Using Bayesian belief networks in adaptive management[1]

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Abstract: Bayesian belief and decision networks are modelling techniques that are well suited to adaptive-management applications, but they appear not to have been widely used in adaptive management to date. Bayesian belief networks (BBNs) can serve many purposes, from illustrating a conceptual understanding of system relations to calculating joint probabilities for decision options and predicting outcomes of management policies. We describe the nature and capabilities of BBNs, discuss their applications to the adaptive-management process, and present a case example of adaptive management of forests and terrestrial lichens in north-central British Columbia. We recommend that those unfamiliar with BBNs should begin by first developing influence diagrams with relatively simple structures that represent the system under management. Such basic models can then be elaborated to include more variables, the mathematical relations among them, and features that allow assessment of the utility of alternative management actions or strategies. Users of BBNs should be aware of several important limitations, including problems in representing feedback and time–dynamic functions. Nevertheless, when properly used, Bayesian networks can benefit most adaptive-management teams by promoting a shared understanding of the system being managed and encouraging the rigorous examination of alternative management policies.

Résumé : Les réseaux bayésiens de décision et d'appréciation (RBDA) sont des techniques de modélisation bien adaptées aux applications de l'aménagement adaptatif mais, à ce jour, ils ne semblent pas avoir été largement utilisés à cet effet. Les RBDA peuvent servir à plusieurs fins, depuis l'illustration de la compréhension conceptuelle des relations entre systèmes jusqu'au calcul de probabilités conjointes d'options décisionnelles et à la prédiction de conséquences de décisions d'aménagement. Nous décrivons la nature des capacités des RDBA, discutons de leurs applications dans le processus d'aménagement adaptatif et présentons une étude de cas d'aménagement adaptatif de forêts et de lichens terrestres dans le centre-nord de la Colombie-Britannique. Nous recommandons à ceux qui ne sont pas familiers avec les RDBA de commencer d'abord par développer des diagrammes d'influence avec des structures relativement simples pour représenter le système sous aménagement. De tels modèles de base peuvent ensuite être rendus plus complexes pour inclure plus de variables, les relations mathématiques entre elles ainsi que les éléments permettant d'évaluer l'utilité de stratégies ou d'actions alternatives d'aménagement. Les utilisateurs de RBDA doivent être conscients de plusieurs limitations importantes, incluant des problèmes de représentation des rétroactions et des fonctions dynamiques dans le temps. Quoiqu'il en soit, les réseaux bayésiens bien utilisés peuvent rendre service à la plupart des équipes d'aménagement adaptatif en favorisant une compréhension partagée d'un système sous aménagement et en encourageant l'examen rigoureux de politiques alternatives d'aménagement.

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Introduction

In adaptive management (AM), models are commonly used to describe the system being managed and to forecast expected outcomes of management. Such models take many forms, from conceptual "box and arrow" diagrams developed by citizen groups (Margoluis and Salafsky 1998) to sophisticated mathematical simulations and risk-analysis tools developed by scientists (Walters 1986). Depending on their type, models can serve many important technical purposes in AM, including documenting the current state of knowledge of the system, clarifying assumptions, identifying key uncer-

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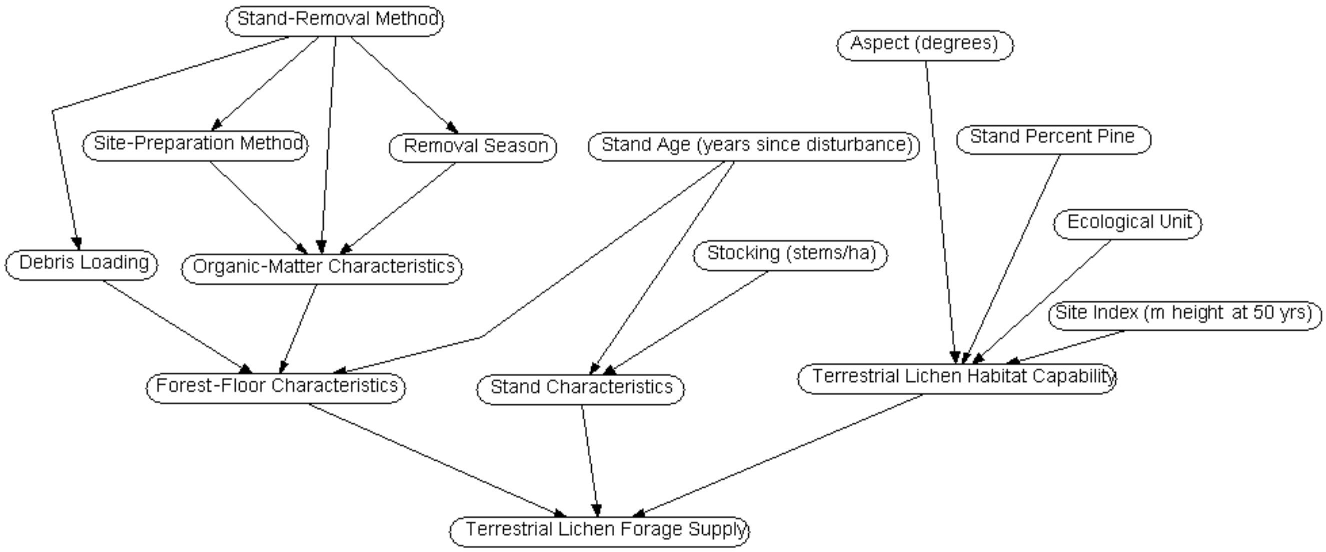
Fig. 1. An influence diagram illustrating the structure of Bayesian belief networks. This diagram represents the influences of environmental factors and forest management on the abundance of terrestrial lichens that provide forage for woodland caribou (*Rangifer tarandus caribou*) in north-central British Columbia.



tainties and thresholds, testing sensitivities, and evaluating consequences of alternative decisions. In addition, AM participants often find the process of building a model together helps to create a sense of teamwork and a shared understanding (Holling 1978).

Despite their fundamental place in the origins of AM (Holling 1978), models are not universally used in AM programs. There are probably two reasons for this: AM project teams may not recognize the usefulness of simple conceptual models of systems, or they may not be capable of building more complex mathematical or computer models. Doubt about the usefulness of modelling may arise for many reasons, including previous experience with unsuccessful models and expectations that models will be complicated or must be driven with massive amounts of field data that cannot be obtained. The perceived lack of modelling skills or confidence in some AM teams may derive from the historical emphasis in the AM literature on computer-based simulations of populations and systems, which usually require high levels of modelling expertise (e.g., Lackey 1979). In other cases, AM teams may reject simple conceptual or diagram-style models because such models lack rigour and provide no means for simulating decisions and changes over time.

Given the proven value of models to AM programs, many AM teams could benefit from a powerful yet easily grasped modelling approach. We propose that Bayesian belief modelling is such an approach and is worthy of much wider use in AM. Bayesian belief modelling has been used in a wide variety of natural resource management fields, including as an aid to water-resource planning (Bromley et al. 2005), evaluating population viability of salmonids (Lee and Rieman 1997; Rieman et al. 2001), and managing Baltic cod (*Gadus morhua callarias* Linnaeus, 1758) (Kuikka et al. 1999). Kangas and Kangas (2004) identified several approaches to developing useful risk-assessment tools for forestry decision analysis, including the use of Bayesian methods. Other examples of Bayesian belief modelling in natural-resource management are reviewed elsewhere (Bacon et al. 2002; Marcot et al. 2006). Although the use of such tools is becoming more common, we found no examples of use that fully spanned all steps in the AM process.

Here we describe the nature of Bayesian belief networks (BBNs) and Bayesian decision networks (BDNs), explain their benefits in AM applications, illustrate their use in a specific case example, and discuss their shortcomings and alternatives. We make the distinction here between BBNs and BDNs: the latter contain decision nodes and, optionally, utility nodes. For simplicity we use BBN to include both types of networks, and use BDN when it is necessary to denote a decision network only.

Nature and benefits of Bayesian belief networks

BBN concepts and software

BBNs are easy for most people to use, especially when constructed with one of the commercially available software "shells" such as Netica (Norsys Software Corporation, http://www.norsys.com/netica.html), Hugin Expert (Hugin Expert A/S, http://www.hugin.com/), Bayesware Discoverer (Bayesware Limited, http://www.bayesware.com/), and Microsoft Bayesian Network Editor and Toolkit (MSBNx) (Microsoft Research, http://research.microsoft.com/adapt/MSBNx/).

BBNs (Fig. 1) are constructed as networks of variables and their interactions, referred to as nodes and directed links, and can represent a very wide array of problems in ecological assessment and prediction (McCann et al. 2006). In this paper we use "parent" and "child" to describe the positions of nodes in the BBN structure, and "nature", "decision", and "utility" to describe the types of nodes. Below we briefly describe the nature and formulation of BBNs; more details are provided in Marcot et al. (2006).

In BBNs, nature nodes represent empirical or calculated parameters and probabilities of various states of those parameters. Input (or "parentless") nodes (e.g., stand-removal method in Fig. 1) are structured as constants or as categorical states with associated prior probabilities. Prior probabilities can be assigned according to known frequencies of various states, or based on an assumed statistical distribution, a special case being a uniform distribution that represents complete uncertainty. Input nodes often are grouped into summary child nodes (latent variables) (e.g., terrestrial lichen habitat capability in Fig. 1) that use either equations or conditional probabilities to merge conditions of their parent (input) nodes. States associated with final outcome node(s) (terrestrial lichen forage supply in Fig. 1) are calculated as posterior probabilities using Bayes' Theorem (O'Hagan et al. 2004).

Decision nodes in BDNs represent two or more choices that influence the values of other response nodes. Choices in a decision node do not have probabilities associated with them. For example, a decision node representing whether to precommercially thin a forest stand could be linked to response nodes representing resulting tree density and slash biomass. Specifying the type of thinning would then trigger the response-node states according to the conditional-probability tables for those response nodes.

Utility nodes in BDNs represent the value — cost or benefit — of some outcome or decision, and can be linked to either outcome nodes or decision nodes. More than one utility node can be linked to the same node, and utility nodes need not be parameterized on the same unit of measure (e.g., dollars), although doing so makes it far easier to interpret model results. For example, utility nodes linked to the decision node for precommercial thinning could variously represent per hectare operational costs and some social benefit (e.g., a scoring index or willingness to pay) of various thinning options. Utility nodes linked to calculated outcome nodes would show costs or benefits of each possible outcome state. Once parameterized, BDNs can be queried to determine the decision pathway (the best choice in each decision node) that minimizes costs or maximizes benefits, and the sensitivity of such best decisions to changes in utility values and prior conditions. The BDN displays expected values for each choice in the decision nodes by combining all pertinent utilities and their calculated probabilities.

BDNs are similar to traditional decision-tree analysis but are far more flexible in the type of questions and analyses they can help answer. For example, one can specify an outcome — such as the best ecological response to thinning — and then determine the optimal decision pathway with the highest likelihood of producing that response. This type of backward calculation cannot generally be done with decision trees, although some decision-tree software (e.g., DecisionPro, Vanguard Software Corp., http://www. vanguardsw.com/vanguard.htm) can display the influence of risk attitudes on decisions.

Benefits for AM

Many formulations of the AM process have been described, most or all of which derive from the initial description by Holling (1978). Here we follow Nyberg (2004) in recognizing a six-step AM sequence: (1) assess the management problem or opportunity at hand; (2) design a management experiment to facilitate learning; (3) implement the experiment; (4) monitor system responses; (5) evaluate outcomes and learn from them; (6) adapt future decisions on the basis of what was learned.

BBNs work well in this systematic approach to AM for two key reasons. First, the conceptual basis of Bayesian inference parallels the concepts behind AM (Holling 1978). Both presume that we begin with some understanding of a system and then seek to improve and update our understanding by gathering and interpreting data. Bayesian inference uses prior knowledge (represented as the basic BBN structure and as prior probability distributions) before data are collected in a study, and posterior probability distributions that result when new data are accounted for. In a parallel fashion, AM frameworks often include "impact hypotheses" that are developed early in a project and more refined hypotheses that are developed by evaluating the outcomes of management experiments. BBNs can be developed as testable impact hypotheses that are evaluated and refined with new information. Second, the software toolbox provided in many popular BBN programs provides functionality, such as sensitivity testing and incorporation of new case data that supports several of the steps in the AM process.

In the following sections we outline some of the potential applications of BBNs to the six AM steps outlined above, and discuss techniques that are particularly helpful in AM projects. We are not aware of examples in the literature illustrating the use of BBNs throughout a complete AM sequence such as that described here; in fact, there is little or no literature on BBN applications beyond step 2. We therefore provide references where possible to applications of BBNs in situations that parallel some of the stages of AM, such as assessment of policy options during the preparation of environmental-impact statements. We also draw on our own experience in unpublished AM studies, including the case example that appears later in this paper. Table 1 provides a summary of potential AM applications.

AM step 1: Assess the problem or opportunity

Building a conceptual model is a valuable first step in making the structure and function of any system understandable to all AM project participants. AM teams commonly do this when assessing the problem or opportunity confronting them, such as when developing hypotheses of effect or impact-hypothesis diagrams (Jones et al. 1996). Because BBN software programs allow the construction of straightforward hierarchical models of relations among inputs, actions, system parameters, and outcomes, initial BBNs can be derived directly from conceptual or graphical models (or influence diagrams; see Marcot et al. 2006). For example, the simple conceptual models used in some conservation and development projects that include villagers as active participants (e.g., Margoluis and Salafsky 1998, p. 309) could easily be built in BBN format. In these and other projects, conceptual models could be edited, annotated, and distributed electronically using inexpensive BBN software, thus facilitating clear documentation and rapid communication (Lynam et al. 2002).

Other applications of BBNs in the early stages of AM derive from the mathematical complexity behind the nodes and linkages in fully developed networks (e.g., Steventon et al. 2006). These mathematical relations represent the causal factors and functions that drive the system and the outcomes of interest to managers (Cain et al. 1999).

Table 1. Applications of Bayesian belief networks (BBNs) to steps in the adaptive-management (AM) process.

Adaptive-management step	Pertinent BBN applications
1. Assess the problem or opportunity	Represent graphically the structure of the system being managed, including (*i*) displaying linkages between potential management actions, system components, and outcomes; and (*ii*) defining measurable indicators and outcomes that reflect objectives. Explore the effects of alternative actions on outcomes by forecasting explicit indicator responses to a wide range of management options. Identify key gaps in understanding (uncertainties). Assess the sensitivity of forecasted outcomes to various inputs, actions, variables, and alternative hypotheses. Document current understanding of system structure and relations for communication among members of project team and to interested stakeholders or public
2. Design a management experiment	Select the management actions to be compared in the experiment by evaluating sensitivities, key uncertainties, forecast effect sizes, and utilities, including costs of implementation and monitoring
3. Implement the experiment	Use the BBN as a reference for the team and resource manager to maintain focus on important questions and selected management policies
4. Monitor system responses	Compare monitoring results with forecast system responses to test whether monitoring effort is sufficient to detect important effects; look for more sensitive indicators in the BBN structure or, if necessary, increase monitoring effort
5. Evaluate outcomes and learn	Update conditional probabilities using data from monitoring; refine the model to incorporate reductions in uncertainties; restructure the model to add system relations and components that were not previously recognized or to delete those that are unnecessary
6. Adapt future decisions	Use the revised model to guide future decisions about management practices, including any future experiments and monitoring

Note: The AM steps are as outlined in Nyberg (2004).

BBNs can incorporate both empirical data and expert judgment into the same tool (e.g., Martin et al. 2005). Typically, such models are first structured on the basis of expert knowledge. Model structure refers to establishing the nodes and their discrete states, value ranges, or calculations, and the linkages among the nodes. In general, a modeller may serve as a "knowledge engineer" by working closely with subject-matter experts to build the initial model and help test and refine it. The modeller helps the experts articulate their understanding of a system or decision framework, and this can be done individually or in expert-panel settings. We advocate using peer-review and -refinement procedures to craft credible models (Marcot et al. 2006).

Although "rule-induction" algorithms exist that can help build or refine the model structure from case data, we advocate building the initial structure at least in part from human expertise. Artificially induced BBN model structures tend to be very shallow, with many nodes feeding into outcome nodes with few intermediate variables; thus they are not intuitive and are difficult to understand and parameterize with conditional probabilities. Also, rule-induction algorithms generally are incapable of identifying decision and utility nodes, which are best denoted through collaboration of experts and stakeholders (Failing et al. 2004). Instead, empirical (or even modelled) case data can be used later once the primary model is built, to further test the model, refine the node states, and update the prior and conditional probabilities (see below and Marcot et al. 2006).

Some BBN models require use of mathematical equations to determine values and conditional-probability tables (CPTs) for a node. An example of an equation to specify the state values of a node is the use of a continuous-diffusion equation to determine population persistence of marbled murrelets (*Brachyramphus marmoratus* (J.F. Gmelin, 1789); Steventon et al. 2006). An example of an equation to specify CPT values is the joint probability function for determining capture likelihood for northern flying squirrels (*Glaucomys sabrinus* (Shaw, 1801); Marcot et al. 2006). If equations are used to determine state values or CPTs, then to run the BBN model the node first must be "discretized", that is, turned into discrete states. This is because BBN calculations of posterior probabilities use discrete conditions. Node discretization is a standard BBN process that is handled in most of the BBN modelling shells, and some BBN modelling shells can handle fully continuous probability values under specified probability distributions such as the normal distribution.

BBNs usually are designed to immediately calculate and display the results of any changes made to parent node states. With BBNs that posit cause and effect relations within a system, AM teams can explore "what if" questions by compiling the network and then entering different sets of findings (evidence) for the parent nodes. As explained above, these findings can be based on either expert knowledge or data (Raphael et al. 2001). The resulting changes in the states of the child nodes reflect the team's modelled understanding of the system and the interactions among its variables (i.e., the probability structure of the model). This ability to forecast outcomes or "game" with management options is a crucial step in assessing AM opportunities and designing management experiments.

Another approach to forecasting outcomes and sorting among decision options is to run simulations of changes in the system outside the BBN. Then the states of simulated variables (e.g., vegetation parameters) at selected time steps can be fed as inputs to a BBN that translates them into summarized outcomes, expressed as indicators relevant to management. This approach can be used for modelling habitat changes over large areas and long time periods, as in Raphael et al. (2001), Sutherland (2005), McNay et al. (2006), and Steventon et al. (2006). With this approach, a series of workshops is usually required, with simulations being run in the intervals between workshops.

Once a model is built, it can be tested with historic data and used to guide further collection of validation data sets. Validation refers to determining the accuracy, precision, or bias of predictions or forecasts. It also can refer to determining the correctness of the statistical or causal model used to generate those predictions or forecasts. Historical (including retrospective) data can be used in various ways, such as with bootstrapping by randomly splitting the data set into two parts, one for model parameterization and the other for testing results. This tests how well a model performs given a set of known outcomes. Another approach to validation is to use new observations that would be gathered as part of the AM experiment under conditions that are expected to be similar to those under which the model was devised and intended for use.

Sensitivity analysis plays a central role in many stages of BBN model development, testing, and application (see discussions and formulae of sensitivity analysis in Marcot et al. 2006). At this first AM step it can help guide and determine appropriate model structure (Marcot et al. 2001).

Our experience and that of others (Lynam et al. 2002; Heemskerk et al. 2003) have shown that most who participate in building BBNs find the process to be stimulating and enjoyable, especially in team workshops. The cross-discipline communication that is required (Heemskerk et al. 2003) and the collaborative focus on the BBN product help to form strong and committed teams with a thorough understanding of each member's views and knowledge. We recommend constructing and refining the network using a BBN program on a computer run by one team member who is familiar with the software, and who can extract and represent knowledge and experience from the experts. With the network projected on a screen visible to all, participants can follow each change as the workshop proceeds, first building a simple network structure and then elaborating the relations behind it, including constructing conditional-probability tables. One of the most powerful advantages of this approach to AM modelling is that it allows any participant — resource manager, scientist, or stakeholder — to contribute ideas or data and almost immediately see them represented in the outcome of the BBN. We also advocate building multiple or competing (and testable) BBN models if experts disagree on model structure; this too can be done with relative ease.

AM step 2: Design a management experiment

Regardless of whether an actively adaptive (deliberately experimental) or passively adaptive approach to AM (Walters 1986) is preferred, a decision-maker must select one or more management policies or regimes to put into effect. A BBN can be used to suggest policy options from the full set tested in the previous step that meet specified performance criteria such as low cost or a high level of effectiveness, especially if decision or utility nodes have been included in the model (Rieman et al. 2001). It can help guide the design of management experiments by highlighting areas of uncertainty and sensitivity where better information is needed (Cain 2001). Sensitivity analysis can identify the more influential input variables for prioritizing validation data collection and designing the monitoring program based on those input nodes (e.g., environmental-condition attributes) that most influence the model predictions.

AM step 3: Implement the experiment

Step 3 is the most straightforward stage of AM, when the management policy is carried out. At this step, BBNs are of most value in maintaining the commitment of the AM team and the resource manager to the goals and design of the project. The BBN can serve as a touchstone for the team, keeping everyone focussed on the selected management policy or policies and on the importance of staying the course until system responses are known (Salafsky et al. 2001).

AM step 4: Monitor system responses

Often the AM team's understanding of the system can change during the monitoring phase, leading to changes in the BBN. This can result when new information is acquired as interim monitoring results or from sources outside the AM project, such as academic research. This pattern of repeated "tweaks" of a BBN is likely to be common where the implementation and monitoring phases last a long time, as is often the case in forest management and some other fields. Documenting and archiving each BBN update can help provide an administrative record. A BBN can be informative during monitoring if the indicators being measured prove to be relatively insensitive to the implemented management policies. Examination of the BBN may point to other variables (nodes) that are more closely linked to the policies and thus more informative as monitoring indicators. New data may alter the sensitivity structure of the model and also influence the prioritization of variables for further data collection.

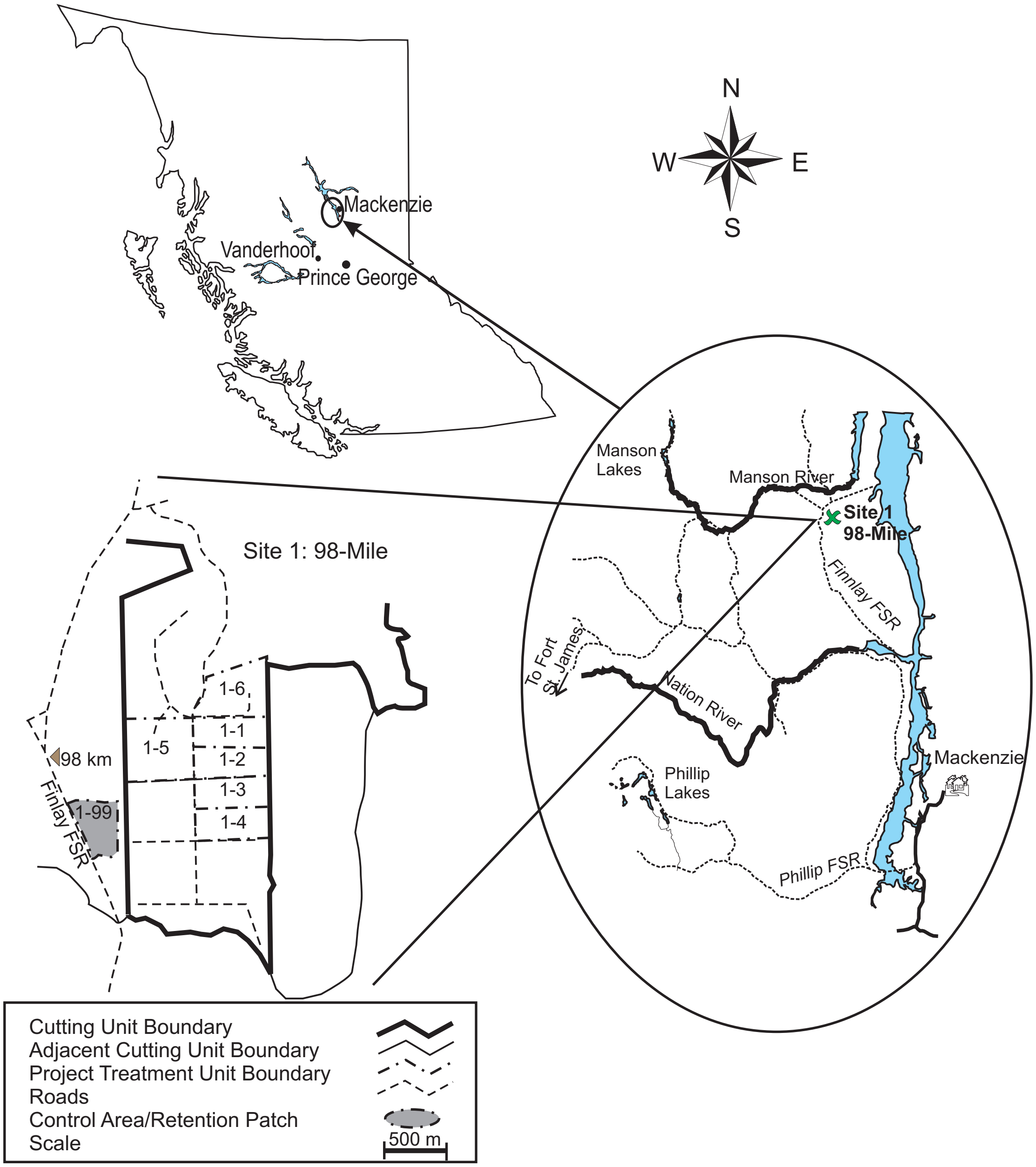
AM step 5: Evaluate outcomes and learn

When monitoring results are in hand, the BBN usually will need to be updated to reflect the new information. BBNs calculate posterior probabilities of the output nodes, given specific conditions of the input nodes. This essentially solves the BBN model for a specific case, and does not change its basic construction or probability structure (CPTs).

Updating is also used in BBN modelling to refer to improving the values of the CPTs by incorporating a case file of known examples. Several methods are used in BBNs to update CPTs, one of the more popular of which is the expectation maximization algorithm (Watanabe and Yamaguchi 2003). In expectation maximization updating, a set of examples is compiled typically from field surveys or studies, but the examples also could be developed from simulated data. The examples contain information on some or all values of the input nodes and the resulting state of the output node, such as forest stand conditions and associated known presence or absence of some rare species. The BBN is fed the examples, and the expectation maximization algorithm updates the underlying CPT values to better fit the known data by integrating over missing variables. CPT updating can be very important in the AM process, the prediction models being incrementally improved with collection of new data.

A third kind of updating can be done by using case files of known (or simulated) examples to improve the very con-

Fig. 2. Location map of site 1 (of three sites) of the terrestrial lichen adaptive management project in the Williston Reservoir area of north-central British Columbia.



struction of the BBN model itself, that is, its specification of nodes, states, and linkages. There are automated algorithms that can specify model structure, but we suggest defining and updating BBN model structure manually or based on external statistical analysis to best conform with ecological concepts, the statistical structure of the data, and appropriate decision structures. Automated structure updating can result in unwieldy and shallow BBN models with no summary intermediate nodes and with many input nodes feeding directly into output nodes; such model structures can be difficult to understand.

AM step 6: Adapt future decisions

In this step, decision-makers will revise management policies, if necessary, based on learning that occurred in the previous steps. BBNs will almost certainly need to be updated or even completely rewritten. Once the BBNs have been made current with new knowledge, they can again be used to evaluate new policy options, determine key uncertainties, and guide experiment and monitoring designs.

Application of BBNs to AM: terrestrial lichen and caribou case study

To illustrate the value of BBNs in AM, we describe our experience with a project investigating responses of terrestrial lichens to forest management in the Williston Reservoir area of north-central British Columbia (Fig. 2). This project is one component of the study of woodland caribou (*Rangifer tarandus caribou* (Gmelin, 1788)) habitat and population described by McNay et al. (2006). The goal of the project is to determine whether forest-management techniques can be used to maintain or promote terrestrial lichens, principally *Cladina* spp., that supply critical winter forage for caribou in the area.

Caribou forage lichens grow abundantly on the forest floor on dry, nutrient-poor sites, with overstory vegetation dominated by 70- to 140-year-old lodgepole pine (*Pinus contorta* Dougl. ex Loud. var. *latifolia* Engelm.). Many of the key wintering sites for caribou are also part of the land base used to supply timber to local mills, but terrestrial lichens are known to decline following logging in many parts of Canada (Rowe 1984) and often remain depressed for decades. Evidence from north-central British Columbia, however, suggests that development of terrestrial lichen communities may occur more rapidly than in other parts of the country (Sulyma 2001), and that appropriate forestry practices may allow terrestrial lichens to be maintained at levels suitable for providing forage for caribou. The AM project described here arose from this issue.

Project development and progress

Concerns about caribou and their winter forage supply in the Williston Reservoir area were highlighted during development of the regional land use plan for the Mackenzie area (Province of British Columbia 2000). These concerns were further intensified in 2000 when the Committee on the Status of Endangered Wildlife in Canada listed the local caribou population as threatened. As a result, government agencies, forest companies, and local communities were motivated to explore means of sustaining caribou while continuing forest harvesting on a large part of the forested land base.

Preliminary work on a BBN model for caribou population and habitat in the area brought together a core team of biologists, foresters, and government resource managers. This team, supported by scientific advisors, recognized that there might be combinations of forest-harvesting and silviculture techniques that could maintain or restore terrestrial forage lichens following logging on caribou winter ranges. Impacts of forestry practices on lichens in the area were, however, not well documented, through either formal research or monitoring programs. The core team recognized that active or experimental AM (Walters 1986) offered an approach that could help them resolve uncertainties and learn about opportunities for maintaining lichens.

The team constructed an initial BBN linking environmental conditions, fire, logging, and silvicultural practices with terrestrial lichen abundance. This became one of the submodels in the early development of the Caribou Habitat Assessment and Supply Estimator (CHASE) package (McNay et al. 2006). It was also recognized as the potential basis for planning and guiding an active AM approach to managing forest stands for both lichen and timber production. The core team, recognizing that it needed to draw on a wider range of expertise, ideas, and involvement, organized a small workshop that followed the principles and approach of adaptive environmental assessment and management workshops (Holling 1978; Taylor and Nyberg 1999) (see AM step 1; Table 1).

The workshop took place over 2 days in January 2001 and was led by a trained facilitator who solicited expert opinions from the attendees according to their respective areas of knowledge and expertise (Failing et al. 2004; also see other methods such as those described by Geneletti 2005; Sheppart and Meitner 2005). When used correctly — particularly in combination with empirical data — incorporating expert opinions into BBN and statistical models can provide great value (Holthausen et al. 1994; Pearce et al. 2001; Martin 2005; McCarthy and Masters 2005). Seoane et al. (2005) found that combining expert opinion with independent data yielded more accurate predictions of bird presence.

The core team was represented by the senior CHASE biologist, a local lichen expert, a forester with Slocan Forest Products, and a wildlife-habitat ecologist with the British Columbia Forest Service. Others present included three other foresters and managers from local forest companies, an Alberta biologist, a biometrician, a forest ecologist, and the senior author. The facilitator and the senior author had experience with AM workshops and had designed the agenda; the facilitator and two members of the core team were experienced with BBN software. All BBNs were implemented in Netica (version 2.17).

After discussing the basics of the caribou–lichen issue, the workshop team discussed and confirmed by consensus the scope of the issue in space and time, the management actions that could be employed, the indicators that could be tracked to judge success, and the key uncertainties they faced. Throughout the workshop, the draft terrestrial lichen BBN was displayed on a poster on the wall and on a computer projection. As the discussion proceeded it was used to illustrate linkages between environmental conditions (ecological unit, stand age, stand composition, site index, aspect); disturbance effects, including wildfire and forest-harvesting options (season of logging, whole-tree vs. cut-to-length harvesting); and silviculture options (site-preparation techniques and regeneration methods). Using the BBN software, the team was able to quickly illustrate new ideas by adding or deleting nodes and states within nodes. Conditional probabilities for some key child nodes were entered during the workshop by drawing on the judgement and knowledge of those present, following the BBN modelling principles outlined by Marcot et al. (2006).

The initial BBN for terrestrial lichens (Fig. 1) included three categories of data input: site ecology, stand structure, and growing-medium condition. The site ecology inputs (i.e,. aspect, stand percent pine, ecological unit, and site index nodes) were an important component of the CHASE model framework used to predict where lichen types would occur on the landscape. The growing-medium inputs (i.e., debris loading and organic matter characteristics nodes) and stand-structure inputs (i.e., stand age and stocking nodes) are site-level factors used to define the condition of a terrestrial lichen community on a given site (Sulyma 2001; Sulyma and Coxson 2001). All inputs were summarized to produce a single value that represented the capability of a site to provide terrestrial lichen winter range for caribou (terrestrial lichen forage supply node). The full BBN further elaborates the value of a site for caribou by including nodes for seasonal requirements and potential influence of predation (McNay et al. 2006), but for simplicity those nodes are omitted from Fig. 1.

In the AM experiments that the team proposed, all activities were intended to promote an understanding of what would happen to lichen productivity under different disturbance and stocking regimes. Key study questions were focussed on determining the response of terrestrial lichens to various levels and combinations of mineral soil and forest-floor disturbance (affected by stand treatment and season of treatment), debris loading (affected by the stand-removal method), and insolation levels (affected by the development of the regenerating stand).

The site ecology conditions (summarized in the terrestrial lichen habitat capability node in Fig. 1) were specified in the model to predict the capability of pine–lichen sites from input (parentless) data sources. The draft conditional probabilities had been formulated prior to the workshop, based on other work in the Williston Reservoir area (Sulyma 2001) and were presented to participants in the form of maps. Based on personal experience in the study area, participants provided feedback regarding their level of satisfaction with the model for predicting the location of pine–lichen woodlands. This portion of the model was used to help delineate potential study sites for replication of the AM trials.

The stand-structure and growing-medium components (summarized in the stand characteristics and forest-floor characteristics nodes in Fig. 1) were configured to provide management choices whereby site conditions could be manipulated to assess effects on lichens. The model included choices of stand-removal method, site-preparation method, removal season, and stocking level (stems/ha). The state values created for these nodes correspond to typical forestry operations in the region. The CPTs for these components were more expert-based than those for the site-ecology component. As with the site-ecology component, however, the CPTs were drafted by a lichen expert prior to the workshop and then presented for review and updating by all participants.

After reaching consensus about appropriate forestry regimes that could be tested, the participants proposed sites where field trials could be conducted and forest company representatives stated whether they would be willing to implement the trials (AM step 2; Table 1). Following the workshop, two divisions of one major forest company agreed to participate in an active AM project to study nine different regimes of treatments. Regimes were selected to represent a range of soil organic matter disturbance, debris loading, and stocking. All treatments were incorporated into the BBN as state values (i.e., the conditions or factors expressed in a single node) for the child nodes feeding the debris loading, organic-matter characteristics, and stand characteristics nodes (Fig. 1). The workshop team considered forest harvesting and site preparation to be primary disturbance events that would cause the greatest site change. Forecasts of outcomes for three time intervals following stand disturbance by logging or wildfire, represented by the stand age node, were derived using the BBN. The forecasts indicated that the probability of a beneficial lichen response was highest with a combination of winter harvesting, a whole-tree ground-based harvest system, no site preparation, and natural regeneration, and lowest with summer harvesting, a cut to length ground-based harvest system, drag scarifying, and regenerating by planting more than 1200 seedlings/ha.

The field AM project used a randomized incomplete block design (Sulyma and Alward 2004). Three treatment sites were established (AM step 3; Table 1) beginning in 2001 with a site near Williston Reservoir (98-Mile site; Fig. 2). Preharvest measurements were undertaken at all sites to document undisturbed stand conditions.

The forest floor vegetation community at each treatment site was sampled using modified Daubenmire transect methodology (Daubenmire 1959; Stohlgren et al. 1998). Visual estimates and photographic-image analysis were completed to produce a summary of percent cover and distribution for all species encountered. Coarse woody debris was evaluated following procedures outlined by Marshall et al. (2000) and standard forest mensuration activities were used to characterize the forest overstory.

Treatment activities were undertaken at all sites, and remeasurements of the vegetation community and coarse woody debris have been completed. A modified mineral soil disturbance survey (British Columbia Ministry of Forests 2001) was applied to characterize disturbance of the forest floor. Post-treatment sampling was scheduled for years 1, 3, and 7 following harvesting and silviculture activities. At the site in the Williston Reservoir area, the first set of post-treatment measurements has been completed (AM step 4; Table 1).

In the original development of the model, debris loading was summarized from the harvest method and denoted as a parent node to forest-floor characteristics. The concept applied by the project team was that soil disturbance should be summarized in one child node and debris loading in another, and that the two nodes were independent. Experience during post-treatment monitoring, however, revealed that the critical factor of concern was disturbance to the microsites for lichen growth, and that soil disturbance and debris loading were therefore best represented as different states of a single node rather than as separate nodes. This led to an update of the model, producing a more explicit structure with state values that had defined measurables (Fig. 3; AM step 5; Table 1).

The project team updated the organic matter characteristics node (now called organic-matter disturbance) to include states of organic-matter accumulation: organic matter undisturbed, removed, buried, or reduced (i.e., partially burned but not exposing mineral soil). The CPT for that node was likewise updated to reflected the findings from the initial field surveys. The forest floor characteristics node and corresponding CPT were then updated to reflect only the influence of time (succession processes). The representation of succession was based on other work completed in the Williston Reservoir area (Coxson and Marsh 2001). The new model better represented ecological functions, with disturbance to the terrestrial lichen community summarized at one node and succession of lichen communities at another. Thus, this is an example of how field testing under AM resulted in new understanding, which led to improvement of the BBN model structure.

Management uses of the BDN

The updated BBN included three decision nodes and three utility nodes (Fig. 3), thus creating a BDN. The utility values in this BDN example represent initial estimated costs per hectare of the various forestry treatments (Table 2).

Fig. 3. Bayesian decision network model illustrating the most favourable combinations of forestry treatments and ecological conditions for terrestrial lichens. For a description of regeneration methods see Table 2.

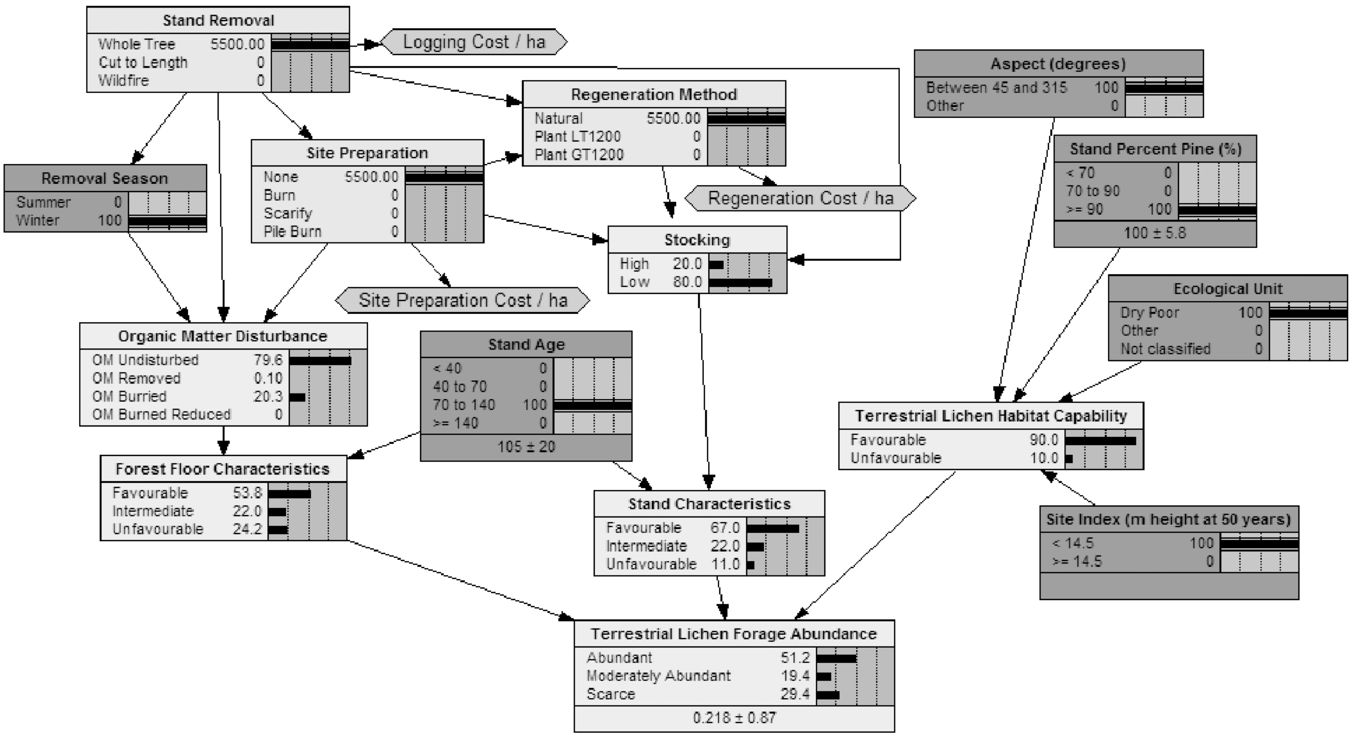


Table 2. Values (cost, in 2005 Canadian dollars) underlying the utility nodes shown in the Bayesian decision network (BDN) model (Fig. 3).

Utility node	Input (management) node	Input node choice[a]	Utility value (cost, $/ha)[b]
Logging cost	Stand removal	Whole tree	5500
		Cut to length	6050
		Wildfire	0
Regeneration cost	Regeneration method	Natural	0
		Plant LT1200	400
		Plant GT1200	640
Site-preparation cost	Site preparation	None	0
		Burn	600
		Scarify	400
		Pile burn	900

Note: Utility values are specified by the modeller.

[a]"Plant LT1200" refers to planting of <1200 seedlings/ha and "plant GT1200" to planting of >1200 seedlings/ha; planting costs are based on an estimated $0.40 per planted tree. "Whole tree" refers to ground-skidding the entire tree and processing at a local landing or roadside, with costs based on $20/m^3 and "cut to length" to processing trees at the stump or log bunch within the stand, then yarding the cut or processed logs to the local landing or roadside, with costs based on $22/m^3; both options assume a harvestable timber volume of 275 m^3/ha.

[b]Estimates of costs were confirmed by T. Lazaruk, Registered Professional Forester (personal communication).

The structure and performance of well-specified, tested, and calibrated BDNs can be explored to reveal much about influence of alternative decisions and to help determine best decision pathways (AM step 6; Table 3). The simplest approach is to specify choices in each decision node and combinations of choices in multi-decision-node models, and record the probabilities associated with the output variables. One or more choices or combinations of choices may result in acceptable probability levels of outcomes. In our example, the BDN predicted that a regime of winter whole-tree harvesting with no site preparation would result in about a 50% probability of abundant terrestrial lichen forage (lichen abundance index = 0.218; Table 3) once lodgepole pine stands on favourable sites reach 70–140 years of age (Fig. 3). This probability is largely unaffected by regeneration method, but it drops to 36% under a cut-to-length harvesting system. By varying the combinations of management activities and site and stand conditions, the decision-maker

Table 3. An example of the use of the BDN model (with site conditions as specified in Fig. 3) to determine the overall expected value (cost, in 2005 Canadian dollars) of winter stand management and abundance of terrestrial lichen forage (bottom node in Fig. 3), given 24 combinations of forestry treatments.

Stand-removal options	Site-preparation options	Regeneration-method option[a]	Expected value (cost, $/ha)	Terrestrial lichen abundance index
Whole tree	None	Natural	5500	0.218
		Plant LT1200	5900	0.210
		Plant GT1200	6140	0.192
	Burn	Natural	na	na
		Plant LT1200	na	na
		Plant GT1200	na	na
	Scarify	Natural	5900	0.112
		Plant LT1200	6300	0.103
		Plant GT1200	6540	0.087
	Pile burn	Natural	na	na
		Plant LT1200	na	na
		Plant GT1200	na	na
Cut to length	None	Natural	6050	–0.054
		Plant LT1200	6450	–0.058
		Plant GT1200	6690	–0.069
	Burn	Natural	6650	0.169
		Plant LT1200	7050	0.169
		Plant GT1200	7290	0.171
	Scarify	Natural	6450	–0.002
		Plant LT1200	6850	–0.004
		Plant GT1200	7090	–0.009
	Pile burn	Natural	6950	0.067
		Plant LT1200	7350	0.052
		Plant GT1200	7590	0.041

Note: Expected values of costs and the lichen abundance index are calculated by the model. The expected value is the total costs of stand removal + site preparation + regeneration method. Because the removal season is specified as winter, the wildfire option of stand removal does not pertain; na, not applicable (burning and pile and burning is not done with whole-tree stand removal). The lichen abundance index is the expected value of terrestrial lichen forage abundance where 1 = abundant, 0 = moderately abundant, and –1 = scarce; na, not applicable.
[a]For a description of options see Table 2.

can explore and compare the implications of providing lichens derived from various other decision pathways. This is a simple form of risk management.

Another, more sophisticated use of BDNs is to specify utility nodes and values and compile the model to determine the decisions with lowest costs or highest values. Utility nodes can be specified with values representing costs, such as dollars per hectare of forest-thinning operations (Table 2); or with benefits, such as dollars per hectare of resulting commercial-grade timber; or with other values and units, such as social costs or benefits of forest condition outcomes or maintaining rare species. Unlike decision-tree and linear-programming models, different utility nodes in the same BDN model do not even need to use the same unit of measure, such as dollars.

When a BDN is compiled, joint values of all utilities are summed and shown as expected overall utility values next to each pertinent choice in the decision nodes. The manager could then select as the best decision pathway those choices with the lowest overall costs or highest overall benefits, depending on how the utilities were specified. This is similar to the backward calculations of expected values of decisions in traditional decision-tree analysis, except that BDNs are far more flexible in being able to specify a particular state in an output node and determine best decision pathways to achieve that state, and in being able to handle missing information. Also, expected utility values associated with each choice in BDN decision nodes can change depending on the specification of conditions (and of the underlying probability structure) in the model. This can be a useful way to determine how decisions may be sensitive to external conditions (and alternative model structures, such as those developed by different experts or from different data sets), and which conditions should first be determined in order to make appropriate decisions.

Our example showed that, with no site preparation and natural regeneration, the expected cost of whole-tree harvesting ($5500/ha) is less than that of cut to length harvesting ($6050/ha) (Fig. 3, Table 3). Then, if whole-tree harvesting and natural regeneration are specified, the expected cost with no site preparation ($5500/ha) is less than that with scarifying ($5900/ha); also, the expected abundance of terrestrial lichens is greater with the lower cost option. In this way the manager can identify a sequence of lowest cost decisions, given particular site and stand conditions, and the optimal decisions that would best balance forestry costs and lichen abundance.

When BDNs contain decision nodes with preconditions, that is, with other nodes that feed into a decision node, then solving the network can involve finding a decision value for each possible set of conditions of the parent nodes. This is akin to a contingency plan whereby choices are made on the basis of prior conditions, such as deciding on a particular stand-management option on the basis of forest stand structure and intensity of a recent fire. Solving the BDN in this way yields a "decision function" for each decision node, which shows the joint utility values for each decision given the input node values. If there are multiple decision nodes in a BDN, then the set of decision functions for all decision nodes becomes what is known as a decision policy. This is a conditional plan that specifies actions (multiple or sequential decisions) for each possible contingency (Table 3).

In our case example, if stand-removal and site-preparation activities are specified, the BDN then displays expected values for the options concerning regeneration method. Changing the choice of stand removal or site preparation affects the expected values for regeneration and thus the overall expected costs. In this way, the BDN can be queried for alternative decision pathways given all combinations of prior decisions (and states of the site and stand), thus collectively determining the overall decision policy.

Shortcomings of BBNs

BBNs are useful for displaying interactions of variables, implications of conditions for optimal decisions, effects of decisions on expected outcomes, and influence of utilities on decision structures. BBNs in general, however, have several shortcomings. BBNs do not strictly permit feedback functions either within a node or from response (output) variables back to predictor (input) variables. Feedback can be important in many systems such as density-dependent survivorship and reproduction in wildlife population models and consumer performance in economic models. Discretizing continuous-variable distributions, as is necessary in most BBNs, might oversimplify state responses. Some of these shortcomings may be better handled by modelling constructs other than BBNs; for instance, graph theory and loop analysis are able to depict feedback functions (e.g., Dambacher et al. 2003; Allesina et al. 2005), and some fuzzy logic or rough set theory approaches are better able to depict continuous-response variables (e.g., Berger 2004; Iliadis 2005). Although these were not drawbacks for the case-study model presented here, they may be important considerations for other adaptive forest management models using BBNs.

Also, BBNs handle time–dynamic functions poorly. Feedback loops and time functions can be depicted in BBNs by replicating a model structure and linking specific nodes between the replicates. This is called time expansion, which requires time-delay links. However, this can be a cumbersome way to depict functions that other modelling approaches could represent more elegantly.

BDNs, like other decision models, can oversimplify criteria affecting a decision and fail to depict subtle variations of decisions and changing conditions that so often occur in real-world situations. For these and other reasons, we suggest that BDNs be viewed as decision-aiding tools to help inform and advise the decision-maker who, ultimately, must weigh the ramifications of decisions that can be far more subtle and complex than any model can depict.

Conclusions and recommendations

Many AM projects follow a loosely defined process that lacks much of the structure recommended by AM's original proponents, including Holling (1978) and Walters (1986). Modelling is often not used effectively, which can limit AM teams' understanding of system structure, relations, and potential responses to management (Walters 1997; Salafsky et al. 2001; Gray 2002). In many cases these teams would benefit from the learning and communication that are promoted when BBNs are developed early in projects, as is described in our terrestrial lichen case example.

We recommend that AM practitioners consider using BBNs or other models that depict causal relations among variables, including effects and utility values of alternative decisions, as basic elements of their projects. They are tools that can serve multiple purposes in various AM steps (Table 1).

BBNs must be used with appropriate knowledge of their strengths and weaknesses. Marcot et al. (2006) provide useful guidance on development and application of BBNs and caveats concerning their use; introductory references on BBN construction are available in the literature (e.g., Jensen 2001; Neopolitan 2003) and with the commercial BBN software shells.

Those unfamiliar with BBNs should begin by developing influence diagrams with relatively few nodes and links, as a simple representation of the system of interest. Once a basic BBN structure is in place, the AM team or a smaller group can specify conditional probabilities, further elaborate the model by adding more nodes, depict effects of management options by including decision and utility nodes, and explore the effects of changing inputs and management choices. In our experience this incremental process, when supported by committed team members, quickly leads to learning and exploration of alternative management policies that are the foundation of AM.

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