Bayesian adaptive management of ecosystems

Tony Prato

Center for Agricultural, Resource and Environmental Systems, University of Missouri, Columbia, MO, USA

Received 16 October 2003; received in revised form 9 June 2004; accepted 6 July 2004

Abstract

Frequentist statistics is not well adapted to handling uncertainties inherent in managing natural resources. A frequentist approach typically involves estimating unknown parameters of ecosystem relationships and testing their statistical significance. While such information is useful, natural resource managers have a greater need to know the most likely current state of an ecosystem and whether particular management actions improve that state in cases where it is not sustainable. Bayesian inference overcomes many of the deficiencies of frequentist statistics and is particularly well suited for implementing adaptive management (AM). Passive and active AM are distinguished and a Bayesian approach to active AM in static and dynamic settings is described for a hypothetical decision problem. The problem is deciding whether or not imposing restrictions on road density and use (referred to as road policy) in northwest Montana’s Flathead National Forest improves habitat for the threatened grizzly bear. The proposed Bayesian approach to this decision problem specifies competing hypotheses about the effects of road policy on habitat suitability and evaluates those hypotheses using Bayes theorem and Bayes action.

© 2004 Elsevier B.V. All rights reserved.

Keywords: Bayesian inference; Adaptive management; Grizzly bear

1. Introduction

Most experiments and decisions in natural resource management rely heavily on frequentist statistics, which involves sampling, experimental design, parameter estimation, hypothesis testing, regression analysis and others. In frequentist statistics, experiments are carefully designed to generate data for different treatments. Experimental data are often evaluated using analysis of variance based on a linear model of treatments effects. The model is used to test hypotheses about whether treatments effects are statistically significant relative to a control. A common null hypothesis is that treatments effects are zero. Regression analysis, another frequentist statistical method, is often used to estimate parameters and test hypotheses about them. Frequentist statistics assumes that ecological experiments are repeatable, which is generally not the case due to the occurrence of unique weather and disturbance events. Another limitation of frequentist statistics is independent treatment of the results of different experiments or studies, which does not allow synthesis of those results (Bergerud and Reed, 1998).
Even if the prerequisites for valid application of frequentist statistics are satisfied, it typically does not provide the kind of information needed by natural resource managers. The latter are often more interested in knowing the most likely current state of an ecosystem and how that state might be altered by alternative management actions than in estimating parameters of ecosystem relationships. This need is especially acute when uncertainty reduces the ability of managers to infer ecosystem states from data on ecological conditions. What managers would like to know, especially those practicing adaptive management (AM), is the probabilities for all possible states of an ecosystem. In addition, classical statistical methods do not provide an adequate framework for handling uncertainties that arise in making management decisions (Peterman and Peters, 1998). Such uncertainties occur in predicting outcomes of management actions and result from incomplete control of management actions, errors in measurement and sampling of natural resource systems, and environmental variability in or incomplete knowledge of ecosystem dynamics (Williams, 1996).

Bayesian statistics is an alternative approach to frequentist statistics that allows natural resource managers to evaluate ecosystem consequences of management decisions and actions in an AM framework (Box and Tiao, 1973; Berger, 1985; Gelman et al., 1995; Berry, 1987). This approach uses Bayes’ theorem to determine posterior probabilities of ecosystem states by combining the prior probabilities for those states and a probability model for newly collected data (likelihood function). This article describes the application of Bayesian statistics to AM of ecosystems.

2. Principles of adaptive management

Traditional approaches to ecosystem management are based on the simplifying assumption that managers know with certainty whether the current state of an ecosystem is sustainable and, if not, which management action is most likely to achieve a sustainable state. This is not the case for several reasons. First, variability in social, economic, demographic and ecological factors makes it difficult to infer ecosystem states from observed conditions and forecast their responses to management actions. Second, sampling and measurement errors and incomplete knowledge make it challenging to identify ecosystem states and measure ecosystem conditions with accuracy. Third, there is often disagreement and/or uncertainty about what constitutes a sustainable ecosystem state (Peterman and Peters, 1998; Conroy, 2000).

AM is well suited to managing ecosystems when there is uncertainty regarding how they respond to management actions (Holling, 1978; Walters and Holling, 1990; Irwin and Wigley, 1993; Walters, 1996; Parme, 1998; Prato, 2003). Specifically, AM increases the rate at which policy makers and resource managers acquire knowledge about ecological relationships, aids management decisions through the use of iterative hypothesis testing, enhances information flows among policy makers, and creates shared understandings among scientists, policy makers and managers (Peterman, 1977; Holling, 1978; Clark et al., 1979; McLain and Lee, 1996; Wondolleck and Yaffee, 2000). Lee (1993) points out that human interaction with nature [e.g., management actions] should be studied in an experimental context because human understanding of nature is imperfect. Kohm and Franklin (1997) state that AM is the only logical approach for handling uncertainty and the continued accumulation of knowledge.

AM can be passive or active. Passive AM formulates predictive models of ecosystem responses to management actions, makes management decisions based on those models and revises model parameters based on monitoring data (Walters and Hilborn, 1978; Hilborn, 1992). Since passive AM is done without controls, it is relatively simple and inexpensive. Unfortunately, lack of controls, replication and randomization causes passive AM to provide unreliable information about ecosystem responses to management actions (Halbert, 1984; Wilhere, 2002). For these reasons, AM has evolved away from the passive mode toward the active mode, which incorporates controls, replication and randomization of management actions (treatments) (Wilhere, 2002). Active AM provides reliable knowledge about whether a particular management action attains its intended objective (Lee, 1993).

2.1. Examples of AM

A variety of ecosystems are being managed or proposed for management using AM. Washington State’s Timber, Fish, and Wildlife Agreement is being implemented using a passive AM approach (Halbert, 1993).
Banff National Park in Alberta, Canada is using passive AM to implement a human use management strategy for the park (Parks Canada, 2001). An adaptive landscape management approach is being used to manage populations of elk and bison in Elk Island National Park in Alberta, Canada (Woodley, 2002). The National Research Council (NRC) recommended that natural regulation of ungulates in Yellowstone National Park’s northern range be implemented using AM (National Research Council, 2002a). The Comprehensive Everglades Restoration Plan (CERP) for restoring the hydrology of South Florida and the Florida Everglades is based on an adaptive learning approach, which is the learning component of adaptive management. (Best, 2000; Kiker et al., 2001; Sklar et al., 2001).

The Northwest Power and Conservation Council adopted active AM for managing the Columbia River Basin’s salmon recovery program (Lee, 1993, 1995; McLain and Lee, 1996). The National Research Council recommended immediate development and implementation of “an [active] adaptive management approach to reverse the ecological decline of the Missouri River” (National Research Council, 2002b). British Columbia is using active AM to develop bio-physical and economic models, experiment with alternative management actions, and test hypotheses related to salmon recovery. An active AM approach is being implemented in the lower Colorado River to improve understanding of how water releases from Glen Canyon Dam influence sediment, fish, vegetation, wildlife and habitat, endangered and other special status species, cultural resources, air quality, recreation, hydropower and non-use values (Glen Canyon Adaptive Management Program, 2002).

3. Comparison of active and passive AM

Active and passive AM are compared using the hypothetical problem of deciding the extent to which reducing road density and use in a national forest (hereafter referred to as road policy) improves habitat for grizzly bear. The hypothetical decision problem reflects conditions in northwest Montana’s Flathead National Forest. The Final Environmental Impact Statement for the 2001 Moose Fire in the Flathead National Forest evaluated “…the amount of road restrictions and decommissioning needed to provide adequate security for grizzly bear … in terms of miles of road proposed for decommissioning; and miles of road currently open to motorized access yearlong or seasonally changed to ‘restricted’ yearlong” (Flathead National Forest, 2002a). One action in the Record of Decision is to “Implement the road strategy identified in Alternative 3 with some modifications. This includes wheeled motorized restrictions on 11 miles of open road and 56 miles of road decommissioning” (Flathead National Forest, 2002b). Studies indicate that the effectiveness of grizzly bear habitat decreases and bear mortality increases with higher road density and human presence (Mace et al., 1996). Bear mortality typically increases with human use of roads because it increases human-bear encounters and, hence, bear mortality (Harris and Gallagher, 1989). Therefore, decreasing road density by decommissioning roads and restricting road use are expected to enhance recovery of grizzly bear, which is a threatened species in the Flathead National Forest and much larger Northern Continental Divide Ecosystem (NCDE).

Table 1 compares the data, evaluation and management actions for passive AM versus active AM in the context of the hypothetical decision problem. Events and conditions in Table 1 do not reflect actual events and conditions in Flathead National Forest. An important difference is that the Final Environmental Impact Statement for the 2001 Moose Fire does not consider using AM. Passive AM of the decision problem is appropriate when there is reasonable certainty about how alternative road policies influence grizzly bear habitat. As the top half of Table 1 indicates, passive AM involves selecting a preferred management action based on a comparison of expected outcomes to desired outcomes of alternative road policies taking into account public comments, applicable statutory requirements and management objectives for the Flathead National Forest.

The bottom half of Table 1 indicates that active AM tests the effects of alternative road policies on grizzly bear habitat. Since it is likely to take several years for grizzly bears to fully respond to implementation of road policies and associated changes in habitat conditions, active AM experiments should be long term. Other conditions influence habitat effectiveness for grizzly bear besides road policy, namely food availability, weather, fire and management practices in land fragments, e.g., clearcutting versus selective cutting of
Table 1
Comparison of passive and active adaptive management for evaluating impacts of road policies on grizzly bear habitat in a national forest

<table>
<thead>
<tr>
<th>Data Evaluation</th>
<th>Management action</th>
</tr>
</thead>
<tbody>
<tr>
<td>Passive AM</td>
<td></td>
</tr>
<tr>
<td>Historical records indicate that grizzly bear habitat in the Flathead National Forest is being adversely affected by road policy.</td>
<td>Based on historical records and expert knowledge, a preferred road policy is selected. The preferred policy assumes a particular relationship between road use/density and grizzly bear habitat, e.g., reducing road use and/or density by 20% would improve grizzly bear habitat by 30%.</td>
</tr>
<tr>
<td>The preferred road policy is implemented. Monitoring is used to determine the effectiveness of the policy.</td>
<td></td>
</tr>
<tr>
<td>Active AM</td>
<td></td>
</tr>
<tr>
<td>Historical records indicate that grizzly bear habitat in the Flathead National Forest is being adversely affected by road policy. Experiments are conducted to test hypotheses about how alternative road policies influence grizzly bear habitat.</td>
<td>Based on historical data and simulation, alternative ecological models are selected to explain how grizzly bear habitat is influenced by alternative road policies. Each model reflects a unique hypothesis concerning the effects of road policy on habitat:</td>
</tr>
<tr>
<td>Alternative road policies specify particular changes in road use/density, e.g., 20% for $H_2$, etc. Alternative road policies are compared to the control ($H_1$). Hypotheses with more posterior support are used to determine the most preferred road policy.</td>
<td></td>
</tr>
</tbody>
</table>

timber. AM experiments for evaluating habitat effects of road policy should attempt to account for these other factors, particularly fire and management practices in land fragments. The latter are more likely to exhibit spatial variability within the national forest than food availability and weather.

4. Frequentist versus Bayesian statistical inference for active AM

Hypotheses regarding the effects of road policy on bear habitat can be tested using frequentist or Bayesian statistical inference. Frequentist statistical inference could be used to estimate the parameters of a model that relates the quality of grizzly bear habitat to various road policies or treatments as done in landscape ecology (Forman and Godron, 1986; Forman, 1995; Turner et al., 2001). Randomly assigning treatments to different sections of the forest and replicating treatments would provide data for estimating habitat effects of road policies and testing their statistical significance. This type of statistical analysis provides useful insights into the relationship between grizzly bear habitat and road policy, it does not allow determination of which hypothesis (e.g., $H_1, \ldots, H_n$ in Table 1) is true. This is the kind of information that forest managers would like to have. It can be generated using a Bayesian approach to active AM. Dorazio and Johnson (2003) concluded that “Bayesian inference and decision theory provide a coherent, theoretical framework for decision making in problems of natural resource management.”

Bayesian decision theory posits several unknown ecosystem states ($\theta_1, \theta_2, \ldots, \theta_n$) and several feasible management actions ($a_1, a_2, \ldots, a_m$). The decision-
maker’s task is to choose one action. If $a_j$ is chosen when the ecosystem state is $\theta_i$, then the expected loss is $L(\theta_i, a_j)$, where $i = 1, \ldots, n$ and $j = 1, \ldots, m$. Expected gain is $G(\theta_i, a_j) = -L(\theta_i, a_j)$. The best management action, referred to as Bayes action, minimizes expected loss or equivalently maximizes expected gain over all possible actions with respect to the prior or posterior distribution. Expected loss is the weighted sum of the magnitude of different losses with weights equal to the probability of occurrence of each loss (Morgan and Henrion, 1990).

Bayesian inference is based on the posterior probabilities for ecosystem states calculated using Bayes theorem. The theorem combines the prior probability that a hypothesis is true with the likelihood function or probability of observing the newly collected data given the hypothesis is true. Prior probabilities are subjective and are determined based on previously collected data or expert knowledge. Some analysts have recommended using a reference or non-informative prior on posterior probabilities. Since the only way that data influences posterior probabilities is through the value of the likelihood function, Bayesian inference does not influence posterior probabilities is through the value of the likelihood function, Bayesian inference does not

Bayesian statistics has been criticized on the grounds that use of prior probabilities and the likelihood principle bases conclusions about the value of a parameter (e.g., How road policy affects grizzly bear habitat) on posterior probabilities. Since the only way that data influences posterior probabilities is through the value of the likelihood function, Bayesian inference does not consider sample space probabilities, such as the probability that a test statistic exceeds a critical value, in drawing inferences about parameters (Dennis, 1996).

5. Static active AM

This section describes how to apply active AM to the hypothetical decision problem in a static Bayesian framework. For simplicity, two habitat states are considered, $\theta_S$ and $\theta_U$. $\theta_S$ signifies the forest provides suitable habitat and $\theta_U$ indicates that the forest provides unsuitable habitat for grizzly bear. Two competing hypotheses are tested about the two ecosystem states: $H_S$ and $H_U$. $H_S$ states that the forest provides suitable habitat ($\theta_S$) and $H_U$ states that the forest provides unsuitable habitat ($\theta_U$) for grizzly bear in terms of road disturbances. The decision problem is to determine whether $H_S$ or $H_U$ is true.

The problem is evaluated using a prior probability of $p(\theta_S) = 0.84$, which implies $p(\theta_U) = 0.16$. A high value of $p(\theta_S)$ implies that landscape fragmentation caused by road disturbance adversely affects grizzly bear habitat in the forest. The experimental design is to select a random sample of $n$ sections (each section is 640 acres) from the national forest, classify each section as suitable (S) or unsuitable (U) habitat for grizzly bears based on road density and road use, and count the number of sections (X) with unsuitable habitat.

Using information on displacement, responses of individuals and family groups to roads, and mortality, Mace and Manley (1993) found that use of areas by grizzly bears in the NCDE declined significantly when total road density exceeded 2 miles per square mile or open road densities exceeded 1 mile per square mile. Research conducted in the Swan Mountains (Mace et al., 1996), which are in the NCDE, indicate that grizzly bears are deterred by road use in excess of 10 vehicles per day. Hence, sections having total road density greater than or equal to 2 miles per square mile or open road densities greater than or equal to 1 mile per square mile, and road use in excess of 10 vehicles per day are judged to have unsuitable habitat. Sections falling below these limits are judged to have suitable habitat for grizzly bears. A proxy can be used when data on road use are unavailable. For example, a study done by the Mistakas Institute for the Rockies (2002) treated high human use of an area with respect to grizzly bear habitat as more than 100 visitors per month. Based on this
criterion, a section is judged to have unsuitable habitat if it has more than 100 visitors per month, and suitable habitat if it has less than 100 visitors per month. This proxy assumes that most forest visitors travel by road.

Another issue is the level of uncertainty regarding the classification of sections as containing suitable or unsuitable habitat. Such uncertainty is expected to be low for the hypothetical example. Road densities can be determined from up-to-date road maps or high-resolution remote sensing data. Road use can be based on visitor use surveys or road counters in areas where surveys have not been done.

Since there are only two habitat states ($\theta_0$ and $\theta_1$), the decision regarding selection of $H_0$ or $H_1$ is based on the posterior probability for $\theta_0$ or $\theta_1$. The posterior probability for $\theta_0$ is used for this purpose. Bayes theorem states

$$p(\theta_0 | X = x) = \frac{p(x | \theta_0)p(\theta_0)}{p(x)} = \frac{p(x | \theta_0)p(\theta_0)}{\sum_{\theta} p(x | \theta_0)p(\theta_0)}$$

where $p(x | \theta_0)$ is the likelihood of observing $x$ if $\theta_0$ is true, $p(\theta_0)$ is the prior probability of $\theta_0$, and $p(x)$ is the marginal probability of $x$. The decision regarding selection of $H_0$ or $H_1$ is based on the posterior probability of $\theta_0$ given the data $x$.

Since there are only two habitat states ($\theta_0$ and $\theta_1$), the decision regarding selection of $H_0$ or $H_1$ is based on the posterior probability for $\theta_0$ or $\theta_1$. The posterior probability for $\theta_0$ is used for this purpose. Bayes theorem states

$$p(\theta_0 | X = x) = \frac{p(x | \theta_0)p(\theta_0)}{p(x)} = \frac{p(x | \theta_0)p(\theta_0)}{\sum_{\theta} p(x | \theta_0)p(\theta_0)}$$

where $p(x | \theta_0)$ is the likelihood of observing $x$ if $\theta_0$ is true, $p(\theta_0)$ is the prior probability of $\theta_0$, and $p(x)$ is the marginal probability of $x$. The decision regarding selection of $H_0$ or $H_1$ is based on the posterior probability of $\theta_0$ given the data $x$.

Since there are only two habitat states ($\theta_0$ and $\theta_1$), the decision regarding selection of $H_0$ or $H_1$ is based on the posterior probability for $\theta_0$ or $\theta_1$. The posterior probability for $\theta_0$ is used for this purpose. Bayes theorem states

$$p(\theta_0 | X = x) = \frac{p(x | \theta_0)p(\theta_0)}{p(x)} = \frac{p(x | \theta_0)p(\theta_0)}{\sum_{\theta} p(x | \theta_0)p(\theta_0)}$$

where $p(x | \theta_0)$ is the likelihood of observing $x$ if $\theta_0$ is true, $p(\theta_0)$ is the prior probability of $\theta_0$, and $p(x)$ is the marginal probability of $x$. The decision regarding selection of $H_0$ or $H_1$ is based on the posterior probability of $\theta_0$ given the data $x$.

Since there are only two habitat states ($\theta_0$ and $\theta_1$), the decision regarding selection of $H_0$ or $H_1$ is based on the posterior probability for $\theta_0$ or $\theta_1$. The posterior probability for $\theta_0$ is used for this purpose. Bayes theorem states

$$p(\theta_0 | X = x) = \frac{p(x | \theta_0)p(\theta_0)}{p(x)} = \frac{p(x | \theta_0)p(\theta_0)}{\sum_{\theta} p(x | \theta_0)p(\theta_0)}$$

where $p(x | \theta_0)$ is the likelihood of observing $x$ if $\theta_0$ is true, $p(\theta_0)$ is the prior probability of $\theta_0$, and $p(x)$ is the marginal probability of $x$. The decision regarding selection of $H_0$ or $H_1$ is based on the posterior probability of $\theta_0$ given the data $x$.

Table 2 summarizes hypothetical likelihoods or probabilities that the forest provides unsuitable grizzly bear habitat for $0 < X < 12$ for each habitat state, the posterior probability that the forest is in state $\theta_1$ given each of the values of $X$, the most likely habitat state and the resulting management decision. For example, the posterior probability that $X = 7$ is:

$$p(\theta_0 | X = 7) = \frac{[p(\theta_0)p(X | \theta_0)]}{\sum_{\theta} [p(\theta_0)p(X | \theta_0)]}$$

Table 2

| Number of sections with unsuitable habitat (X) | Likelyhood forest provides unsuitable habitat when $p(X^i = \theta_1)$ | Likelyhood forest provides unsuitable habitat when $p(X^i = \theta_0)$ | Posterior probability* for $\theta_0$, $p(\theta_0 | X)$ | Most likely state of forest habitat | Road policy decision | \(\alpha\) | \(\beta\) |
|---|---|---|---|---|---|---|---|
| 0 | 0.000 | 0.001 | 0.000 | $\theta_0$ | No restrictions/removals | 0.068 |
| 1 | 0.000 | 0.008 | 0.000 | $\theta_0$ | No restrictions/removals | 0.068 |
| 2 | 0.000 | 0.034 | 0.000 | $\theta_0$ | No restrictions/removals | 0.068 |
| 3 | 0.000 | 0.092 | 0.000 | $\theta_0$ | No restrictions/removals | 0.068 |
| 4 | 0.001 | 0.170 | 0.030 | Inconclusive | Ambiguous | 0.068 |
| 5 | 0.003 | 0.222 | 0.066 | Inconclusive | Ambiguous | 0.068 |
| 6 | 0.016 | 0.212 | 0.284 | Inconclusive | Ambiguous | 0.068 |
| 7 | 0.053 | 0.149 | 0.651 | Inconclusive | Ambiguous | 0.068 |
| 8 | 0.133 | 0.076 | 0.922 | Inconclusive | Ambiguous | 0.068 |
| 9 | 0.256 | 0.028 | 0.978 | $\theta_0$ | Restrict/remove | 0.068 |
| 10 | 0.283 | 0.007 | 0.993 | $\theta_0$ | Restrict/remove | 0.068 |
| 11 | 0.206 | 0.001 | 0.999 | $\theta_0$ | Restrict/remove | 0.068 |
| 12 | 0.069 | 0.000 | 1.000 | $\theta_0$ | Restrict/remove | 0.068 |

Adapted from Bergerud and Reed (1998).

* Assumes $p(\theta_1) = 0.84$.
are less than 0.05, the commonly specified value of \( \alpha \) (Type I error, or probability of deciding not to implement a road policy when the habitat is unsuitable). A road policy is justified (do not reject \( H_U \)) for \( 9 \leq X \leq 12 \) because the posterior probabilities for these values of \( X \) exceed 0.95. The latter is the probability of deciding to implement a road policy when the habitat is unsuitable (power of test). Since the posterior probabilities for \( 5 \leq X \leq 8 \) are between the Type I error (0.05) and power of the test (0.95), the most likely state of grizzly bear habitat is inconclusive and the road policy decision is ambiguous for these values of \( X \).

Ambiguous decisions can be eliminated by determining the Bayes action. The latter requires information about the expected losses or gains from alternative management actions. To simplify the explanation of Bayes action, suppose the forest manager can select one of two actions: \( a_1 \) is to implement a road policy and \( a_2 \) is not to implement a road policy. In general, there are multiple policy actions involving different mileages of restricted and decommissioned roads (e.g., see Flathead National Forest, 2002a). For two habitat states and two actions, there are four categories of expected losses (or gains). First, if a road policy is implemented (\( a_2 \)) and the forest provides suitable habitat for grizzly bear (\( \theta_S \)), then losses (negative gains) result from lower recreational opportunities and fewer roads for harvesting timber and accessing forest fires, and the costs of enforcing road restrictions and decommissioning roads. Second, if a road policy is not implemented (\( a_1 \) and the forest provides unsuitable habitat for grizzly bear (\( \theta_U \)), then there is a potential loss (negative gain) associated with continued unsuitability of grizzly bear habitat, which could ultimately lead to extinction of the species. Third, if no road policy is implemented (\( a_2 \)) and the forest provides suitable habitat for grizzly bears (\( \theta_S \)), then the gain is the avoided costs of road restrictions and decommissioning. Fourth, if a road policy is implemented (\( a_1 \)) and grizzly bear habitat is unsuitable (\( \theta_U \)), then there can be a gain or loss depending on the benefits of improved habitat relative to the cost of imposing road restrictions, decommissioning roads and reducing forest access.

Suppose the expected gains from the two management actions \( a_1 \) and \( a_2 \) are as given in Table 3. Bayes action based on prior probabilities involves comparing Bayes prior gain (BRG) for the two management actions, where:

\[
BRG(a_1) = p(\theta_S)G(\theta_S, a_1) + p(\theta_U)G(\theta_U, a_1) \\
= (0.84)(500) + (0.16)(-1000) = 260
\]

\[
BRG(a_2) = p(\theta_S)G(\theta_S, a_2) + p(\theta_U)G(\theta_U, a_2) \\
= (0.84)(-1500) + (0.16)(800) \\
= -1132
\]

Since \( BRG(a_1) > BRG(a_2) \), \( a_1 \) is the Bayes action. Since BRG is based only on the prior probabilities and expected gains, it is the same for all values of \( X \).

A more informed decision is possible using Bayes posterior gain (BPG), which is Bayes gain calculated using posterior probabilities rather than prior probabilities. For \( X = 10 \), the BPGs for \( a_1 \) and \( a_2 \) are:

\[
BPG(a_1) = p(\theta_S|X = 10)G(\theta_S, a_1) \\
+ p(\theta_U|X = 10)G(\theta_U, a_1) = 448
\]

\[
BPG(a_2) = p(\theta_S|X = 10)G(\theta_S, a_2) \\
+ p(\theta_U|X = 10)G(\theta_U, a_2) = 1489
\]

Bayes action is \( a_1 \) if \( BPG(a_1) > BPG(a_2) \), and \( a_2 \) if \( BPG(a_2) > BPG(a_1) \). Since \( BPG(a_2) > BPG(a_1) \) for \( X = 10 \), \( a_1 \) (implement a road policy) is Bayes action for this value of \( X \).

Table 4 indicates the BPGs and posterior Bayes decisions for all possible values of \( X \). These hypothei-

### Table 3: Hypothetical expected gains for two road management actions and two habitat states

<table>
<thead>
<tr>
<th>State of habitat</th>
<th>Possible road actions</th>
<th>( a_1 )</th>
<th>( a_2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unsuitable (( \theta_U ))</td>
<td>( G(\theta_U, a_1) = $ 500/acre )</td>
<td>( G(\theta_U, a_2) = $ 800/acre )</td>
<td></td>
</tr>
<tr>
<td>Suitable (( \theta_S ))</td>
<td>( G(\theta_S, a_1) = -$ 1000/acre )</td>
<td>( G(\theta_S, a_2) = $ 1500/acre )</td>
<td></td>
</tr>
</tbody>
</table>
Table 4
Hypothetical Bayes posterior gains and Bayes posterior decisions for different values of $X$

<table>
<thead>
<tr>
<th>Number of sections with unsuitable habitat ($X$)</th>
<th>Posterior probability* for $\theta_U (\mid X)$</th>
<th>Bayes posterior gain for $a_1$ ($/acre$)</th>
<th>Bayes posterior gain for $a_2$ ($/acre$)</th>
<th>Posterior Bayes road policy decision</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.00</td>
<td>0.000</td>
<td>−1000</td>
<td>800</td>
<td>No restrictions/removals</td>
</tr>
<tr>
<td>1.00</td>
<td>0.000</td>
<td>−1000</td>
<td>800</td>
<td>No restrictions/removals</td>
</tr>
<tr>
<td>2.00</td>
<td>0.000</td>
<td>−999</td>
<td>799</td>
<td>No restrictions/removals</td>
</tr>
<tr>
<td>3.00</td>
<td>0.000</td>
<td>−996</td>
<td>793</td>
<td>No restrictions/removals</td>
</tr>
<tr>
<td>4.00</td>
<td>0.030</td>
<td>−976</td>
<td>763</td>
<td>No restrictions/removals</td>
</tr>
<tr>
<td>5.00</td>
<td>0.066</td>
<td>−891</td>
<td>632</td>
<td>No restrictions/removals</td>
</tr>
<tr>
<td>6.00</td>
<td>0.284</td>
<td>−585</td>
<td>163</td>
<td>No restrictions/removals</td>
</tr>
<tr>
<td>7.00</td>
<td>0.651</td>
<td>−22</td>
<td>−500</td>
<td>Restrict/remove</td>
</tr>
<tr>
<td>8.00</td>
<td>0.902</td>
<td>353</td>
<td>−1275</td>
<td>Restrict/remove</td>
</tr>
<tr>
<td>9.00</td>
<td>0.978</td>
<td>467</td>
<td>−1449</td>
<td>Restrict/remove</td>
</tr>
<tr>
<td>10.00</td>
<td>0.995</td>
<td>493</td>
<td>−1449</td>
<td>Restrict/remove</td>
</tr>
<tr>
<td>11.00</td>
<td>0.999</td>
<td>499</td>
<td>−1449</td>
<td>Restrict/remove</td>
</tr>
<tr>
<td>12.00</td>
<td>1.000</td>
<td>500</td>
<td>−1500</td>
<td>Restrict/remove</td>
</tr>
</tbody>
</table>

Adapted from Bergerud and Reed (1998).

As expected, there is only partial agreement between the Bayes actions based on prior and posterior probabilities. For $X \leq 4$ and $X \geq 9$, the two actions result in the same decision, namely do not implement a road policy ($a_2$) if $X \leq 4$ and implement a road policy ($a_1$) for $X \geq 9$. Choosing Bayes action results in a positive gain for all values of $X$ except 7, in which case Bayes action results in a loss of $22/acre$.

Dynamic active AM

Static Bayesian AM requires only one experiment, and is appropriate, when operating budgets are limited and experimental costs are high. However, the maximum advantage of AM is realized when temporal data from several experiments are used to sequentially test hypotheses. This approach, called dynamic Bayesian AM, requires the decision-maker to implement Bayes action in multiple sequential experiments. To illustrate how dynamic active AM works, suppose the first experiment indicates $X = 6$. In this case, $H_U$ is rejected, which does not support implementation of a road policy. Suppose that during the 3 years following the first experiment, additional roads are constructed in the forest to allow removal of harvested timber. Since new roads can degrade grizzly bear habitat, the forest manager decides to conduct a second experiment (similar to the first) three years after the first experiment. The posterior probability for $X = 6$ in the first experiment, namely 0.284 (see Table 2), becomes the prior probability of $\theta_U$ in the second experiment. Suppose the second experiment indicates $X = 8$. $H_U$ cannot be rejected when $X = 8$, and there is support for implementing a road policy. In this case, habitat conditions worsened between the first and second experiments. Suppose that several years after the second experiment is completed, the forest manager conducts a third experiment to determine whether the road policy implemented after the second experiment improved grizzly bear habitat. The relevant posterior probability from the second experiment becomes the prior probability for the third experiment. Since benefits and costs of...
road policies are likely to change over time, the BPGs should be updated before each new experiment.

7. Conclusions

Frequentist statistics has several limitations in terms of implementing adaptive ecosystem management. It focuses on estimating unknown parameters of ecosystem relationships, whereas natural resource managers are generally more interested in knowing the most likely current state of an ecosystem and how management actions might alter that state. Bayesian inference overcomes many of the deficiencies of frequentist statistics, and is suitable for both static and dynamic AM. AM is particularly well suited to handling uncertainties regarding ecosystem relationships.

Passive AM formulates predictive models of ecosystem responses to management actions, makes management decisions based on model results and revises model parameters based on monitoring. Passive AM does not provide reliable information on ecosystem states and ecosystem responses to management actions due to a lack of replication and randomization of treatments.

Active AM uses experiments to generate data for testing hypotheses about ecosystem states and how alternative management actions influence those states. Each management action is viewed as a treatment in a statistically valid experiment. Active AM experiments incorporate replication and randomization of management actions, which allows managers to test alternative hypotheses. Passive and active AM are being used to manage a variety of ecosystems.

Implementing static and dynamic AM in a Bayesian framework is illustrated for the hypothetical problem of deciding whether to restrict road use and/or decrease road density in order to improve grizzly bear habitat in Flathead National Forest in northwest Montana. Bayesian AM for this problem involves specifying and evaluating competing hypotheses about the states of grizzly bear habitat and selecting the management action that is most compatible with that state.

Bayesian AM determines the posterior probabilities for habitat states using Bayes theorem, and identifies Bayes action and Bayes posterior decision. The latter minimizes the expected loss of an action, and requires information about the expected gains associated with all combinations of habitat states and management actions. In static AM, the state of an ecosystem is inferred based on the results of one experiment. In dynamic AM, ecosystem states are determined through sequential experiments in which the relevant posterior probability from one experiment becomes the prior probability in the next experiment. In summary, Bayesian AM is a compelling way to adaptively manage ecosystems subject to multiple sources of uncertainty.

References
