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Natural Resource Assessment and Risk Management

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I. Introduction

Recently, BBNs are being used as forecasting and hindcasting models in wildlife and natural resource management and land use planning. Wildlife and natural resource management deals with difficult problems of determining optimal management strategies and activities to meet multiple and often conflicting environmental and social objectives. An example is conserving or restoring biological diversity of native forest ecosystems and at the same time providing for a wide variety of goods and services from those same forests, such as timber, recreation, clean water, and livestock forage. Such problems are "ill-conditioned," meaning that there is typically no single or even optimal solution.

Over recent years, BBNs have been used by ecologists to depict the response of wildlife species and ecosystems to differing conditions, and also as decision-aiding tools to help managers evaluate implications, including costs and benefits, of alternative natural resource management actions and to suggest best decision pathways (Varis 1997). Some authors have developed network advisory systems which are BBNs that include decision and utility nodes. Network advisory systems are used to determine effects of alternative management decisions and the best set of decisions to achieve certain outcomes.

Examples of BBNs as decision-aiding tools include use of network advisory systems to aid regeneration management of aspen woodlands (Haas 1991), to predict quality of aquatic systems for fisheries management (Reckhow 1999, Kuikka et al. 1999, Schnute et al. 2000) or for integrated water resource planning (Bromley et al. 2005), to aid management decision-making by forest rangers (Haas 1992), and to aid in evaluating restoration of habitat for rare species (Wisdom et al. 2002a). In these and other examples, it is typically the resource specialist, such as the hydrologist or ecologist, who develops and runs the BBN models to evaluate effects of alternative management actions in the context of risk analysis, and who then informs the decision-makers, such as governmental agency line officers, who must choose a course of action in the context of risk management.

This chapter reviews the use of BBNs in wildlife and natural resource management. The scope of this chapter is largely western North America, from which examples are provided of BBNs developed for evaluating and managing rare species, wildlife habitats, and forest resources.

II. Review of Methods

This section reviews various methods and approaches to BBN modeling as used in the field of wildlife and natural resource management.

Why BBNs?

For some uses, BBNs have key advantages over other modeling constructs (Marcot et al. 2001). BBNs provide a useful communication medium that clearly displays relations among conditions and outcome events, particularly how habitat conditions influence wildlife populations. BBNs also provide a means of combining: prior knowledge with new information; categorical, ordinal, and continuous variables; and empirical data with expert judgment. Managers and decision-makers often like the BBN approach because outcomes are expressed as probabilities which are expressions of uncertainties and which fit well into risk analysis and risk management. Some of these attributes of BBNs may be found in other modeling constructs, but it is this unique suite of all attributes that make BBNs attractive to natural resource specialists and managers. Other approaches to modeling that could complement use of BBNs include many traditional statistical techniques such as ordination and correlation models, and use of other ways to depict expert opinion and understanding such as fuzzy logic models, neural network models, and expert systems.

Methods of Creating BBNs

This section reviews various methods and approaches for creating BBNs, and also discusses a basis for choice of BBNs.

Creating BBNs for wildlife and natural resource management uses similar methods for creating BBNs in other domains. Building a BBN involves several stages: (1) listing the variables that most influence some outcome of interest; (2) specifying the states or values that each variable can take; (3) linking the variables ("structuring the model"); and (4) specifying probabilities of the linkages.

Use of influence diagrams.-- The first three steps essential entail developing what is called an influence diagram which can be a simple figure of boxes and arrows showing relations and causes among variables (Reckhow 1999, Schachter and Kenley 1989). Influence diagrams are best constructed with various box and arrow symbols to differentiate directly measured variables, latent or calculated variables, correlations, direct causal relations, and unexplained variation (Marcot, 2006a; Fig. 1a). Influence diagrams are often used in wildlife and natural resource management to depict how habitat and environmental conditions influence wildlife species and resources.

Assigning probabilities to variables.-- Once the main variables and influences are structured, then probabilities can be assigned to each variable in the model. Variables with no other influences are called parentless or input nodes, and their states or values are specified with unconditional (prior) probability distributions. Variables that are influenced by other variables are called child nodes (and their influencing variables are called parent nodes), and their states or values are specified with condition probability distributions. The overall BBN model is usually solved through standard Bayesian learning or updating that calculates a posterior probability distribution for various states of the output node(s).

Building BBNs from expertise and data.-- BBN models can be built strictly from empirical data sets, strictly from expert judgment, or from a combination of both. These methods pertain to specifying the basic structure of the influence diagram as well as to defining the prior and conditional probability distributions of the input and child nodes in the model.

Strictly using empirical data sets to structure and parameterize a BBN is a case of rule induction, that is, in which patterns within data sets are used to define links among variables and their probabilities. Experience suggests that building a BBN strictly using rule induction for models of wildlife and natural resource management tends to overfit the data. This creates a model that is pertinent only to the specific historic data set and that should not be used more generally to predict new circumstances (Clark 2003). Also, strictly using rule induction ignores a wealth of expert knowledge, which could be quite helpful for building more robust predictive models.

On the other hand, if a BBN is constructed strictly from expert judgment, the model becomes no more than a belief system (Newberry 1994) unless it is at least peer reviewed or, better, calibrated and validated with external data. The challenges of modeling wildlife and natural resources is that large, robust empirical data sets rarely exist; experts often disagree about the “causal web” of environmental and habitat influences on wildlife species; and ecosystems are usually quite open systems in which the context and degree of influential factors tend to shift over time.

The best approach for building BBN models in wildlife and natural resource management is to use expert judgment with peer review to initially structure the model; then to use a combination of expert judgment and empirical data to specify the probability distributions of each node; and then to use an independent, empirical data set to test, calibrate, validate, and refine the model (Fig. 2). In this way, the model reaches an acceptable balance between robustness and accuracy. Of course, each model and circumstance may require a different balance depending on the purpose, audience, and availability of both experts and data sets. This procedure has been used to successfully create and apply BBN models that predict the probability of presence of rare plant and animal species given local environmental and habitat conditions (Marcot 2006b).

Use of proxy variables.-- In some cases, where there is no empirical basis by which to set the prior probabilities for direct causal variables (input nodes), one could link proxies to those variables. A proxy variable is a variable for which data are available and which serves to represent, to some degree, the direct causal variable. For example,in one major regional project in the interior West, U.S., 118 BBN models of wildlife species' response to ecosystem management planning alternatives were created, and 31 of these were applied to evaluate planning alternatives (Marcot et al. 2001, Raphael et al. 2001). In building these models, we often had to use proxy variables to represent the more direct causal variables, because data on the latter generally were not available. To do this efficiently, we created libraries of such proxy representations as submodels, and could thereafter draw upon specific submodels to use as surrogates for specific habitat attributes for individual wildlife species. For example, some species such as wolverine (*Gulo gulo*) and lynx (*Lynx canadensis*) are sensitive to disturbance from roads (a direct causal variable). There were no data strictly on disturbance from roads per se (no one had ever gathered empirical data on this variable for these species), so we modeled disturbance from roads as a proxy combination of road density and human population density, for which we had quantifiable data in our geographic information system (GIS; Fig. 3). Then, when any species model required this type of human disturbance variable, we could just drop in this submodel from the proxy library.

III. Examples of BBN models

Wildlife Prediction Models

Modeling Pygmy Shrews in the Interior Columbia River Basin, U.S. – A first example of a wildlife model is one developed for the Interior Columbia Basin Ecosystem Management Project of U.S. Forest Service and Bureau of Land Management, the regional project mentioned above. The Columbia River runs 1,857 km through western North America and this project focused on the "interior" continental portion east of the Cascade Mountains in the U.S. This model is a BBN predicting habitat quality and population size of pygmy shrews (*Microsorex hoyi*), a rare, native mammal found in the northern portion of the interior western U.S. Pygmy shrews are probably the smallest living mammal by weight and are one of a set of wildlife species associated with wetland environments that have garnered conservation interest on public lands.

To build the pygmy shrew model, we first convened an expert panel of mammalogists to determine the key environmental correlates of this (and other) species. The panel suggested that pygmy shrew key environmental correlates include type of substrates (ground burrows, down logs [large logs on the ground], and ground organic layers in which they tunnel), macroenvironments (seeps, bogs, and wet meadows), and food availability (insects and other small animals). We then linked the correlates in an influence diagram to represent a causal web (Fig. 1a), identified the simplest and most parsimonious set of states for each correlate (e.g., presence/absence of habitat elements), and used expert judgment to denote probability distributions for each variable in the model, thus creating a functional BBN (Fig. 1b). The BBN was then used to predict habitat quality and potential population size for the species in each subbasin of the interior western U.S. planning region.

To make it easy to specify the probability tables, we simplified many of the continuous variables in the model to only 2 or 3 discrete states. For example, the response variable "pygmy shrew population size" (Fig. 1b) was denoted by just the two categorical states of "large" and "small." There did not need to be any finer distinction for the purpose of using the model to aid land use planning for this project, nor were data available by which to predict more discrete states. In this model, a "large" pygmy shrew population was one that would be found in fully "adequate" pygmy shrew habitat; no specific population size was denoted in the model. In this way, the model was simple, understandable, and did not require quantitative population data which were unavailable.

For this particular project, we developed BBN models of this type on 31 wildlife species (Raphael et al. 2001). We ran each model in batch mode using an input file from our GIS, where the records (rows) in the file were subbasins and the columns were the state values for each input node in the model (that is, the habitat conditions in each subbasin). The models produced output files which depicted probabilities of habitat (adequate, inadequate) and population size (large, small) in each subbasin. We fed this output file back into GIS to produce color-coded maps showing the distribution of habitats and populations and to conduct further spatial statistics on habitat fragmentation and population dispersion patterns under each of 3 management alternatives at various future time periods. We then summarized overall effects on each wildlife species from each management alternative and conveyed results to decision-makers, who in turn considered the wildlife effects with other factors in their choosing a preferred management alternative.

Modeling Greater Sage-grouse in the Interior Columbia River Basin, U.S. – Another example of a wildlife model developed for this project are the BBNs and GIS habitat models of greater sage-grouse (*Centrocercus urophasianus*) in the interior sagebrush steppe (Wisdom et al. 2002a, 2002b). The BBN model, developed along the same lines as that for the pygmy shrew, used five key environmental correlates: density of sagebrush steppe habitat, percent of the land in uncharacteristic levels of domestic ungulate grazing, road density, human population density, and degree of departure from historic disturbance regimes (notably fire). Sage-grouse environmental quality was related positively with the first of these five variables, and negatively with the rest. For example, domestic ungulate grazing is an index of how livestock grazing reduces the quality of native grasses and forbs important for sage-grouse, and departure from historic disturbance regimes is an index of the likelihood that exotic plants unsuitable to sage-grouse have displaced native sagebrush-steppe vegetation (Wisdom et al. 2002b). Model output was a posterior probability distribution of greater sage-grouse habitat quality.

Model results were mapped in GIS (Fig. 4) and interpreted in terms of the level of expected sage-grouse population outcome. Population outcomes were denoted as five classes ranging from being continuous, well-distributed, and with a high likelihood of persistence, to sparse, highly isolated, and with a high likelihood of extirpation (local extinction).

This particular model was validated by Wisdom et al. (2002b) who compared site-specific predictions with known population status. Validation was done by comparing model predictions of population response to historical and current distributions of the species separately for the historical range of the species currently occupied and that currently unoccupied. Validation outcomes showed that the sage-grouse BBN models provided reliable predictions for current conditions although future projections could not be tested. Overall results suggested that the model could be used dependably for evaluating management of public lands for habitat of this species. By inference, BBN models, produced along the same methods, of other wildlife species evaluated in this same project likely produced reliable and useful results as well.

Wildlife of the Pacific Northwest U.S. – Another major regional land planning project is the so-called Northwest Forest Plan of federal public lands in western Washington, western Oregon, and northwestern California. This Plan, established in 1994, established numerous reserves of late-successional and old-growth forest[1] for conservation of hundreds of associated plant and animal species and ecological communities. One part of this Plan entails surveying for occurrence of many of these rare and little-known species outside the reserves in "matrix" lands where timber harvesting and other forest management activities may proceed for other purposes (e.g., commercial forestry). The purpose of the surveys is to determine if any of these species occur, and if so, how to amend the proposed management activities to ensure their persistence.

To help prioritize matrix sites for surveys, a series of BBN models have been created that predict the probability of occurrence of selected species given habitat conditions on sites potentially affected by proposed management activities. Among the species modeled to date – all of which are relatively rare -- are 2 fungi, 3 lichens, a moss, 2 vascular plants, 2 mollusks (terrestrial slugs), an amphibian (a salamander), and a mammal (a tree vole). One of the fungi species modeled is called fuzzy sandozi (*Bridgeoporus nobilissimus*). This model is notable in that it has undergone substantial testing and validation through use of field survey data (Marcot 2006b).

As with the other models listed above, this fungi model was developed by consultation with a species expert and peer reviewed by another species expert, and then field data were used to determine the accuracy of the resulting model predictions. Accuracy was evaluated by comparing the most likely model outcome (species presence or absence) with actual field results under known conditions. Accuracy was depicted in a "confusion

[1] Late-successional and old-growth forests are dominated by mature trees of advanced age and large size. In this region, late-successional forests have conifer trees approximately 80-180 years old and 50-75 centimeters diameter and with a simple tree canopy structure; old-growth forests have trees older and larger than this with a more complex canopy structure.

matrix" that lists the number of cases of correct and incorrect predictions of presence and absence. In this case, the model was found to correctly predict all 31 known cases of species presence, but only 3 of 14 cases of species absence. The model's overprediction of presence, however, was not seen as problematic. The model was designed to be used to prioritize unknown sites for survey of the species, so that false positives meant sometimes conducting surveys where the species is absent. Failing to survey when the species is present could result in local extirpation of the species but the testing did not suggest problems with such false negative predictions.

Throughout both the Pacific Northwest and interior western U.S., other BBN models have been developed and used for evaluating wolverine (Rowland et al. 2003) and Townsend's big-eared bat (*Corynorhinus townsendii*; Marcot et al. 2001), as well as salmonid fish species (Lee and Rieman 1997) including bull trout (*Salvelinus confluentus*; Lee 2000) and Fraser River sockeye salmon (*Oncorhynchus nerka*; Schnute et al. 2000). Other BBN species-habitat models have been developed that predict site suitability to prioritize sites for survey of a rare butterfly species, the Mardon skipper (*Polites mardon*) in its disjunct ranges in Washington and southern Oregon (B. Marcot, in prep.).

Wildlife of Western Canada.— BBN models have been developed and used for a variety of other terrestrial wildlife species in western Canada. These include models to predict capture probability of northern flying squirrels (*Glaucomys sabrinus*; Marcot 2006b), habitat quality of woodland caribou (*Rangifer tarandus caribou*; McNay et al. 2003, 2006), and populations of marbled murrelet (*Brachyramphus marmoratus*; Steventon et al. 2006). Other BBN models have been developed for mapping ecosystem boundaries (Walton 2004; Walton and Meidinger 2006).

Each of these BBN models were structured and parameterized from a combination of expert judgment and field data but differed in significant ways. For example, the population models of marbled murrelet, a small sea bird that nests in the canopy of inland old-growth forests, were developed to predict the probability of persistence and resilience (ability to rebound if the size or distribution of the population is depressed) of the population to management policy by modeling demography and vital rates of the population by age class. The caribou models were crafted to determine the suitability of 4 seasonal ranges for the species (pine-lichen winter range and post-rutt range, high-elevation winter range, calving and summer range, and movement corridor range) and the response of the species to predation risk from wolves (*Canis lupus*) under various forest management scenarios.

Using BBN Models for Hindcasting

Hindcasting in this context refers to identifying likely circumstances such as environmental or habitat conditions, that produced a known outcome such as presence or abundance of a wildlife species. Whereas a BBN model of wildlife-habitat relationships can be used to specify habitat conditions and predict wildlife response, if wildlife response is known or hypothesized then the same model can be solved "backwards" to determine the most likely prior conditions that would yield that response. In this way, BBNs provide a unique function over other, more traditional models strictly using multivariate statistics, mathematical equations, or time-based simulation.

Solving a BBN “backwards” essentially entails fixing an outcome state and inspecting the most likely states of all input nodes. For example, the BBN model of pygmy shrew can be run by fixing the habitat node to the “adequate” state and determining the most likely states of habitat and environmental conditions that would provide adequate habitat (Fig. 1c). Doing this suggests that pygmy shrew habitat is fully adequate when burrows, and down logs and soil organic layers, are present; seeps, bogs and wet meadows are present; and food availability, particularly of invertebrate larvae, is high. In a more quantitative model, solving a BBN backwards could identify specific numbers, levels, or densities of each environmental variable. But even in a qualitative model such as this one, solving the BBN backwards can be useful in demonstrating the full set of all optimal environmental variables that lend to fully adequate habitat for the species.

Hindcasting can also take the form of sensitivity testing the model to determine the input variables that most influence the outcome, such as which habitat and environmental correlates most influence pygmy shrew habitat adequacy or population size. Mathematics and procedures of BBN model sensitivity testing were reviewed by Marcot et al., (2001, 2006). In general, sensitivity testing entails determining the degree to which small, incremental changes in some input variables affect the value of some response variables. In BBNs (in particular, Netica), this entails selecting a response node for which you want to determine sensitivity, then selecting the input nodes that you want to test, and then running the sensitivity function; the model makes the small, incremental changes and summarizes sensitivity in a table that lists the input nodes in decreasing order of their affect on the selected response node.

Sensitivity-testing the pygmy shrew model suggests that most of the variables are nearly equally influential (Table 1). However, for other wildlife models, such as for Townsend’s big-eared bat (Marcot et al., 2001), influences varied substantially among the input variables. In the bat model, out of 6 key environmental correlates, presence of caves or mines with suitable temperature regimes by far had the greatest influence on bat populations (entropy reduction = 0.029) with lesser influence from large snags or live trees (0.010), forest edges (0.006), cliffs (0.006), bridges or buildings (0.001), and boulder piles (<0.001). The manager could interpret such sensitivity testing results to prioritize site conservation and restoration activities for the species. That is, the manager would focus first on protecting suitable caves or mines and then providing large snags or live trees. If the model had not been calibrated and validated from empirical data, these results could still be useful as working management hypotheses to be tested in the field.

BBN Decision Models

BBNs also can be built with explicit decision and utility nodes which represent, respectively, alternative management actions and the values (costs or benefits) of those actions or of model outcomes. In some BBN modeling shells, such as Netica, if decision and utility nodes are included, when the model is compiled it calculates and displays expected values of each alternative decision in each management node.

BBN models can contain multiple management and utility nodes. If the model includes a sequence of decisions, such as various time-based wildlife conservation activities, solving decision models in this way can reveal optimal decision pathways that minimize costs, maximize benefits, or otherwise optimize utilities. BBN models of wildlife and natural resource management can be most beneficial to decision-makers when they contain management and utility nodes.

In an example from the above-mentioned Northwest Forest Plan in the Pacific Northwest, U.S., a series of BBN decision models have been developed to codify and represent a complex set of management guidelines for determining appropriate conservation categories of dozens of rare and little-known plant and animal species (Marcot et al. 2006). These species conservation decision models and the guidelines they represent were part of a formal annual species review in which new scientific information was evaluated on selected species closely associated with late-successional and old-growth forests. Results from the annual species reviews were summarized as suggestions, made by the review panels to regional agency decision-makers, for retaining or changing species conservation categories or even removing species from the conservation listing as specified by particular evaluation criteria in the guidelines. These BBN decision models were comprised of an overall summary model that depicted the appropriate species conservation category and its implications and costs for further species surveys and site management (Fig. 5), and a series of BBN submodels expanding on each of the inputs of the overall summary model.

For example, one BBN submodel expanded on the node “Geographic range” in Figure 5; this submodel contained explicit criteria to determine the degree to which a given species could be deemed to be in or out of the geographic range of the Northwest Forest Plan (the Pacific Northwest U.S.). The criteria for this submodel were based strictly on the evaluation guidelines published in the Northwest Forest Plan, and included: whether the species range is known to occur within the Plan; and if outside the Plan area, if the range occurs close to the Plan area boundaries or if there is at least suitable habitat for the species within the Plan area. Each submodel was solved for each species to determine the probabilities specified in the input nodes (Fig. 5, top). The combination of these inputs dictated the probabilities of each conservation category for that species. The species conservation category, in turn, dictated the type and cost of surveys and management needed for the species in a deterministic way (Fig. 5, bottom).

These decision models were used to successfully evaluate the appropriate conservation categories of 119 plant and animal species during annual species reviews conducted in 2002 and 2003. One of the advantages of using these decision models was that they depicted possible alternative conservation categories when some of the input information was missing or equivocal. The models helped display availability and uncertainty of the scientific data for each input variable, and the influence on conservation categories. The panelists had the task of making final calls on the appropriate conservation category for each species, and addressed uncertainties in a structured panel discussion process. In the end, the decision models – better termed decision-aiding tools – did not make the final decisions for the panelists and the decision-makers, but, as intended, they instead helped guide and inform the deliberations.

Although most of the wildlife BBN models discussed in the previous section were built as management-aiding tools, the models on woodland caribou were particularly aimed at decision-makers in forest management units in north-central British Columbia, Canada. As with the Interior Columbia Basin wildlife models, results from the woodland caribou models were transferred to color-coded maps representing the suitability of the seasonal caribou ranges, such as winter range (where the caribou go during winter). Results of the modeling and mapping were summarized for the decision-makers by the caribou ecologists in terms of amount over time of suitable seasonal caribou ranges as influenced by forest management activities that, in turn, variously affect presence of lichen forage and wolf predators in the region (Fig. 6). The decision-makers were presented with three modeling results, each representing a possible variation in management for the caribou: (1) continuing the current management policy, (2) restoring or emulating the historic range of disturbances caused by natural events such as windstorms and wildfires, and (3) managing forests to create the best habitat for caribou. Final decisions on management of caribou herd, caribou habitat, forest harvest, and effects on predators are yet to be finalized, but the managers how have the risk analysis results – including clear descriptions of uncertainties -- for making an informed decision.

These caribou models and other BBN models also are being used to garner participation and collaboration from various public stakeholders (Cain et al. 1999) on issues of public land management. For example, Mendoza and Prabhu (2000) used network advisory systems to help guide selection and use of criteria and indicators for sustainable forest management.

IV. Utility of BBN Models in Wildlife and Natural Resource Management

Coupling BBNs With Other Models

Because the knowledge in wildlife and natural resource management comes as much from personal expertise as from statistical data and field research, BBNs are being viewed as attractive tools that can effectively combine prior knowledge, expert judgment, and field data, and that can provide useful results even in the face of missing or incomplete data (Ramoni and Sebastiani 1997).

In general, in wildlife and natural resource management, most of the examples presented here of successfully using BBNs in decision and risk management have involved integrating BBNs with GIS or within other evaluation procedures. GIS in particular provides ecologists, managers, and stakeholders such as the public with clear, intuitive tools by which assessments and decisions can be made. Examples including the use of maps of likely conditions for planning restoration or river floodplains in the Upper

Mississippi River basin in central U.S. (Llewellyn et al. 1996), and for evaluating bio-energy projects in Farsala Plain, Greece (Rozakis et al. 2001).

Adaptive Management

One area in which BBNs can be extremely useful is that of adaptive management, which generally refers to management by implementing trials and learning from experience. More formally, adaptive management involves implementing management activities as strict statistical experiments with treatments and controls, often with BACI (before-after, control-impact) type monitoring designs (Stewart-Oaten and Bence 2001), and evaluating management effects in terms of reaching some clearly-stated objectives. In wildlife and natural resources management, adaptive management has been touted widely but seldom applied in such formal ways. As part of a decision and risk management framework, BBNs and Bayesian analyses can be useful tools for helping to state objectives and management hypotheses, and to evaluate results of adaptive management experiments (Wade 2000). Further, in an adaptive management context, results of BACI experiments and monitoring could be used to statistically fit or update the a priori and conditional probabilities in a BBN model, and even to refine a model's structure itself including identification of variables and their states and linkages. Although it did not use BACI experiments, the successful use of BBN decision models in the annual species reviews of the Northwest Forest Plan, discussed above, constituted a form of adaptive management.

Bacon et al. (2002) developed a decision framework to help evaluate levels of natural resource manager satisfaction with the status quo and the expected outcome of changes, and used BBNs to specifically estimate financial, social, and ecological costs of changing management direction. They provided an example using changes from farming to forestry in marginal upland areas of the U.K., but their general approach could apply to other problems of adaptive management in wildlife and natural resources planning. In another example, Lynam et al. (2002) used BBNs in adaptive management projects to aid local community management of semiarid rangelands in Zimbabwe. Their approach highlighted the need for research to be collaborative to best aid changes in land use policy.

In western Canada, Nyberg et al. (2006) reviewed the advantages and roles of using BBNs in adaptive management. They presented a case study of how the woodland caribou BBN models discussed above are being used in adaptive management decision cycles. These BBN models include decision nodes for forestry (methods of forest stand removal, site preparation, and forest regeneration), utility nodes for costs of each decision, and effects of forestry decisions on abundance of terrestrial lichens as key forage for the caribou. A coordinated team of biologists, foresters, and government resource managers are using these models to explore options for meeting simultaneous goals of forest, fire, and caribou management. As a result, field level management trials are being statistically designed and conducted that will provide key information on effective management direction to meet these goals.

Decision-Making Under Uncertainty and Considering Types of Errors

Wildlife and natural resource management often is hallmarked by extensive uncertainty, such as how particular wildlife species or communities will respond to changes in their environments and habitats from land management activities. The decision-maker often is faced with the challenge of deciding actions in the absence of full information. How the decision-maker views the role of uncertainty depends on their risk attitude. If the decision-maker is risk averse, they may adhere to the precautionary principle and presume that uncertainties mark potentially adverse effects of management activities. However, if they are risk neutral or risk-seeking, they may view uncertainties as lack of evidence of adverse effects and proceed with such activities until such time as evidence is presented that policy changes should be made.

There is no single risk attitude that satisfies all situations of public policy on wildlife and natural resource management. BBNs can be useful tools to help the manager explicitly evaluate the types and implications of uncertainties, which include variations in system response to activities, lack of understanding of the basic causal web underlying system response, and how variations in system response may propagate through successive management decisions.

In particular, two types of error – false positives and false negatives, such as predicting presence of a rare species when it is truly absent, and predicting absence when it truly present – can have very different implications pertaining to opportunity costs of resources not used when sites are protected, or costs expended for rare species inventory and site protection when the species may not even be present. The prediction models of rare species discussed above provided such explicit tests of model accuracy and errors.

Updating and Refining Models

A useful function of some BBN models is their capability of updating the prior and conditional probability distributions from case file data. One example (Marcot 2006b) of such updating is with the BBN model of the rare fungus species discussed above, using the EM (expectation maximization) algorithm in the BBN modeling shell Netica. When incorporating a case file generated from field surveys for the species, the EM algorithm adjusts underlying probability distributions in the model to better fit the observed circumstances. The user can choose weights for the case files depending on how representative they are, and case files can include missing data on some input variables. This proved to be a most useful means of refining the model and improving its accuracy for predicting presence and absence of the species. It also suggested that such dynamic updating processes fit well into an adaptive learning framework, whereby new knowledge or information can be used to improve model accuracy and trigger reevaluations of management direction and policy.

V. Conclusions and Considerations for Future Modeling

This chapter has reviewed use of BBN models for prediction, hindcasting, and decision-aiding in wildlife and natural resource management. BBNs are flexible and useful tools for combining disparate forms of data, for dealing with uncertainties and missing information, and for providing intuitive pictures of how ecological systems work and the implications of management decisions.

BBNs, of course, are only one model form, and for critical evaluation or decision needs, both ecologists and managers alike would do well to compare results from other model structures. These may include traditional statistical analyses, decision tree analysis, and other formal methods for environmental and ecological risk assessment (O'Laughlin 2005, Sampson and Sampson 2005), such as multi-attribute utility theory, goal hierarchy, analytic hierarchy process, and multiple criteria decision making. It is strongly suggested that, to begin most modeling exercises, the ecologist and manager use simple influence diagrams to depict how systems might work and what parts of the system may be affected by management decisions.

Decisions are always made based on current knowledge which, in wildlife and natural resource planning, is typically incomplete and changes over time. Also changing over time are factors influencing a decision and the manager's decision criteria and risk attitudes, which often remain tacit and which typically vary according to expected utilities and probabilities associated with outcome effects of management decisions. The types and values of outcomes and their values (utilities or the "payoff matrix" in game theory parlance) also change over time. BBNs can be most useful as decision-aiding tools in such a changing world, particularly in an adaptive management framework. They can help frame testable management hypotheses, identify key variables and frame management trials as statistical experiments, and incorporate new information to reevaluate management effects and direction.

As such, BBNs and related Bayesian statistical methods, such as empirical Bayesian approaches, can be integral tools in monitoring programs, for example evaluating population viability for habitat conservation plans (Foley 2000). As data are collected, cases can be incorporated to improve model performance using a variety of Bayesian learning procedures, many of which are built into BBN modeling shells. The manager could use the updated models to help determine if their chosen course of action should change or should be retained. In this way, BBN models could be very useful in an adaptive management context, to explicitly show decision criteria, critical cutoff values that would trigger reviewing management direction, expected values of alternative decisions, and uncertainties in outcomes given those decisions.

As with any use of decision-aiding tools, in using BBNs, managers should understand and clearly describe: the models' assumptions; expected outcomes; values of each potential outcome (i.e., the utilities or payoffs associated with outcomes); management directives, priorities, and issues (factors considered in decisions); their specific decision criteria; their risk attitude (tolerance to, and perceived relative importance of, uncertainty of each factor); and even other factors weighed in the decision that are not shown in the decision model such as risk to one's political status, future career advancement, influence on other decisions, and risk of litigation. Modelers can help with most of these attributes, although it remains the onus of decision-makers to use such tools appropriately as aids.

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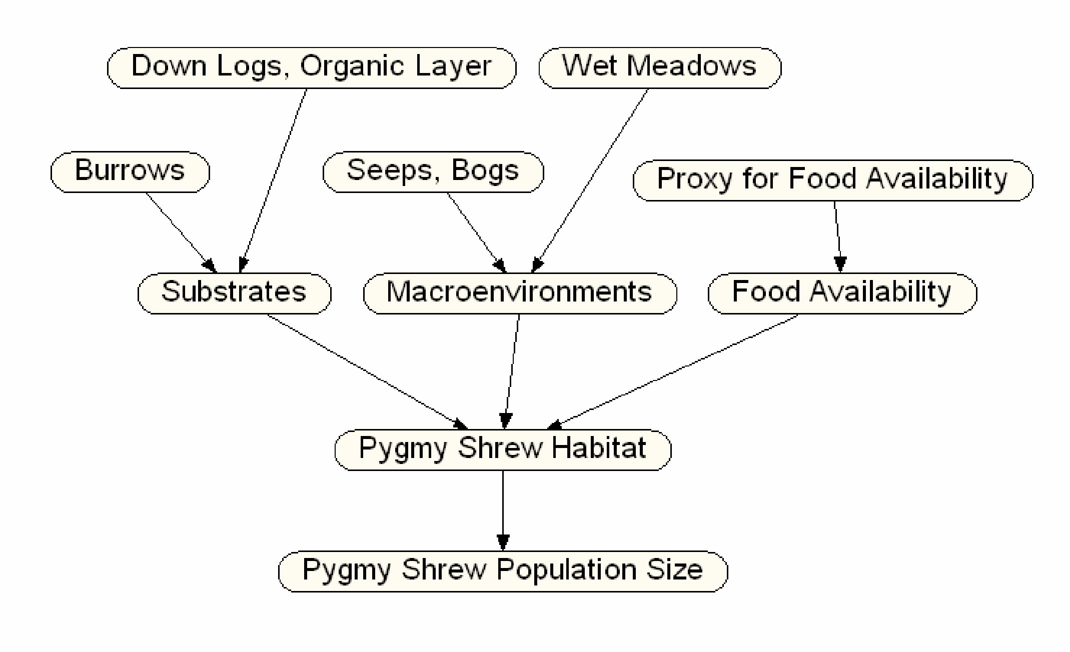
Table 1. Example of sensitivity testing of the pygmy shrew model shown in Figure 1. Entropy reduction refers to the relative influence of each input node on pygmy shrew population size (node A in Fig. 1b); higher values denote greater influence.

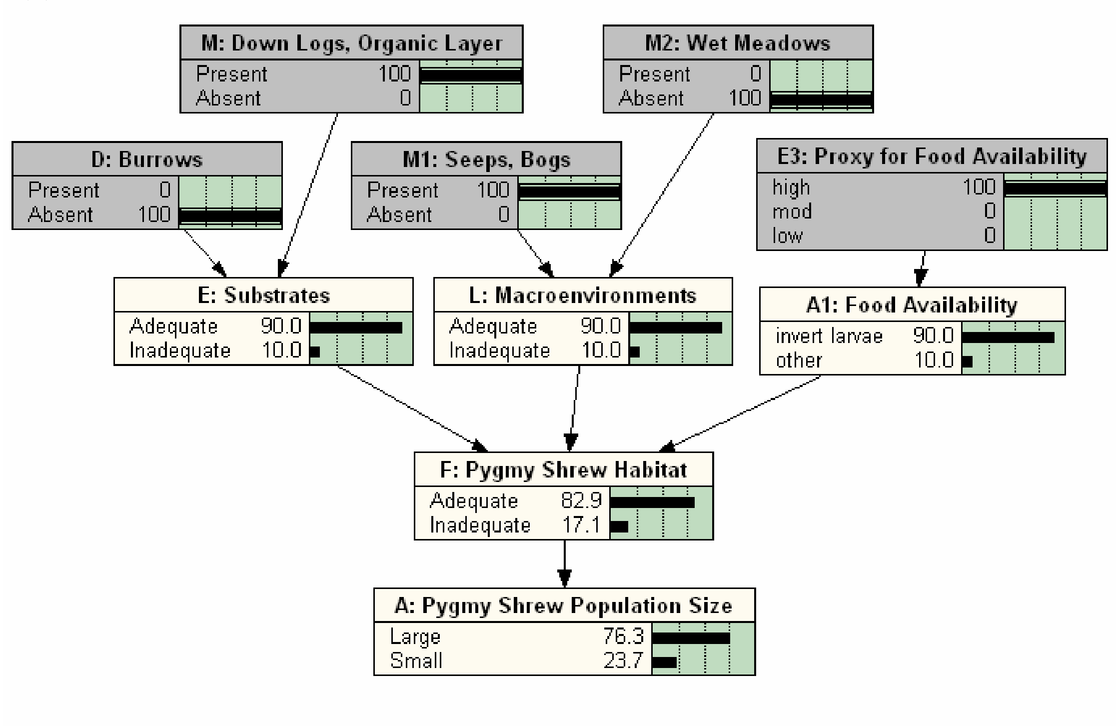
Input node (Fig. 1b)	**Entropy reduction value**
D: Burrows	0.021
M: Down Logs, Organic Layer	0.021
M1: Seeps, Bogs	0.020
M2: Wet Meadows	0.020
E3: Proxy for Food Availability	0.017

Figure 1. Example of a model of habitat quality and population size of pygmy shrew (*Microsorex hoyi*) in the interior western U.S. (a) Influence diagram, showing the main environmental and habitat variables influencing pygmy shrew habitat quality and population size. (b) Bayesian belief network (BBN) model, showing predictions of habitat and population outcomes from conditions, for a particular location, as specified in the input nodes (gray boxes). The bars represent the probability of each state in each node. (c) BBN model, showing hindcasting outcome by forcing the pygmy shrew habitat condition in Box F to the "adequate" state.

1(a)



1(b)


M: Down Logs, Organic Layer
Present 100
Absent 0
M2: Wet Meadows
Present 0
Absent 100
D: Burrows
Present 0
Absent 100
M1: Seeps, Bogs
Present 100
Absent 0
E3: Proxy for Food Availability
high 100
mod 0
low 0
E: Substrates
Adequate 90.0
Inadequate 10.0
L: Macroenvironments
Adequate 90.0
Inadequate 10.0
A1: Food Availability
invert larvae 90.0
other 10.0
F: Pygmy Shrew Habitat
Adequate 82.9
Inadequate 17.1
A: Pygmy Shrew Population Size
Large 76.3
Small 23.7

1(c)

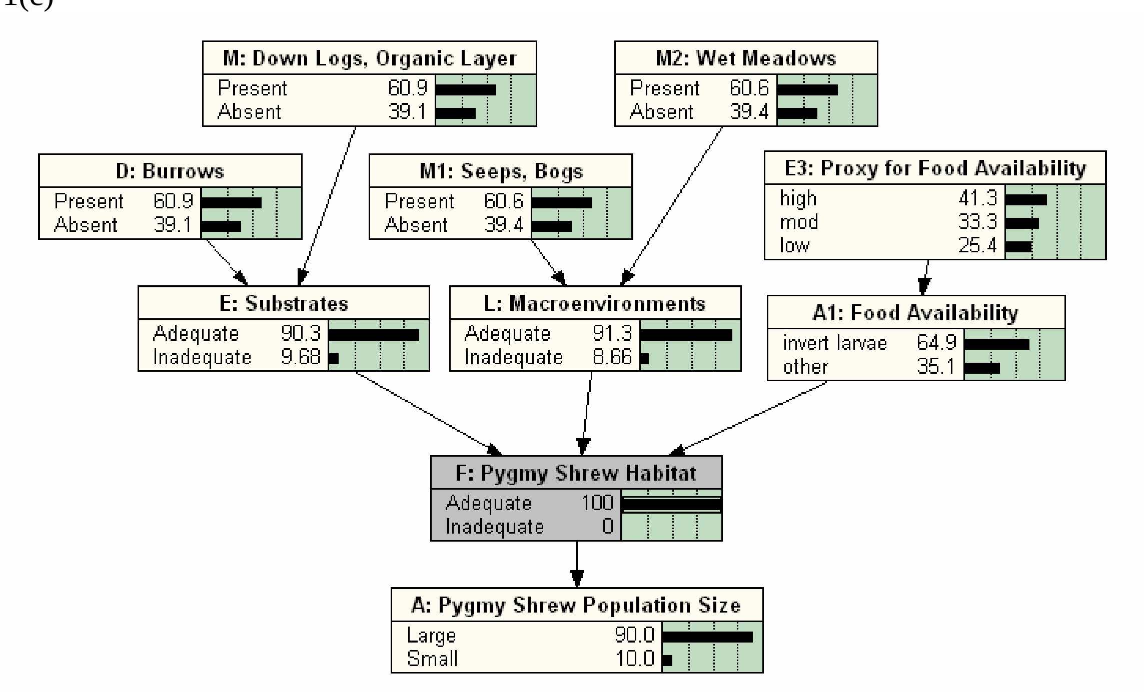

M: Down Logs, Organic Layer
Present 60.9
Absent 39.1
M2: Wet Meadows
Present 60.6
Absent 39.4
D: Burrows
Present 60.9
Absent 39.1
M1: Seeps, Bogs
Present 60.6
Absent 39.4
E3: Proxy for Food Availability
high 41.3
mod 33.3
low 25.4
E: Substrates
Adequate 90.3
Inadequate 9.68
L: Macroenvironments
Adequate 91.3
Inadequate 8.66
A1: Food Availability
invert larvae 64.9
other 35.1
F: Pygmy Shrew Habitat
Adequate 100
Inadequate 0
A: Pygmy Shrew Population Size
Large 90.0
Small 10.0

Figure 2. Overall process of modeling rare plant and animal species using Bayesian belief networks. (Source: Marcot, 2006b)

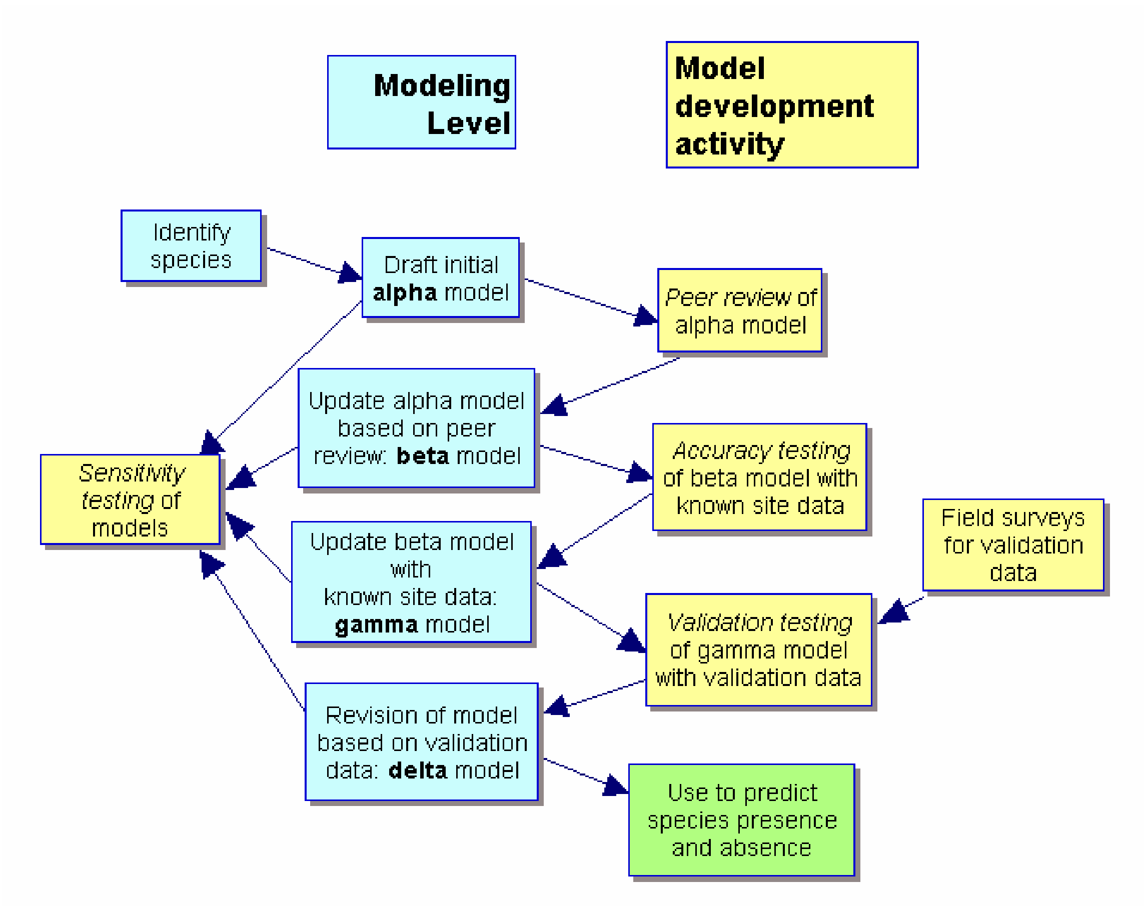


Figure 3. An example of a BBN submodel of road effects using proxy variables of road density and human population density, used in wildlife prediction models in the interior western U.S.. Each state in the road and human density nodes is defined quantitatively; for example, the “Moderate” road density state is defined as 0.4 to 1.1 km/sq km. In this proxy submodel, because humans are the stressor on these species and not necessarily roads per se, the human density variable was weighted more heavily than the road density variable in the conditional probability table for the road effects node. Probabilities of road and population density are shown here as uniform, depicting complete uncertainty, and they would be specified for a particular location such as a sub-basin; alternatively, they can be parameterized with frequency distributions of road and population density values as occurring among sub-basins to predict an overall road disturbance effect throughout the region.

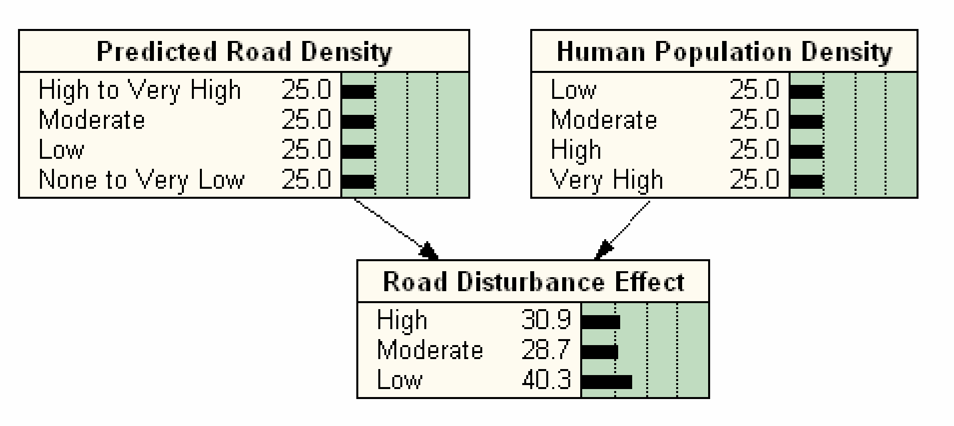


Figure 4. An example of mapping the results from a Bayesian network model of habitat suitability of greater sage-grouse in the inland West U.S., under historic, current, and a potential management alternative, under the Interior Columbia Basin Ecosystem Management Project (ICBEMP). Habitat suitability is represented in three categories (zero, low, high) calculated from the network model that combines the influence of grassland and shrub-steppe habitat with human-caused disturbance. See text for further description. (Source: Raphael et al. 2001.)

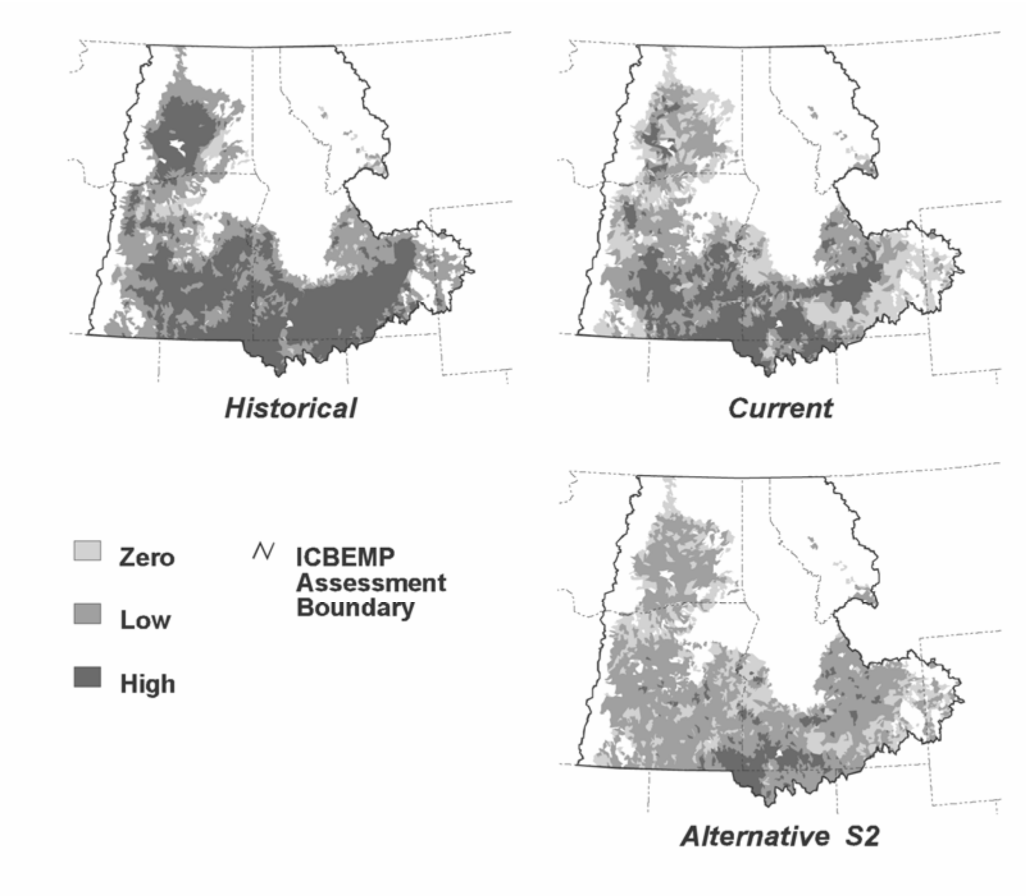


Figure 5. Main decision model to determine the appropriate conservation category (A-F or off) of rare or little-known species associated with late-successional and old-growth forests (see Footnote 1, text) in the Pacific Northwest, U.S. Each of the 6 main categories of information that determine the conservation outcome in turn consist of decision evaluation models (not shown here). The bottom section of this figure shows how each conservation category has implications and costs of conducting species surveys and managing sites; numbers in the management node (bottom left) display expected cost values calculated from the cost utility nodes (bottom right). When the model is run, the states of each of the 6 information input nodes and the final conservation category in the management node are specified. In this model, "geographic range" refers to the Pacific Northwest, U.S.; "plan provides for persistence" refers to whether the guidelines in the existing Northwest Forest Plan would adequately provide for persistence of the species; "strategic" surveys refers to statistically-based species inventories; and "predisturbance" surveys refers to species inventories in locations proposed for ground-disturbing activities such as timber harvests. (Source: Marcot et al. 2006.)

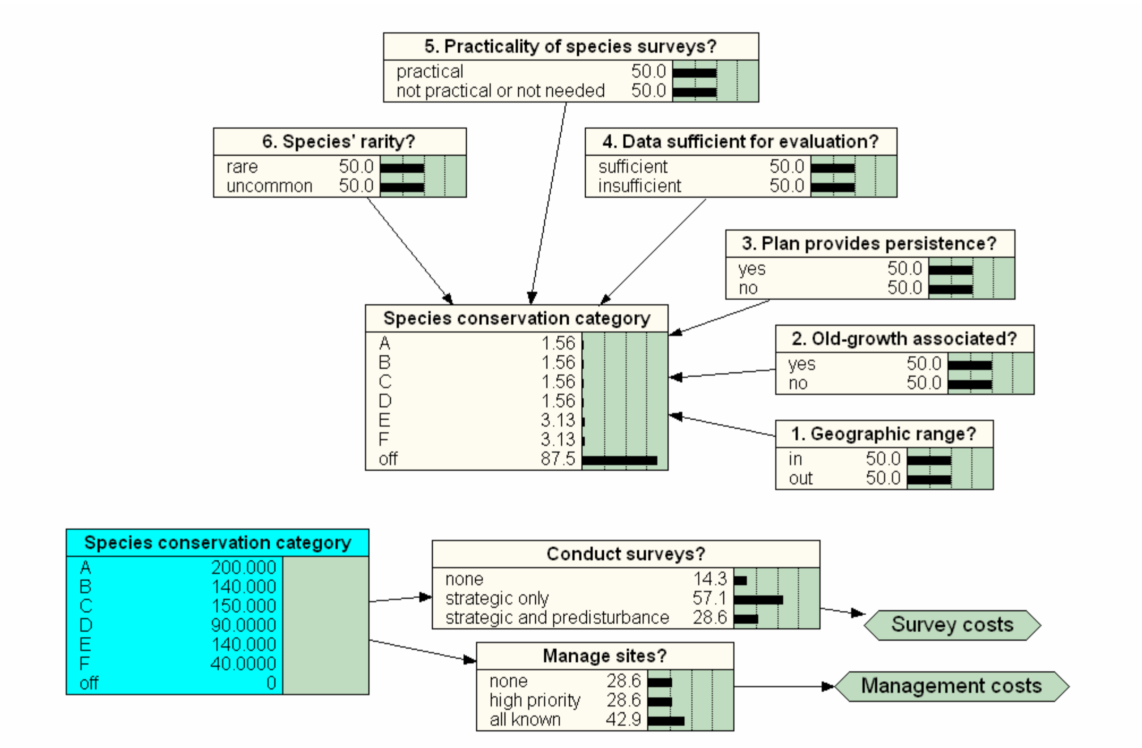


Figure 6. Summary results from a Bayesian network model of woodland caribou habitat suitability, showing total area of habitat in high-elevation winter range in north-central British Columbia, Canada, under conditions before (top) and after (bottom) colonization by moose. The dark dashed line is the theoretical maximum value of habitat area given all optimal conditions and no natural disturbance such as wildfire, the gray line is the value modeled under natural disturbances, and the lower and upper parts of the stacked bars represent the expected caribou response of highly preferred and less preferred portions of the species' habitat. Model results clearly show that the expected area occupied by caribou likely changes over time and is adversely affected by natural disturbances and presence of moose. (Source: McNay et al. 2006)