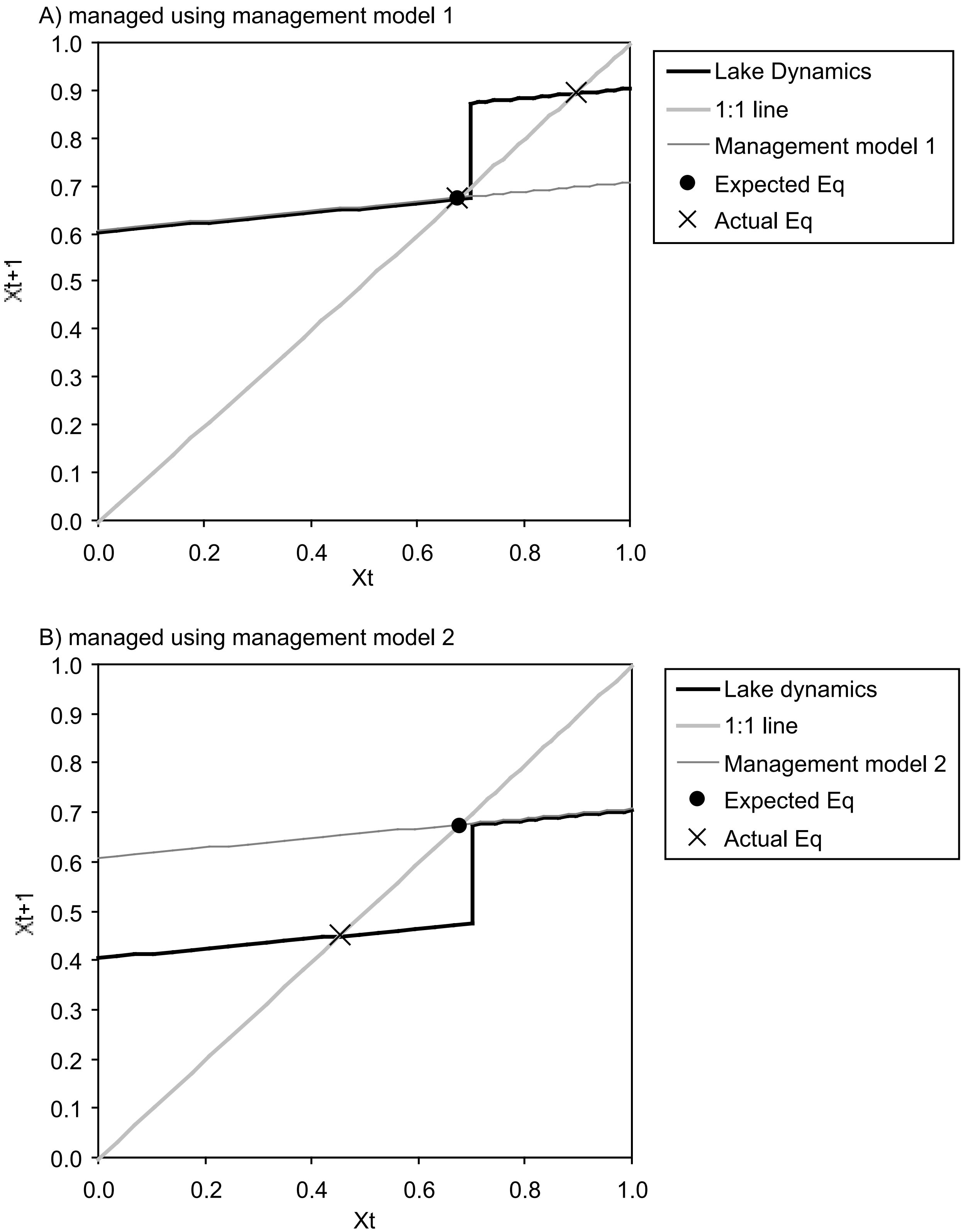
Fig. 6. An example of the dynamics of the model. A) High P loading increases the utility of the lake, but decreases lake resilience, until the lake flips to a eutrophic state. Utility of the lake rapidly declines. As the loading of the eutrophic lake decreases, the resilience of that state gradually decreases, while utility remains low. Eventually the lake once more becomes oligotrophic and the cycle begins again. B) Belief in a model increases as prediction error (surprise) declines. However, as certainty increases, the lake management causes lake resilience

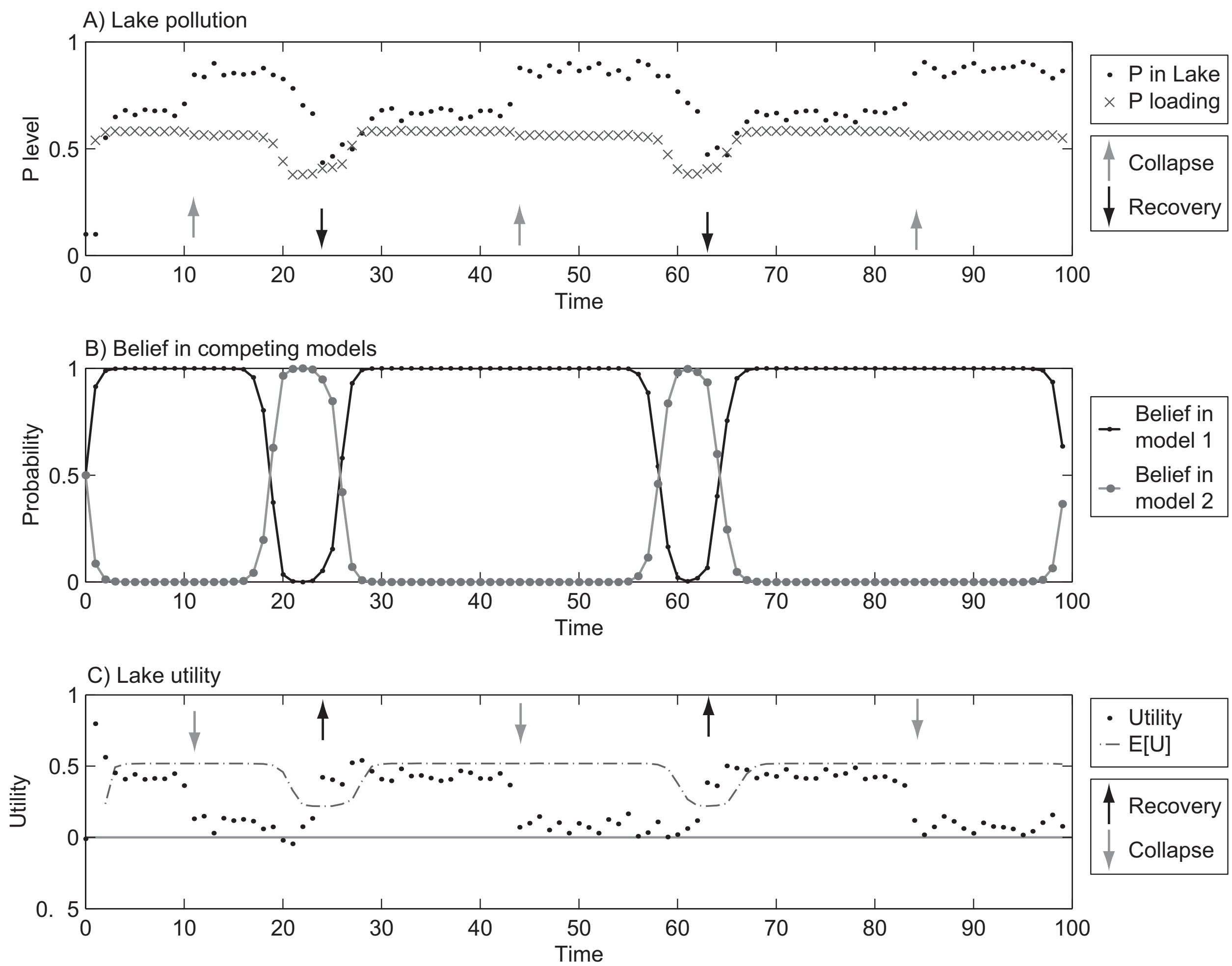
to decrease, increasing the chance that a lake while change state, producing a management surprise. When such a surprise occurs, the degree of belief in a model rapidly declines, causing belief in the other model to increase.

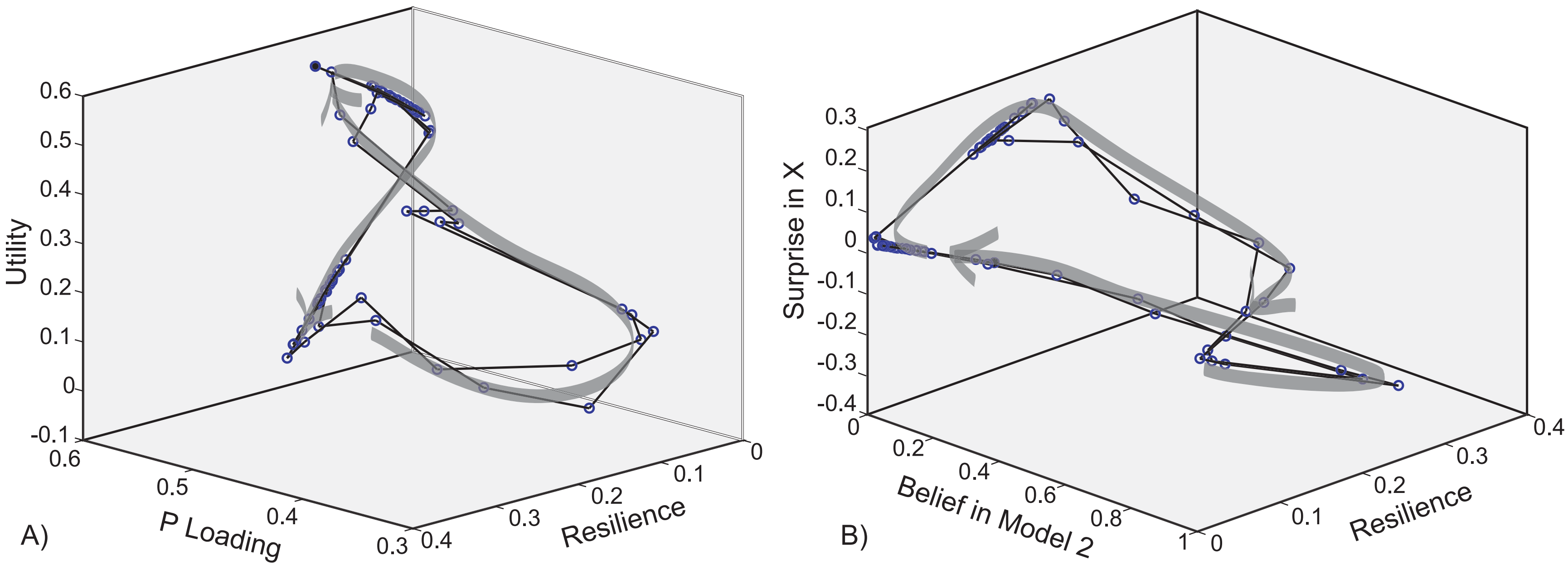

Management
Determine loading that maximizes expected value of tradeoff between ecosystem services and pollution
Understanding of lake
Learning
Model 1
Model 2
Observations
P pollution
Lake
Lake dynamics
Utility


A)
1:1 Line
X_{t+1}
P Recycling
P loading
Xcrit
X_t
B)
1:1 Line
X_{t+1}
P Recycling
Increased
P loading
Xcrit
X_t


0.5
0.4
0.3
0.2
0.1
0.0
-0.1
-0.2
-0.3
-0.4
-0.5
Expected Utility
0.0
0.2
0.4
0.6
0.8
1.0
Loading
Management Model 1
Management Model 2
Optima


A) managed using management model 1
Lake Dynamics
1:1 line
Management model 1
Expected Eq
Actual Eq
Xt+1
Xt
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
0.0
0.2
0.4
0.6
0.8
1.0
B) managed using management model 2
Lake dynamics
1:1 line
Management model 2
Expected Eq
Actual Eq
Xt+1
Xt
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
0.0
0.2
0.4
0.6
0.8
1.0


A) Lake pollution
P level
Time
P in Lake
P loading
Collapse
Recovery
B) Belief in competing models
Probability
Time
Belief in model 1
Belief in model 2
C) Lake utility
Utility
Time
Utility
E[U]
Recovery
Collapse


0.6
0.5
0.4
0.3
0.2
0.1
0
-0.1
Utility
0.6
0.5
0.4
0.3
P Loading
0.4
0.3
0.2
0.1
0
Resilience
A)
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
-0.4
Surprise in X
0
0.2
0.4
0.6
0.8
1
Belief in Model 2
0
0.1
0.2
0.3
0.4
Resilience
B)