Making monitoring manageable: a framework to guide learning

Karen Price and Dave Daust

Abstract: Resource managers, planners, and the public are unified in their calls for monitoring of land-use plans. Unfortunately, many monitoring initiatives fall short of their potential for several reasons: indicators are not explicitly linked to objectives, hindering feedback to planning; knowledge is not represented in a manner that facilitates learning; and monitoring priorities are driven subjectively. We describe a framework that links indicators to existing objectives, presenting knowledge as hypotheses about the probability of achieving an objective as a function of various indicator levels. Uncertainty is explicitly included in the models. The framework can be used for management decision support and to prioritize objectives for implementation, effectiveness, and validation monitoring, and research. Monitoring priority is determined first by probability of success and uncertainty and then by the importance of an objective. We present a case study for the Babine Watershed, an area in the interior of British Columbia with high resource values and decades of controversy and ineffective monitoring. The framework sifted through existing objectives to focus effort on those most critical to monitor. By concentrating on publicly derived, regionally applicable objectives and strategies taken from existing land-use plans, the framework provided relevant results and enabled rapid feedback.

Résumé : Les gestionnaires des ressources, les planificateurs et le public réclament tous le suivi des plans d'utilisation des terres. Malheureusement, plusieurs initiatives de suivi ne se concrétisent pas pleinement pour plusieurs raisons : les indicateurs ne sont pas explicitement reliés aux objectifs, ce qui nuit au processus de rétroaction pour la planification; la connaissance n'est pas représentée de manière à faciliter l'apprentissage; et les priorités de suivi sont choisies de façon subjective. Nous décrivons une démarche qui relie les indicateurs aux objectifs existants en présentant la connaissance comme des hypothèses qui portent sur la probabilité d'atteindre un objectif selon différents niveaux des indicateurs. L'incertitude est explicitement incluse dans les modèles. Cette démarche peut être utilisée pour supporter les décisions d'aménagement et prioriser les objectifs pour l'implantation, l'efficacité et la validation du suivi ainsi que pour la recherche. La priorité de suivi est d'abord déterminée par la probabilité de succès et l'incertitude et ensuite par l'importance d'un objectif. Nous présentons une étude de cas pour le bassin versant Babine, une zone située à l'intérieur des terres en Colombie-Britannique, où la valeur des ressources est élevée, la controverse règne depuis des décennies et le suivi est inefficace. La démarche a permis de considérer chacun des objectifs existants pour se concentrer sur les plus importants à suivre. En se concentrant sur des objectifs provenant du secteur public et applicables régionalement ainsi que sur des stratégies empruntées à des plans d'utilisation des terres existants, la démarche a produit des résultats pertinents et permis une rétroaction rapide.

[Traduit par la Rédaction]

Introduction

Managing natural systems is fraught with uncertainty because relationships can be complex, interactions among factors can be nonlinear, and rare events can drive systems. Decades ago, Walters and Hilborn (1976), Holling (1978), and Walters (1986) described a way to manage resources in the face of uncertainty while enabling managers to learn. Since its first postulation, "adaptive management" has been frequently invoked but rarely realised (e.g., Halbert 1993; Gunderson et al. 1995; but see Bunnell and Dunsworth 2004 for a successful example). Adaptive management is considered to be daunting and expensive by government and industry and to be an excuse for using less ecologically conservative practices by environmental organizations (Walters 1997*a*).

Recent shifts towards ecosystem management, results-based management, and certification programmes have popularized one element of adaptive management — monitoring (Busch and Trexler 2003, Angelstam et al. 2004*a*). In this context, monitoring involves collecting indicator data (i.e., variables that reflect the state of a value; CSA 2002) to assess whether management activities are achieving their aims. Monitoring initiatives have proliferated at local, provincial, national, and international levels. Unfortunately, many initiatives have focused on learning to monitor rather than on monitoring to learn, thus decoupling monitoring from the adaptive management cycle (Gunderson 2003). Indeed, in provincial state-of-the-forest reporting, some certification schemes, and federal criteria and indicator processes, monitoring is considered the end rather than a means (Rempel et al. 2004). To achieve its potential for learning, monitoring must be put back into a cycle, where results can modify management decisions appropriately (Bunnell and Dunsworth 2004; Rempel et al. 2004; Houde et al. 2005).

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K. Price[1] and D. Daust. Bulkley Valley Centre for Natural Resources Research and Management, P.O. Box 4274, Smithers, BC V0J 2N0, Canada.

[1]Corresponding author (e-mail: pricedau@telus.net).

The cycle begins with developing clear, agreed-upon objectives. Objectives define the desired state of a value (CSA 2002). They can vary from broad, "fundamental" objectives to specific, measurable "means" objectives (Keeney 2002). We refer to the broadest objectives (e.g., maintain biodiversity) as goals. In the hierarchical system we describe, more specific objectives (e.g., maintain representative levels of stand structure in wildlife tree patches) contribute to these goals. The next step involves using knowledge to design strategies to achieve the objectives. Strategies can be expressed as target levels (e.g., three) of an implementation indicator (e.g., snags per hectare >30 cm diameter). Once strategies have been implemented, monitoring is useful to measure progress towards objectives, enabling managers to learn which of their strategies are working (Noss 1999; Rempel et al. 2004). Finally, results of monitoring are used to update knowledge and to validate or improve management strategies.

Monitoring programmes typically include three tiers. Implementation (including compliance) monitoring asks whether designed strategies are being followed (e.g., does stand-level retention meet target levels). Effectiveness monitoring asks whether objectives are being met (e.g., are old-growth species maintained in the stands with target levels of retention). Validation monitoring (or monitoring to learn) investigates the relationship between implemented strategies and objectives (e.g., are the old-growth species maintained in the stands because of stand-level or landscape-level retention; Noss and Cooperrider 1994; Busch and Trexler 2003). The latter two monitoring types are closely related and work well in tandem: both are used to improve knowledge about the consequences of implemented strategies.

Managers have been gaining experience at implementation monitoring in recent years but have been struggling with effectiveness and validation monitoring (Landres et al. 1988; Simberloff 1999; Andelman and Fagan 2000; Angelstam et al. 2004*a*, 2004*b*). Strategies can usually be measured easily, because they directly alter land-based attributes, whereas determining consequences to objectives can require intensive, and expensive, field sampling over many years to detect meaningful patterns. Even with significant investment, consequences may not be detectable until change is irreversible (Ludwig et al. 1993). Furthermore, even if an undesirable pattern is detected, the primary cause may remain mysterious, may be hidden among compounded factors (Paine et al. 1998), and may provide few clues about potential solutions. In some regions, numerous effectiveness monitoring studies have been performed over decades, but little useful information has emerged to guide management (Failing and Gregory 2003).

For monitoring to be useful, it must be placed within a framework that fulfills three functions. Firstly, to support decision-making, the framework must explicitly link management strategies to objectives (Rempel et al. 2004). Secondly, to identify knowledge needs and facilitate feedback to management, it must summarize existing knowledge in a way that is easily updated and easily communicated to managers and planners (Lee 1993; Kinzig et al. 2003; Angelstam et al. 2004*b*). Thirdly, to focus studies on the most relevant issues and because monitoring is expensive and time is limited, it must be able to prioritize all types of monitoring across all objectives in a manner that it disciplined, transparent, and comprehensive (Bunnell and Dunsworth 2004).

This paper describes a framework, which is succeeding in the interior of British Columbia, that meets these three requirements. It links agreed-upon objectives and management strategies explicitly. It summarizes existing knowledge and associated uncertainty as hypotheses about the probability that an objective will be achieved for any given management strategy. The hypotheses can be used by decision-makers to understand the best available information describing the relationship between strategies and objectives and by scientists and managers to prioritize and design the most effective monitoring and research programmes. For prioritizing monitoring, the framework considers the best estimate of the probability of achieving an objective, uncertainty around this estimate, resolvability of this uncertainty, and the importance of the objective.

Framework

A knowledge summary forms the heart of the framework. The summary begins with conceptual models of the relationships among goals, objectives, and strategies (the latter represented by target values of implementation indicators; Fig. 1). The summary describes the relative importance of each objective and then presents graphical hypotheses showing how the probability of achieving the objective changes with indicator value. These hypotheses can be used to estimate the probability of achieving an objective as described below.

Cause–effect hypotheses

The framework considers objective–indicator pairs as the primary units for analysis. Graphical cause–effect hypotheses link each objective to management strategies. We represent strategies by target values of implementation indicators, for example, the amount of old forest or road length per unit area. Indicators are selected for their ability to influence an objective strongly, to describe the full spectrum of a relevant management activity, and to be measurable at an appropriate scale. Cause–effect hypotheses model the best-estimated relationship between an implementation indicator and the probability that an objective will be achieved (Fig. 2). For example, Fig. 2 could represent the probability of maintaining a particular species (the objective) as a function of the amount of habitat retained (the indicator). Cause–effect hypotheses are completed for each objective–indicator pair.

We use the probability of achieving an objective (or "probability of success") as a common currency to allow comparison across an entire suite of objectives dealing with values ranging from biodiversity and water to recreation and timber supply. All objectives we have considered have been agreed to by multi-stakeholder committees and signed by government. Hence, we assume that failure to achieve any agreed-upon objective is a consequence that requires evaluation and potential management response.

The points on the vertical axis, representing the probability of achieving an objective, must be well defined. If literature is available, one way of defining this probability is to consider whether studies detect negative consequences to the objective due to a particular strategy. If well-designed

Fig. 1. Example of a high-level conceptual model of relationships for the value grizzly bears. The bands show goals, objectives, implementation indicators, and targets, respectively. Within the goal of maintaining grizzly bears, there are three fundamental objectives. Strategies designed to achieve the objectives include protecting 100% of critical habitat, limiting accessible road density, and controlling the timing of logging.

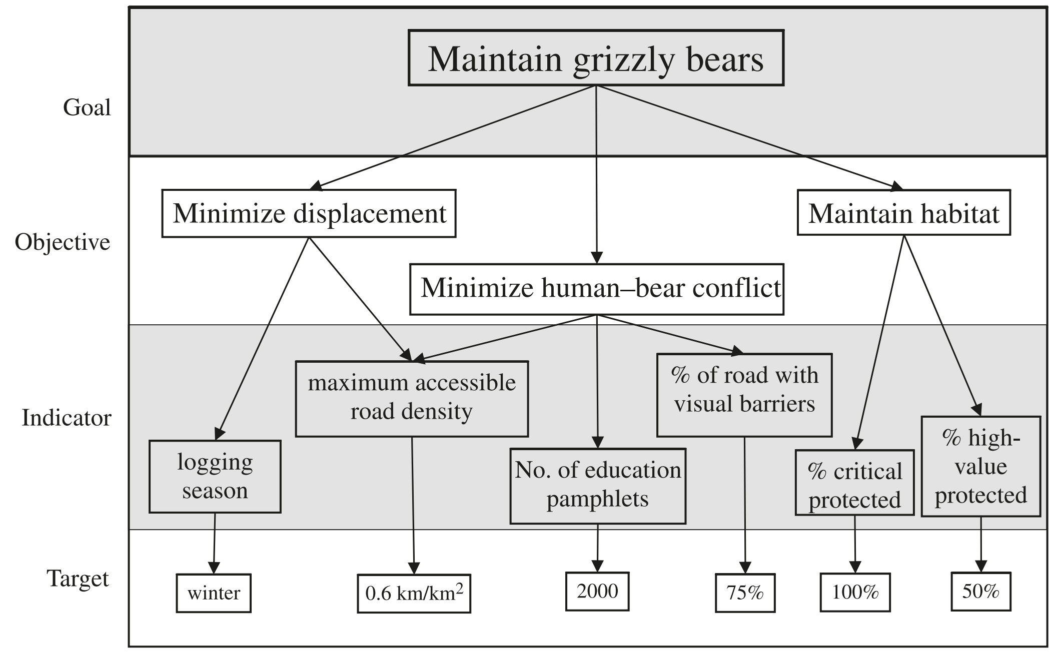
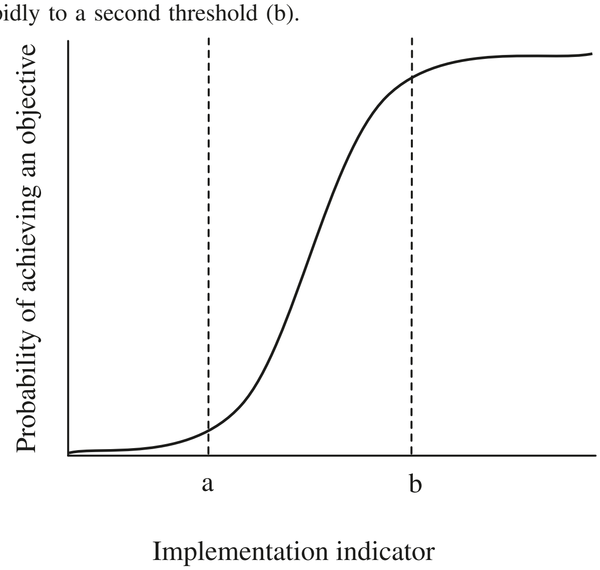


Fig. 2. Hypothetical cause–effect curve where the probability of success is low and relatively insensitive to the indicator value up to a threshold (a), beyond which the probability of success increases rapidly to a second threshold (b).



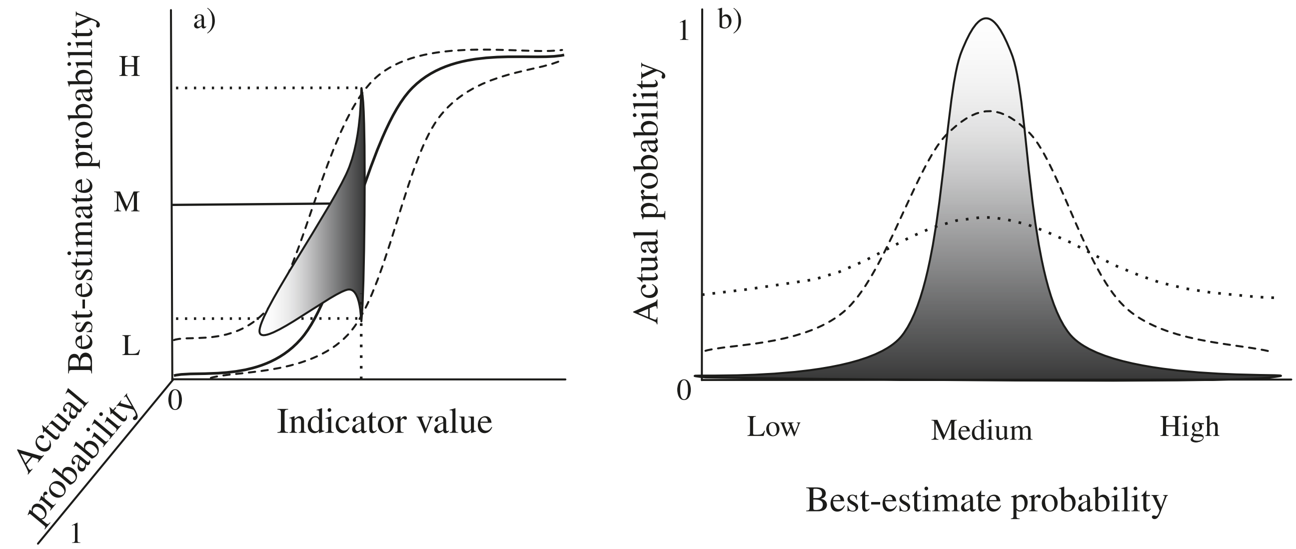
studies do not detect negative consequences to the objective, we define the probability of achieving the objective as high for that indicator value. If most studies detect negative consequences, we define the probability of achieving the objective as low. In between, some studies detect negative consequences, and others do not. Consider the literature on habitat-amount thresholds as an example: very few studies have found thresholds at levels of habitat loss <40%, whereas two-thirds of studies detected thresholds before 70% loss (Price et al. 2009). Plotting these data against habitat loss creates a sigmoidal curve similar in shape to Fig. 2 with 40% loss at “a” and 70% at “b”. This curve is based on a variety of studies of different species in different habitats; additional analyses of specific habitats, matrix quality, organism sensitivity, and other variables could be used to design more specific curves.

Ideally, cause–effect hypotheses should be derived from peer-reviewed meta-analyses of studies conducted in the region of interest. A somewhat more realistic option is to use expert workshops to discuss the applicability of studies within and outside the region of interest. When published information is particularly sparse, expert opinion alone can be used to draft preliminary models while recognising that experts may be biased, overconfident, and suffer similar difficulties in assessing probability as lay people (Burgman 2005). Encouraging experts to consider potential errors is a useful way to improve estimates (Morgan and Henrion 1990). Hence, the next step in building the cause–effect hypothesis is to explicitly partition and document uncertainty around the best-estimated curve.

Uncertainty is represented by a density distribution of actual probability of success around the best-estimated probability of success for a given indicator value. Uncertainty is most accurately represented by a third dimension; hence the best-estimated line resembles a long hill (Fig. 3*a*). As uncertainty increases, the density distribution becomes flatter and wider (Fig. 3*b*). The best-estimated probability is always the most likely outcome. If uncertainty is low, other outcomes are unlikely. As uncertainty increases, other outcomes become more likely. Uncertainty can vary in width along the best-estimated curve.

Uncertainty is partitioned by source and by resolvability. Resolvable uncertainty arises from lack of study. Irresolv-

Fig. 3. (*a*) Determining the actual probability of success for a given estimated probability and uncertainty. H, high; M, medium; L, low. (*b*) Density distributions of actual probability of success for high (dotted line), medium (dashed line), and low (solid line) uncertainty classes around an objective with a best-estimated medium probability of success.



able uncertainty may result from inherent stochasticity (e.g., the location of a mountain pine beetle, *Dendroctonus ponderosae* Hopkins, outbreak) and cannot be reduced by research (Walters 1997*b*).

Using cause–effect hypotheses to prioritize monitoring, research, and planning

The estimates of probability of achieving an objective, including uncertainty, can be used to determine priorities for all types of monitoring as well as for research and planning. There are two stages in the procedure. The first stage groups objective–indicator pairs into priority classes based on the estimated probability of success and associated uncertainty. The second rates objective–indicator pairs within these classes based on measures of importance.

The first stage estimates the likelihood of delivering useful information. It uses estimates of current and target indicator state (where "state" simply represents the value of an indicator along the *x* axis of the cause–effect hypothesis, e.g., 70% of the forest is old). Current state is based on results of implementation monitoring or on estimates from current knowledge (e.g., 60% of ecosystem A is currently old). Target state is provided by established values in land-use plans (e.g., target is for 30% of ecosystem A to be old). If current indicator state is not available, the objective–indicator pair has a high priority for implementation monitoring to collect these data. If there is no target, an objective–indicator pair has high priority for planning.

If current and target state are known, the cause–effect hypothesis can be used to determine best-estimated probability of success and associated uncertainty at these states (read off the *y* axis). These measures can then be used to determine priorities among the objective–indicator pairs for effectiveness and validation monitoring, research, and planning. To simplify comparison and interpretation and because current knowledge does not generally support more precise estimates, in practice, we consider nine distinct predictions from cause–effect curves: the best-estimated probability of success is divided into three equally sized classes (low, moderate, and high probability of success), each with three different potential levels of uncertainty (low, moderate, and high uncertainty). In this system, low uncertainty means that the actual probability of success lies within the best-estimated class, moderate uncertainty allows actual probability to fall in immediately adjacent classes of the best-estimated value, and high uncertainty allows it to lie within any of the three classes.

For effectiveness monitoring, intended to detect consequences, it is most important to monitor an objective when probability of achieving the objective is low. Hence, priority is inversely proportional to the mean expected probability of success $E(Y)$ for a given indicator state, i.e.:

$$E(Y) = \sum_{i=1}^{n} p_i y_i$$

where n is the number of probability of success classes, y is the midpoint probability of success for each class i, p is the probability that the actual probability of success for a particular state falls in a given class.

Theoretically, we assume that the probability distribution for the actual Y follows a normal distribution around the best-estimated probability of success truncated at high and low levels. Thus, for moderate probability of success, $E(Y)$ is the best-estimated probability of success whether uncertainty is low or high (because errors are symmetrical). For high and low probability classes, when uncertainty is low, $E(Y)$ approximates the best-estimated probability. However, as uncertainty increases, $E(Y)$ approaches medium probability of success because the distribution is asymmetrical.

Practically, objective–indicator pairs with low estimated probability of success and low to moderate uncertainty rank as top priorities for effectiveness monitoring (Table 1). Conversely, objective–indicator pairs with high $E(Y)$ have low priority for effectiveness monitoring. Where current and future estimates of priority differ, current priority is weighted

Table 1. Priority for effectiveness monitoring for nine combinations of best-estimate probability of success and uncertainty (1 is the highest priority).

	Best-estimate probability of success		
Uncertainty	Low	Medium	High
Low	1	2	3
Medium	1	2	3
High	2	2	2

Table 2. Priority for validation monitoring for nine combinations of best-estimate probability of success and uncertainty (1 is the highest priority).

	Best-estimate probability of success		
Uncertainty	Low	Medium	High
Low	3	3	3
Medium	2	1	2
High	1	1	1

more because negative consequences may be imminent. For objectives with a high priority for effectiveness monitoring, the best available data and hypotheses suggest that strategies will not likely achieve objectives. Because designed strategies are likely ineffective, these objectives also have a high priority for further planning to improve management strategies.

For validation monitoring, it is more important to study objective–indicator pairs with higher uncertainty (Table 2). Hence, priority is proportional to the breadth of the uncertainty. Objective–indicator pairs with the highest resolvable uncertainty have high priority for validation monitoring and those with low or irresolvable uncertainty have low priority. Note that, because we assume error follows a truncated normal distribution, moderate best estimates have broader uncertainty than low or high best estimates. If current and future priority differ for validation monitoring, future priority is weighted more because reducing uncertainty allows for a potential change in strategy. Priorities for classical research will be similar. Figure 4 summarizes the key points of the prioritizing process.

Completion of the first stage results in lists of objective–indicator pairs with high, moderate, and low priority for monitoring. Those with low priority for study (e.g., the strategy is fairly certain to achieve the objective, or uncertainty is irresolvable) can be filtered out at this point. The second stage then rates objective–indicator pairs with high or moderate priority for monitoring by overall measure of importance. In our system, importance measures include the degree of influence an objective has on a broader goal (e.g., the amount of habitat is more important than pattern for maintaining biodiversity), the recovery period for an objective (e.g., the visual quality of a harvested landscape recovers more quickly than does old-forest structure), the importance of an implementation indicator to an objective (e.g., road density impacts grizzly bear, *Ursus arctos horribilis* Ord, populations more than habitat availability), and the influence of one broad goal on other goals (e.g., water quality influences fish, biodiversity, and recreation or tourism, whereas mountain goats, *Oreamnos americanus* (Blainville), do not influence any other goals to a major extent). As for the cause–effect hypotheses, these values are obtained from workshops considering empirical evidence, as available and applicable, and expert opinion.

An important feature of our approach is that monitoring priority is determined, firstly, by probability of success and uncertainty and, secondly, by the importance of an objective–indicator pair. This approach avoids projects that — although studying important objectives — are unlikely to deliver useful information (for example, because uncertainty is irresolvable). The second stage ensures that those objective–indicator pairs most important or sensitive to management will receive attention first within priority classes.

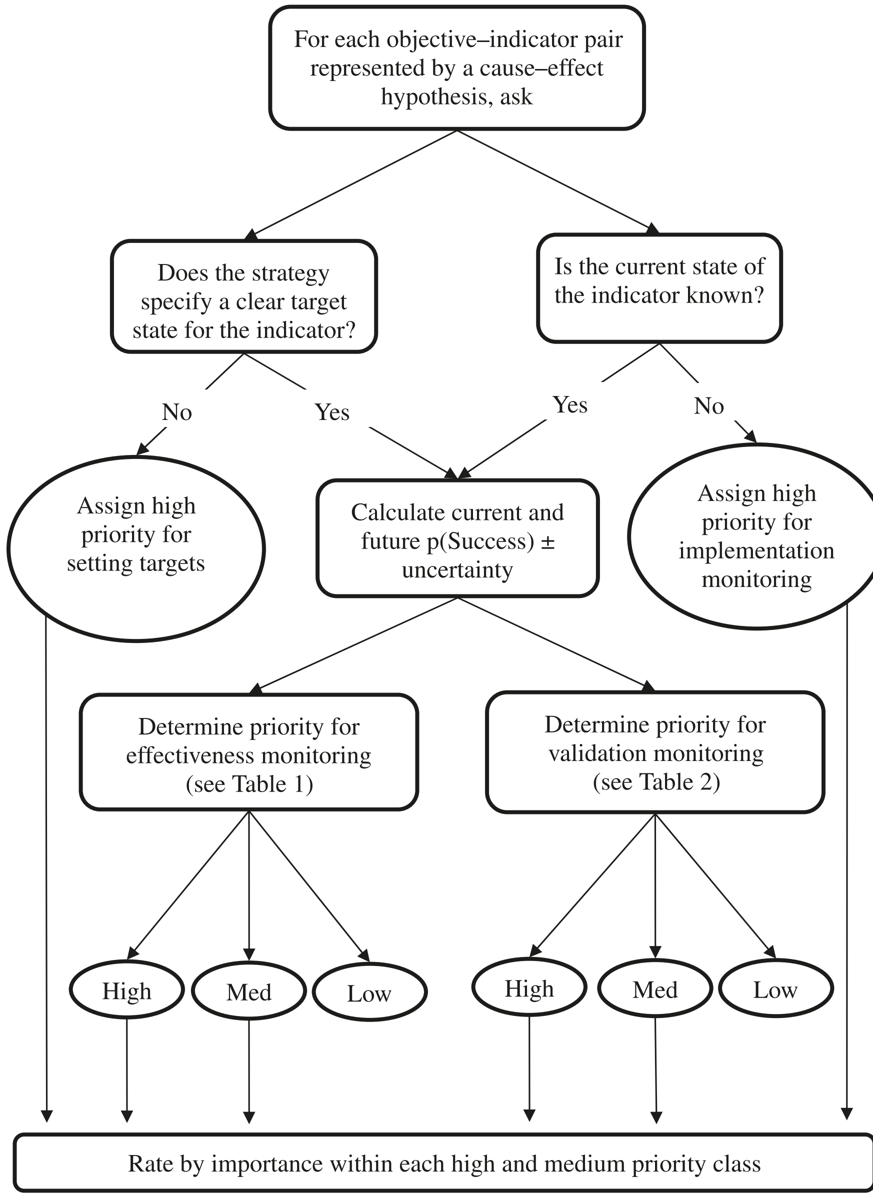
Monitoring is one step in an iterative adaptive management process. Completed implementation monitoring projects feed back data on current indicator state to verify implementation and to inform monitoring decisions in future iterations. Completed effectiveness or validation monitoring projects, which are designed to detect consequences or reduce uncertainty, update the cause–effect hypotheses and inform future monitoring priorities and selection of management strategies. Although there is a logical starting point for adaptive management (i.e., planning), the process can begin anywhere in the cycle. Through iterations, strategies will be revised or confirmed. Occasionally, objectives may be modified to be more realistic, especially when they are incompatible with other objectives.

The analysis used to prioritize monitoring also provides decision support by revealing if any planned strategies are unlikely to achieve objectives (Ludwig 2001; Failing and Gregory 2003). For example, if analysis shows probability of success is low with low uncertainty, planning direction should be reviewed; that is, if an existing target is unlikely to achieve an objective, either the objective or target should be submitted for revision. If strategies are misaligned with objectives, then failure to achieve the objective cannot be attributed to lack of knowledge but to a calculated decision. Also, if uncertainty is high but irresolvable, validation monitoring is wasted. In this case, planners may wish to select precautionary targets. Conversely, if probability of success is high with low uncertainty, planning direction is confirmed, and implementation monitoring is likely sufficient to achieve the objective.

Case study: prioritizing monitoring projects in the Babine Watershed

The Babine Watershed, a 400 000 ha watershed north of Smithers in the interior of British Columbia, is subject to a series of special management requirements: forestry activities are expected to protect high-value salmon, steelhead (*Oncorhynchus mykiss* Walbaum), grizzly bear, biodiversity, and wilderness resources. Public interest (regionally and internationally among anglers) in the area is high, and a multistakeholder group (representing the interests of forest industry, three government agencies, private tourism operators, environmental nongovernmental organisations, and local residents) met for over a year to design a governance model to oversee monitoring in the Babine. Their goal was an impartial, transparent process to decide on monitoring studies. The group formed the Babine Watershed Monitoring

Fig. 4. Schematic of key features of process used to prioritize implementation, effectiveness, and validation monitoring as well as target setting.



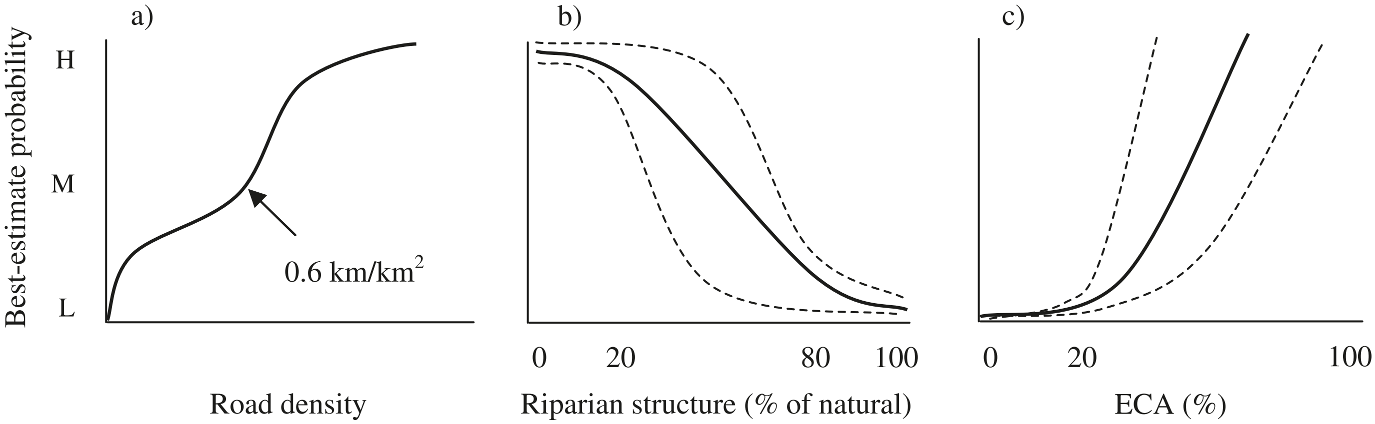
Trust (BWMT), a group of five neutral trustees, that now coordinates monitoring projects in the watershed according to a legally binding agreement (Babine Watershed Trust Agreement 2005; www.babinetrust.ca/DocumentsBWMT). The trust agreement requires trustees to follow the prioritization framework described below. The BWMT has a small budget of about $50 000 / year, some of which is used to leverage funds for larger projects.

Prior to the establishment of the BWMT, the Babine Watershed had been the focus of formal land-use planning efforts for 12 years and of monitoring for five decades. However, monitoring projects had not been linked to land-use plans; hence, results had not fed back into management. Between 1946 and 2004, nearly 200 monitoring, inventory, research, and planning reports had been completed for this single watershed — a huge investment (A. de Groot, Bulkley Valley Centre for Natural Resources Research and Management, Smithers, B.C., unpublished report to BWMT, 2004). However, very little in this vast collection of monitoring reports includes information useful for testing the success of strategies designed to achieve the agreed-upon objectives. In an effort to improve the relevance of monitoring, the BWMT used the monitoring framework described in this paper to prioritize monitoring projects.

Planning context

Existing plans defined the scope of the framework. Goals (e.g., conserve grizzly bear populations), objectives (e.g., minimize human–bear interactions), and strategies (e.g., minimize accessible, active road networks) already existed in six government-approved land-use plans applying to the Babine Watershed. The plans varied in detail, clarity, and approach. Two land and resource management plans had been completed as part of a provincewide initiative to pro-

Fig. 5. Example curves from the Babine knowledge summary: (*a*) probability of minimizing human–grizzly bear interaction versus road density within watersheds; (*b*) probability of maintaining fish habitat versus riparian structure; and (*c*) probability of maintaining hydrological function versus equivalent clearcut area (ECA). Dotted lines represent uncertainty bands (there are several sources of uncertainty around the grizzly bear curve; these are described in text in the knowledge summary). H, High probability; M, medium probability; L, low probability.



vide strategic direction (broad goals and more specific objectives) for the management of all public resources, through collaborative planning tables open to all parties with an interest in land-use and resource management issues (Canadian Environmental Assessment Agency 2002).[2] Subsequently, more detailed plans refined these objectives and provided operational strategies (framed sometimes as indicators and targets) that aimed to achieve each objective. Although these latter plans are more detailed in relation to forestry issues (with the exception of a park plan), they are also narrower in scope, omitting those objectives and strategies not directly linked to forest management activities.

Ideally, goals and objectives are developed collaboratively with input from all stakeholders and expressed clearly and unambiguously (Albert et al. 2003; Calbick et al. 2003). Unfortunately, consensus wording and clarity are often mutually exclusive, resulting in abstruse immeasurable objectives (e.g., “to manage for a variety of values and activities in an integrated and compatible manner”; Bulkley Land and Resource Management Plan 1998; ilmbwww.gov.bc.ca/slrp/lrmp/smithers/bulkley/plan/files/toc.htm). In many cases in the Babine plans, objectives and strategies were not clearly linked. Strategies in the more detailed plans did not always match the intent of the original objectives either because initial objectives were vague or were incompatible (e.g., “maintain current populations of organisms” and “maintain a constant timber supply”). In addition, some objectives lacked strategies.

Methods

The first task was to integrate the direction from the six plans into a single, clear document that ensures correspondence between objectives and strategies but leaves intent unaltered. We consolidated wording from different plans to simplify the summary. This process necessitated some interpretation and subsequent review by stakeholders. Strategies did not always match objectives one-to-one: sometimes several strategies applied to one objective, and sometimes, a single strategy was designed to achieve several objectives. Cross reference to the original plans and wording allowed stakeholders to follow lines of logic and interpretation and to accept the resulting document.

We then held small workshops and interviews with local experts to summarize knowledge for the objectives relating to each general goal (two to six participants for one-half day per goal). Experts discussed existing data, indicator relevance, hypotheses relating indicators to objectives (expressed as explicit cause–effect curves), degree and sources of uncertainty, and likelihood of success in monitoring to reduce uncertainty or to detect consequences. Experts also estimated the relative importance of each objective with respect to the goal, the recovery period of each objective, and the influence of other goals on the focal goal. Each completed section was reviewed by independent peers and revised.

Figure 5 shows examples of cause–effect relationships derived through this process. The curves were included in a knowledge summary that records a rationale and documents sources for each curve and lists modifying factors. For example, the grizzly bear curve (Fig. 5*a*) could be shifted left or right depending on habitat value and mitigative practices, such as screening along roads. The knowledge summary also describes types and sources of uncertainty, factors useful for estimating importance, and potential monitoring projects.

Ideally, the knowledge summary should be completed prior to developing management strategies. Indicators would then be chosen to match objectives, and management strategies would be specified as target levels of each indicator (Rempel et al. 2004). However, in the Babine Watershed, as is typical elsewhere, strategies were already designed and implemented. Because stakeholders had invested considerable time and effort in planning processes, we constrained initial indicators to relate closely to those included in existing plans. When experts considered that better indicators existed, we increased the uncertainty to account for a poor indicator–objective link. For example, the strategy for natural seral stage distribution stipulates retaining a percentage of each ecosystem, as defined by biogeoclimatic variant

[2] Overview of strategic land-use planning in British Columbia; www.ceaa-acee.gc.ca/default.asp?lang=En&n=6AFD257F-1&offset=13&toc=show.

(Banner et al. 1993), in each seral stage. However, each biogeoclimatic variant includes several ecosystems subject to differential harvest (i.e., the more productive ecosystems are more heavily harvested), which increases the uncertainty that maintaining a target level of a biogeoclimatic variant will achieve target levels of old productive ecosystems. Objectives, such as seral stage, with poor indicators ranked highly for validation monitoring — these future studies may suggest and test better indicators. Over time, the high ranking for validation monitoring solves the issue of poor indicators without rejecting existing plans. Better indicators evolve in a manner that is acceptable to stakeholders.

Although some participants in expert workshops were initially sceptical about the process of developing cause–effect hypotheses and partitioning uncertainty, almost all felt comfortable with the final product. We found that drawing explicit curves forced careful consideration of assumptions and uncertainties and encouraged focused discussion.

Results of analysis

About one-half of the 114 objective–indicator pairs had sufficient information to analyse (i.e., current state was known and targets existed). This high level of information was due to recent completion of the first regional-scale implementation monitoring report for British Columbia (Bulkley State-of-the-Forest Report 2004; www.for.gov.bc.ca/dss/StateofForest/foreststate.htm). The remaining indicators either had no targets and (or) current state was unknown. Thus, these indicators were assigned a high priority for planning (i.e., defining targets) and (or) implementation monitoring (i.e., measuring current indicator state).

Of the 62 analysed objective–indicator pairs, 37 ranked as high or medium priority for validation monitoring (i.e., to reduce uncertainty about the cause–effect relationship), and 22 ranked as high or medium priority for effectiveness monitoring (i.e., to detect negative consequences). Objective–indicator pairs can be on both lists; 19 pairs had no need for monitoring in the short term. Within high- and medium-priority classes, objective–indicator pairs were subsequently rated by importance scores. Estimates of the probability of monitoring success and relative cost of projects designed to monitor each objective–indicator pair, which were generated from the expert workshops, accompanied the list.

We met with the BWMT several times during the development of the framework to ensure that trustees understood the approach, including the cause–effect relationships, used to create priority lists. Most trustees were satisfied with verbal descriptions of probabilities of success and uncertainty, but some scrutinized the graphical hypotheses. Given the prioritized lists and an understanding of the process that produced them, trustees have been able to reach consensus-based decisions about the top priority projects to fund in a single meeting each year.

Monitoring projects selected for funding by the BWMT in their first 3 years represented a variety of values and all three types of monitoring: implementation monitoring of riparian forest and stream crossing practices, validation monitoring of water quality, and effectiveness and validation monitoring of wilderness values. Because of limited funds, proposal development was funded for two larger projects that have subsequently been initiated: implementation and effectiveness monitoring of open road density in relation to grizzly bears and implementation and validation monitoring of structure in young natural and managed stands.

The BWMT excluded projects from funding for several reasons: new data would be available soon, uncertainty was irresolvable within the Babine (e.g., the effects of education projects in relation to human–bear interactions could only be studied over a larger area), the objective had low importance within a particular goal (e.g., grizzly bear habitat has much less impact on grizzly bear population than roads), or consequences would be very difficult to detect even with an expensive project (e.g., mountain goat response to timber harvest during the natal period).

In addition to prioritizing monitoring projects, analyses supported planning and management decisions. Cause–effect hypotheses revealed previously unidentified inconsistencies between several objectives and strategies; for example, target levels of old seral forest in one area led to a low probability of achieving the objective of maintaining natural seral stage distribution. They also revealed objectives with missing strategies including, for example, maintaining sustainable levels of recreational use on the Babine River. The BWMT is not responsible for making management decisions but has a formal process for passing information about inconsistencies and missing strategies to agencies and multistakeholder committees responsible for updating land and resources management plans. This process closes the adaptive management loop.

The results from completed projects are used to update the knowledge summary, where they become available for future planning iterations.

Discussion

The framework described in this paper facilitates monitoring and decision-making. It contains three essential elements: explicit links between objectives and strategies; a synthesis of current knowledge that is disciplined, transparent, and easily updated and communicated; and procedures for prioritizing implementation, effectiveness, and validation monitoring. It also highlights inconsistencies in existing objective–strategy pairs, facilitating decision-making even before monitoring begins. Because it bases all projects on existing land-use plans, feedback to management is direct and simple. The heart of the framework is a knowledge summary describing hypothesized relationships between indicators, representing management strategies, and he probability of achieving objectives along with estimates of uncertainty.

Benefits of explicit cause–effect hypotheses

In dealing with complex decisions about environmental management involving multiple parties, explicit graphical hypotheses replace the implicit models that all stakeholders, including scientists, hold in their heads. Implicit models are based on individual experience. They include different data and assumptions and can confound knowledge and values. Conversely, explicit models document assumptions, data, and knowledge transparently and, hence, focus and clarify discussion. The benefits of explicit models are well recognized both for combining expertise and for involving stakeholders (e.g., Holling 1978; Walters 1986; Fall et al. 2001; Failing and Gregory 2003; Burgman 2005). In our experience with the BWMT, the explicit, transparent hypotheses helped trustees to prioritize monitoring projects remarkably quickly. Stakeholders also appreciated the ability to judge when policy decisions included risky strategies.

Cause–effect curves synthesize current knowledge and assumptions. They present knowledge in a manner that can be recorded, communicated, and updated easily, which facilitates learning (Bunnell and Dunsworth 2004; Tear et al. 2005). They model the shape of relationships and express thresholds clearly. Thresholds, particularly between habitat and species response, have received considerable attention over the past 10 years because they can indicate regions where ecological risk increases rapidly (e.g., Andrén 1994; With and Crist 1995; Muradian 2001; Huggett 2005). Rempel et al. (2004) suggest that learning about thresholds is facilitated through a monitoring framework, such as ours, that connects cause and effect. Our framework extends beyond the species–habitat relationships discussed by Rempel et al. (2004); in the Babine case study, curves (some linear, many not) describe the probability of achieving objectives for a variety of values including hydrology, wilderness, visual quality, and timber supply.

Recently, several authors have suggested similar curves for examining the effectiveness of strategies (e.g., Failing and Gregory 2003; Angelstam et al. 2004*b*; Rempel et al. 2004), although with a response variable (e.g., population), rather than probability of achieving the objective, on the *y* axis. Our modification uses the common currency of probability on the *y* axis across all objectives, which provides explicit connections between management strategies and objectives and facilitates comparison among objectives.

Social learning about the consequences of management requires more than scientific information (Lee 1993; Gunderson et al. 1995; Pannell and Glenn 2000; Kinzig et al. 2003). However, as a first step, the science, including uncertainty and tradeoffs, must be summarized and communicated clearly. Kinzig et al. (2003) suggest expected utility theory and Bayesian updating as methods of combining science and perspective. Utility theory identifies possible consequences of actions, determines the probability of each, and assigns a value (utility) to each consequence. Probabilities are based on best available information and updated according to Bayes' theorem. The curves we describe are a special set of utility functions. We have chosen a single outcome — the probability of not achieving an objective — and assigned a high value to this consequence, assuming that objectives reflect consensus decisions about utility. This simplification makes working with multiple curves and nonlinear functions much more tractable. The curves reflect data and subjective expert opinion and are eminently suited to Bayesian updating. Although the method produces curves for consequences to all objectives, it does not include a methodology for dealing with value-based trade-offs among objectives. However, the explicit representation of cause–effect hypotheses provides the technical information required to support such value-based judgements through expected utility methods (multiattribute trade-off analysis). Expanding the approach within a multiattribute trade-off analysis might present interesting possibilities.

Although cause–effect curves appear simple, and perhaps naive, they can summarize models of any level of complexity that can be supported by current information. In most cases, the precision of current data precludes anything more specific than a generalized curve with considerable uncertainty. Simple models are transparent, encourage a focus on concepts, and can quickly capture a range of views. More sophisticated models can provide more quantitative, perhaps more precise (but not necessarily more accurate), predictions of potential consequences. Such complex models can be useful when interactions are nonlinear and when considerable sensitivity analysis is desired, but it is not possible to reduce uncertainty simply by using more sophisticated models (Walters 1997*a*). In our framework, the possibility of failing to achieve an objective triggers more detailed examination of the utility of the new condition and consideration of management options and trade-offs among objectives.

Because they use a common currency, the curves can be used to prioritize monitoring efficiently across objectives. The most important objective is not necessarily the one to monitor if the probability of achieving the objective is high or if uncertainty is irresolvable. If probability of success is fairly certain to be low, effectiveness monitoring should be designed to detect negative consequences quickly, and policy decisions about the planned strategy should be revisited. If uncertainty is relatively high and is resolvable, validation monitoring and research should be designed to improve knowledge about the cause–effect relationship. If uncertainty cannot be resolved until after actual harm occurs, options to proceed include revising planned strategies using a higher level of precaution or designing an adaptive management experiment with the expectation of negative consequences (Ludwig et al. 1993).

An alternative to drawing explicit curves is to assume that current knowledge is insufficient and begin with a hypothesis of no information about the relationship in question (such an assumption could still be drawn explicitly with uncertainty bands covering all possibilities). This approach ignores the considerable research and management experience to date (Failing and Gregory 2003) and can result in ad hoc monitoring programmes, where research is driven by personal interest.

Selecting indicators

The framework provides guidance on which objectives should be the focus of effectiveness monitoring but does not select effectiveness indicators. Selecting effectiveness indicators has spawned a vast literature of controversy (e.g., Simberloff 1998, 1999; Noss 1999; Andelman and Fagan 2000; Lindenmayer et al. 2000, 2002; Rempel et al. 2004,). Although there is no way to remove the necessity for careful monitoring and research to validate management hypotheses, starting with a focused list of issues can reduce the task. Rather than a blanket prescription to define effectiveness indicators for everything, the framework filters objectives and pinpoints those most in need of monitoring. Thus, easily measured landscape indicators (e.g., forest age, type, and structure) will be sufficient for most objectives. These indicators can be validated selectively by species responses if and when analysis suggests that the extra step is a priority.

Closing the loop

The explicit hypotheses about the relationships between strategies and objectives and the emphasis on learning included in this framework are some of the basic elements of adaptive management. Adaptive management is generally defined as a formalized approach to learning that encompasses both passive and active approaches (Walters 1986). In past practice, adaptive management has frequently considered one objective at a time and designed management experiments to improve knowledge about the relationship between activities and that objective. Even successful, often-cited examples of adaptive management have focused primarily on a single question (e.g., stand-level retention; Bunnell and Dunsworth 2004). Our framework refocuses on the broader goals and interpretation of adaptive management that embraces multiple approaches to learning with the explicit goal of improving management.

Creating an organizational structure to support learning over the long term may be an essential step in implementing this framework. Our work in the Babine Watershed was enabled by two organizations. The BWMT (a neutral body) has a legal mandate to select monitoring projects objectively. The Bulkley Valley Community Resources Board represents multiple interests and values (www.bvcrb.ca/) and is responsible for advising the provincial government about updating existing land-use plan objectives and strategies for part of the watershed.

The traditional three-tiered approach to monitoring, where implementation monitoring is followed by effectiveness and finally validation monitoring, can hinder efficient learning. Implementation monitoring alone cannot be used to improve management strategies. Organizational inertia can result in detailed attention to the implementation monitoring tier while important effectiveness monitoring projects are ignored or carried out haphazardly. In addition, uncertainty around a particular objective–indicator relationship can be too high to determine the probability of achieving an objective; in these cases, validation monitoring should come before effectiveness monitoring. In the Babine Watershed, for example, a study examined natural levels of postdisturbance stand structure to reduce uncertainty about the relationship between targeted levels of structure and biodiversity. Our framework looks at all three tiers simultaneously and prioritizes objectives within each tier so that, at any time, some monitoring projects might collect implementation data, whereas others monitor effectiveness. In the Babine Watershed, even with a small budget, trustees have selected projects representing all three types of monitoring.

Integrating with other monitoring processes

Monitoring initiatives exist at many scales. National programmes (e.g., Canadian Council of Forest Ministers 1997) monitor the status of a suite of consistently measured indicators. These processes are useful for comparing progress over time and among jurisdictions but, essentially, are isolated from feedback to regional strategies. As such, they are unable to inform decisions about management (Failing and Gregory 2003). Inertia is also an issue across scales: national monitoring programmes are unlikely to provide useful information to forest operations sufficiently quickly to change management course (Angelstam et al. 2004*a*).

At provincial and regional scales, a plethora of independent initiatives has blossomed in response to calls for forest certification and results-based management. Provincial government initiatives in British Columbia include a state-of-the-forest report (www.for.gov.bc.ca/hfp/sof/), a programme designed to monitor provincial legislation (Forest and Range Evaluation Program; www.for.gov.bc.ca/hfp/frep), audits by the Forest Practices Board (www.fpb.gov.bc.ca/), and monitoring of land-use plans. Some of these initiatives focus on providing results of implementation monitoring to external sources — in essence, they produce report cards, which is a necessary but insufficient step to improve management. Moving beyond report cards towards adjusting management strategies requires effectiveness and validation monitoring and direct feedback to decision-making. Although some processes call for monitoring effectiveness and for placing monitoring within an adaptive management cycle (e.g., CSA 2002), application of these processes can narrow the definition of effectiveness monitoring to simply checking whether implementation indicator targets have been achieved — insufficient for adaptive management (for an example that is geographically close to the Babine Watershed, see Morice and Lakes Sustainable Forest Management Plan; www.moricelakes-ifpa.com/plan/).

A framework directly based on existing regional land-use plans provides the link to management decisions missing from other initiatives. The approach described in this paper, using curves to link existing, regional objectives to indicators, can test current strategies and facilitate learning in addition to merely providing reports of progress towards objectives. It can be applied to certification schemes and provincial programmes as well as to regional land-use plan monitoring.

Conclusions

The framework described above serves three functions. Firstly, it allows monitoring to fulfill its potential in a learning cycle by linking monitoring to planning via a common knowledge summary. Secondly, it provides an independent, transparent, and efficient procedure for prioritizing monitoring. Thirdly, it provides decision support by highlighting strategies that are unlikely to achieve objectives.

The framework is succeeding in a single, albeit large and complex, watershed in British Columbia. It is possible to extend the approach to a larger geographic area: elements are being applied to British Columbia's northern and central coast (Price et al. 2009). We believe that the framework would be useful to focus monitoring and improve management elsewhere, with consideration of several challenges. Firstly, to separate values from knowledge, the people determining monitoring priorities and maintaining the knowledge summary should be independent from those updating management strategies. In the Babine Watershed, the monitoring group formed a legal trust to ensure neutrality. Secondly, to maintain transparency, interested people must have the time and resources to fully understand and question the framework. Thirdly, those using the framework need to recognize that the priority lists are guides rather than substitutes for thinking.

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