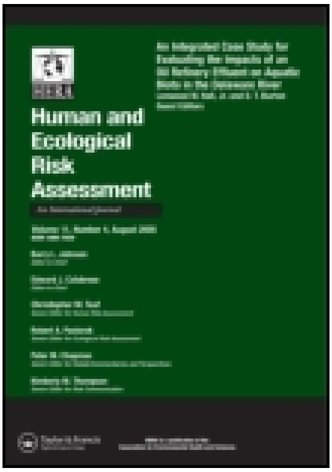

Human and Ecological Risk Assessment: An International Journal
Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/bher20

A Bayesian Approach to Landscape Ecological Risk Assessment Applied to the Upper Grande Ronde Watershed, Oregon

Kimberley K. Ayre [a] & Wayne G. Landis [a]

[a] Institute of Environmental Toxicology, Huxley College of the Environment , Western Washington University , Bellingham , WA , USA

Published online: 27 Sep 2012.

Human and Ecological Risk Assessment: An International Journal, 18: 946–970, 2012

ISSN: 1080-7039 print / 1549-7860 online
DOI: 10.1080/10807039.2012.707925

RISK ASSESSMENT ARTICLES

A Bayesian Approach to Landscape Ecological Risk Assessment Applied to the Upper Grande Ronde Watershed, Oregon

Kimberley K. Ayre and Wayne G. Landis
Institute of Environmental Toxicology, Huxley College of the Environment, Western Washington University, Bellingham, WA, USA

ABSTRACT

We present a Bayesian network model based on the ecological risk assessment framework to evaluate potential impacts to habitats and resources resulting from wildfire, grazing, forest management activities, and insect outbreaks in a forested landscape in northeastern Oregon. The Bayesian network structure consisted of three tiers of nodes: landscape disturbances, habitats, and the ecological resources or endpoints of interest to land managers. Nodes at each tier were linked to lower nodes if ecological and spatial relationships existed between them. All parameters had four potential discrete states: zero, low, medium, and high. Our model reliably predicted probable risk to habitats and endpoints from natural and anthropogenic disturbances. The disturbances most likely to transform habitats and effect ecological resources were forest management and wildfire. Of the six habitats, moist forest (characterized by Douglas fir and grand fir) was found to be at greatest risk of ecological impacts. The management endpoint with the highest likelihood of impact was historical range of variability (HRV) for salmon habitat, followed by recreation (hunting native ungulates) and HRV wildfire. We found that the Bayesian approach to ecological risk assessment was a useful method to assess potential impacts to ecological resources resulting from forest management and natural disturbances.

Key Words: regional risk assessment, Bayesian networks, forestry management, landscape disturbance.

Received 10 May 2011; revised manuscript accepted 19 August 2011.
Address correspondence to Wayne G. Landis, Institute of Environmental Toxicology, Huxley College of the Environment, Western Washington University, 516 High St., ES518, MS9180, Bellingham, WA 98225-9180, USA. E-mail: wayne.landis@wwu.edu

INTRODUCTION

All ecological systems have developed under some type of natural disturbance regime, and in most environments human activities have substantially altered the frequency and severity of these disturbances. For this reason many scientists and government agencies argue that public lands should be managed to keep current disturbance frequency and severity within the natural or historical range of variability for that disturbance (Landres *et al.* 1999; Hann *et al.* 2003). In addition to the difficulties inherent in identifying and characterizing the historical range of variability for a single disturbance, landscapes are typically impacted from multiple disturbances that operate at different spatial and temporal scales (Hemstrom *et al.* 2007). Across most landscapes natural disturbances and anthropogenic activities combined led to direct and/or indirect ecological effects. As a consequence, attempts at sustainable environmental and resource management must consider not only the potential effects from natural disturbances but also the impacts of physically managing these resources.

In the United States there are 759 million acres of forested land, of which 651 million acres are characterized as forest-use land, where resources are obtained from these forests (Lubowski *et al.* 2006). While some private forests may be used exclusively for timber harvests, most forests are managed for multiple uses. The process and activities involved in forest management, therefore, will depend largely on management goals decided on by stakeholders. For public lands the stakeholders may include local, state, tribal, and federal governments; industry; and community-interest groups—all of which may have different goals and perspectives on how to effectively achieve balance between environmental protection and utilization. A further challenge for resource managers is that not all forest products can be maximized at the same time, leading to tradeoffs that impact forest management activities. Forests are dynamic and ecologically complex and our understanding of how to "best" manage these lands continues to evolve.

Ecosystems are integrated, complex levels of ecological organization and some argue that ecosystem management requires a holistic, integrated approach that links science, management activities, and environmental policy (Cortner 2000). Some have argued that decision-making should be based in part on the predicted outcomes of ecological assessment models that have been parameterized by data gathered through environmental monitoring, thus creating a feedback between management, assessment, and policy decision-making (Holling 1978; Walters 1986). Unfortunately there are few examples of this type of integrated decision-making, and most environmental monitoring programs are developed and occur independent of any environmental assessment activities. Aside from the feedback between environmental assessment and decision-making, adaptive ecosystem management differs from traditional resource management in its recognition of uncertainty. Uncertainty is inherent in complex, stochastic ecological systems yet incorrect or incomplete knowledge of system processes can further increase uncertainty and should be reduced to the extent possible.

Forests in the Pacific Northwest are harvested for timber, used for recreation including hunting and fishing, and may also support grazing or mining activities. While the process of forest management on publically owned lands is based on managing these multiple uses, management activities typically fall into one of three categories: harvest (*e.g.,* cutting trees or allowing grazing in specific allotments), restoration, or construction of roads or trails to facilitate the other two activities (Leuschner 1984; Johnson and Peterson 2005). The principal natural disturbance in Pacific Northwest forests is wildfire, although insects and disease threaten vast expanses of forest each year (Torgersen 2001). Forest management activities are directed toward decreasing perceived risk from these disturbances. Recent models of interior Pacific Northwest forest landscapes suggest that forest management can alter the dynamic balance between natural disturbances (Ager *et al.* 2007; Hemstrom *et al.* 2007), but does not eliminate the ecological impacts of disturbances when they occur (Barbour *et al.* 2007).

In this article we present an ecological risk assessment used to evaluate the likelihood of ecological impacts from wildfire, grazing, insects, and forest management activities that occur in multiple habitats across a forested landscape in northeastern Oregon. The approach taken was to develop a Bayesian network model based on the conceptual model developed by Anderson and Landis (2012) and parameterized using spatial data on the occurrences of natural disturbances and forest management activities across the landscape as well as within different habitats as defined by plant community composition.

Ecological Risk Assessment

An ecological risk assessment provides the context and protocol for predicting environmental impacts of various stressors including natural and anthropogenic disturbances. Ecological risk assessments were originally developed to assess the potential for risk to organisms resulting from environmental pollutants released into discrete areas. Soon after the development of the ecological risk assessment protocol (USEPA 1992, 1998) it was recognized that ecological systems are impacted by more than just the introduction of contaminants. Evaluation of ecological consequences across large spatial scales with multiple disturbances necessitated the development of new risk assessment approaches. The relative risk model (RRM) was developed to address the potential for ecological risks in Port Valdez, Alaska, resulting from multiple stressors that operate across different spatial and temporal scales (Landis and Wiegers 1997, 2005). In the RRM, as in most ecological risk assessments today, risk is defined as the likelihood of ecological impacts resulting from identified stressors or ecological disturbances. Since the time of its development, the RRM has been successfully used in ecological risk assessments at landscape and regional scales (Wiegers *et al.* 1998; Obery and Landis 2002; Hart Hayes and Landis 2004).

One of the first steps in applying the RRM to an ecological system is to determine the causal pathways linking the source of potential impacts, the habitat or location of the ecological components of interest, and the potential impacts to those ecological entities. One of the underlying principles of the RRM is that there must be spatial overlap between the location of environmental disturbances (sources) and the location of the ecological entities (habitats) for which risk is being determined for any ecological impacts (endpoints) to occur. Functional and spatial relationships between sources, habitats, and endpoints are depicted in the development of a graphical, conceptual model. The next step in the RRM is to assign ranks to the sources and habitats that represent the extent of spatial overlap for each. One of the final risk characterization steps of most quantitative ecological risk assessments is an uncertainty analysis in which the sources of uncertainty are characterized and in some cases quantified. Uncertainty can result from measurement error, systematic error, natural variation, inherent randomness, subjective judgment, and incomplete knowledge (Regan *et al.* 2002). Incomplete knowledge is often a large source of uncertainty in ecological risk assessments owing to a lack of site-specific data.

An ecological risk assessment is meant to be an iterative process (USEPA 1992, 1998) so that as additional information is obtained, risk can be reevaluated, providing risk managers and stakeholders the information needed to make informed decisions. A problem with many traditional risk assessments is that the risk analysis process often lacks transparency, and estimates of risk and the associated uncertainty may be difficult to communicate to stakeholders. In this article we demonstrate that using Bayesian network models eliminates some of these shortcomings of ecological risk assessments because the model's structure reflects causal relationships and the likelihood of risk to endpoints is graphically presented as a probability distribution. Bayesian network models have the added benefit that a broad array of data types can be used and uncertainty is explicitly incorporated and reflected in the risk estimates, resulting in a model that is versatile and may be more appropriate for modeling complex ecological systems where high uncertainties exist than for traditional approaches (Pollino and Hart 2008).

Bayesian Networks

The difference between classical, or frequentist, statistical methods and Bayesian statistics is that frequentist statistics evaluate the probability of the evidence given a hypothesis while Bayesian statistics evaluate the opposite. Bayesian networks (BNs) are graphical models that use conditional probability distributions to describe relationships between a model's variables. BNs have been previously applied to ecological systems (Lee 2000; Marcot *et al.* 2001; Rowland *et al.* 2003; Borsuk *et al.* 2004; Marcot *et al.* 2006a; Pollino *et al.* 2007a) and are considered to be effective tools for guiding research and monitoring that supports decision-making (McCann *et al.* 2006; Nyberg *et al.* 2006). Using Bayesian methods can reduce uncertainty in a model due to a lack of knowledge because different types of information, including a model's predictions and expert judgment, can be used as data.

Another advantage of using a BN to model ecological systems is that BNs are inherently hierarchical and causal, making them a valuable tool for assessing the synergistic effects of various disturbances and evaluating alternative management strategies The steps involved in developing a BN are: (1) developing a causal structure with relevant variables and dependencies, (2) assigning states to the model's variables, (3) specifying prior probabilities in the form of conditional probability tables linking the model's variables, (4) evaluating the model by conducting a sensitivity analysis, and (5) updating the model with new evidence or knowledge (Pollino *et al.* 2007b). These steps illustrate several similarities between BNs and the framework used in ecological risk assessments; specifically, the importance of an underlying causal framework, sensitivity analysis to determine where additional information is needed to reduce uncertainty, and the importance of updating the model when new data become available.

Uncertainty in a BN is incorporated into the model through the nature of the conditional probability tables or expressions that represent a variable. Because of similarities in analysis structure, BNs are increasingly being viewed as a viable and rigorous tool for ecological risk assessments. Within the last few years there have been a few ecological risk assessments that have incorporated Bayesian network modeling (Borsuk *et al.* 2004; Hart *et al.* 2006; Gibbs 2007; Pollino *et al.* 2007a). While these recent publications reflect an increase in the application of BNs in ecological risk assessments, the approach is still considered novel methodology and none of these ecological risk assessments have tackled the large spatial extent that is required for ecological risk assessments at the landscape or regional scale.

This research is unique because it is the first to apply Bayesian methods to an ecological model of this spatial scale and complexity with direct implications for adaptive forest management in the Pacific Northwest. We developed a BN model to assess the potential ecological impacts to the habitats of the upper Grande Ronde sub-watershed in the Wallowa-Whitman National Forest resulting from wildfire, grazing, forest management activities, and insect outbreaks (the principal disturbances for this area [Hemstrom *et al.* 2007]). We adapted the framework of the RRM (Landis and Wiegers 1997, 2005) into the BN and used spatial analysis data to evaluate the occurrences and potential impacts of wildfires, grazing, pathogenic insects, and forest management activities across multiple habitats using existing geographic information systems (GIS) data available from the U.S. Forest Service Region 6.

Study Area

The study area for this research was a portion of the upper Grande Ronde sub-basin in northeastern Oregon, adjacent to the Oregon–Washington border (Figure 1). The sub-basin has been actively researched for many years, and was the trial region for the U.S. Forest Service's Interior Northwest Landscape Analysis System (INLAS) project; the outcomes of which demonstrated, among other things, that an inherent tradeoff often exists between management goals due to the complex ecological interactions that occur across landscapes over extended periods of time (Barbour *et al.* 2007). The upper Grande Ronde sub-basin encompasses five watersheds (HUC 5), with most of the land under Federal management as part of the Wallowa-Whitman National Forest (U.S. Forest Service, La Grande District). Other land owners/managers in the study area include private owners, the State of Oregon, U.S. Department of the Interior Bureau of Land Management, and the Confederated Tribes of the Umatilla (Barbour *et al.* 2007).

The climate of the upper Grande Ronde region is characterized as having short, dry summers and long, cold winters, with highly variable precipitation levels occurring principally as snow (Taylor and Bartlett 1993). The topography is varied with elevations ranging from 360 to more than 2100 m, encompassing riparian corridors, grazing lands, and several forested plant communities. Three forest types are recognized within the area: warm-dry Ponderosa Pine (*Picea ponderosa*) forests in the semi-arid regions at low elevation, cool-moist Douglas fir (*Pseudotsuga menzesii*) and

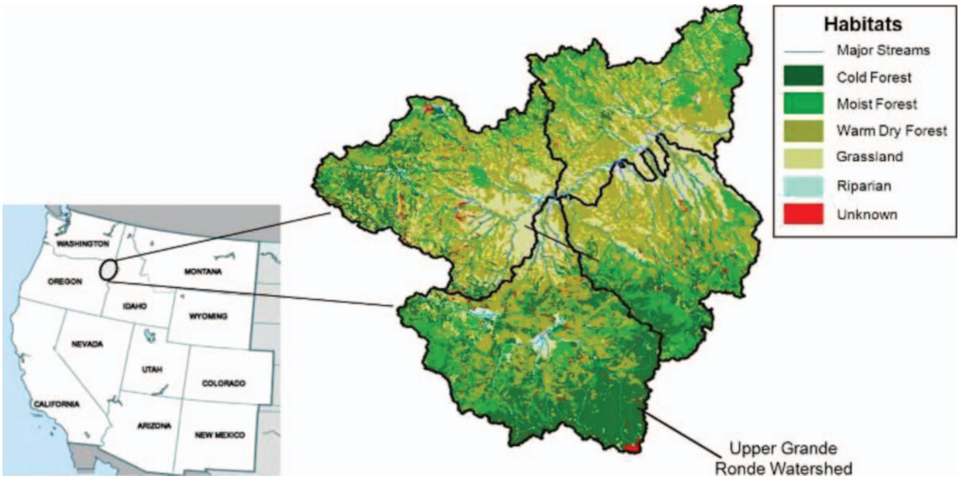

Figure 1. Study area for the terrestrial landscape risk analysis. Analysis focuses on the potential occurrence and impact of natural and anthropogenic disturbance on different habitat types within the Upper Grande Ronde watershed (lower region) in the Blue Mountains of eastern Oregon. (Color figure available online.)

grand fir (*Abies grandis*) dominated forests at mid-elevations, and cold, spruce-fir forests dominated by Engelmann spruce (*Picea engelmannii*) and subalpine fir (*Abies lasiocarpa*) in the high elevations (Figure 1; Barbour *et al*. 2007). These forests are interspersed with grasses, shrubs, and wetlands whose species composition is largely dependent on elevation (Powell *et al*. 2007).

We focused on the southern-most watershed in the sub-basin, the upper Grande Ronde watershed, for our model because it is ecologically variable, contains critical habitat for several federally threatened terrestrial and fish species, is used extensively for recreation, grazing, and the landscape is representative of most watersheds in the region. Based on spatial analysis of satellite imagery data, the vegetation of the upper Grande Ronde watershed is approximately 86% forest, 11% grassland, and 3% riparian habitat that is adjacent to more than 250 km of stream. Within the upper Grande Ronde watershed the habitats of the Canada lynx (*Lynx canadensis*), and gray wolf (*Canis lupus*) have been identified, in addition to those of 40 terrestrial vertebrates of concern (Wisdom *et al*. 2000). Despite the overall decline in Chinook salmon (*Oncorhynchus tshawytscha*), bull trout (*Salvelinus confluentus*), and steelhead (*Oncorhynchus mykiss*) populations in Oregon, these federally threatened species can still be found in the Grande Ronde river (Oregon Department of Fish and Wildlife 2006) making sensitive management of this landscape critical.

The upper Grande Ronde watershed has been extensively grazed by wild and domestic ungulates, most notably by elk (*Cervus elaphus*), mule deer (*Codocoileus hemoinus*), and cattle (*Bos taurus*) (Johnson 1994). Grazing still occurs within the watershed, necessitating the need for resource management that seeks balance of recreational uses (hunting native ungulates) and sustainable grazing while minimizing landscape disturbance. The principal forest management goals for the area include reducing risk from catastrophic fire, decreasing impacts from invasive species, sustaining and enhancing outdoor recreation opportunities, and the restoration and improvement of watershed conditions (U.S. Forest Service 2010). However, these management goals combined may not necessarily be achievable due to the complex ecological interactions that occur across a such a large and variable landscape (Barbour *et al.* 2007), resulting in the need for land managers to have a tool that can help them evaluate different management scenarios and direct monitoring and research activities to improve management decision-making.

METHODS AND MATERIALS

The overall objective of this research was to evaluate if a BN model could be developed using the framework for a regional scale ecological risk assessment and to determine if such a model could be applied as a tool to assess alternative management scenarios. Most of the risk assessment planning and problem formation was conducted in a prior risk assessment project (Anderson 2007; Anderson and Landis 2012). A critical step in risk assessment planning and problem formation is the development of a conceptual model. We used the conceptual model developed by Anderson (2007; Anderson and Landis 2012) as part of a risk assessment using the relative risk model for the same study area so that we could evaluate the model's outcomes for the two risk assessment approaches. The conceptual model consisted of the sources of disturbances, habitats within the risk area (defined by plant communities), and ecological resources of interest that correspond to management goals for the area (Figure 2). In a conceptual model, connections between sources, habitats, and endpoints exist only if there are causal pathways that exist between them. Thus, there is an inherent similarity between the structure of a conceptual model and that of a Bayesian network.

Bayesian Network Structure

A first step in constructing a BN model is to develop the graphical structure. Models consist of nodes and linkages, with linkages representing causal relationships between connected nodes. Our model was developed using the BN software Netica (Norsys Software Corp., Vancouver, BC, Canada). The graphical structure was based on the conceptual model developed by Anderson (2007; Anderson and Landis 2012) with hierarchical nodes that represented the principal landscape disturbances, habitats, and endpoints. Parent nodes and all successive nodes had four potential states: zero, low, medium, and high risk, consistent with the relative risk model for ecological risk assessment (Landis and Wiegers 1997, 2005). These states were chosen to facilitate comparison between the results of this study to that of Anderson and Landis (2012) as a means of validating the model against one that was developed using different procedures. Development of the initial model's structure was followed by a comprehensive survey of relevant literature to verify assumed causal pathways, and extensive evaluation of available GIS data for potential use in the model.

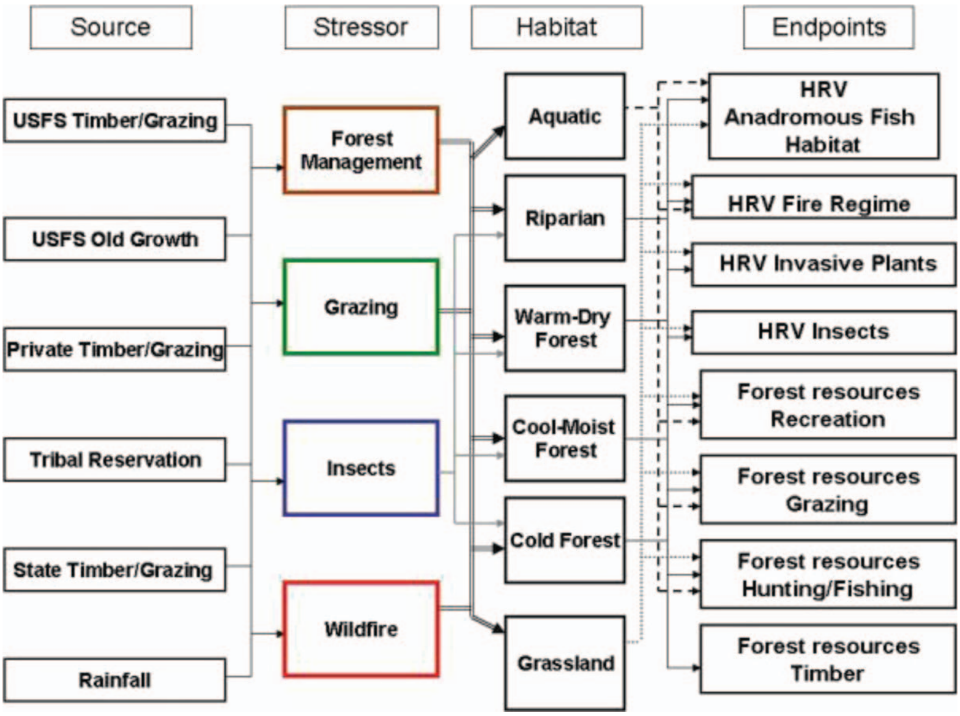

Figure 2. Conceptual model for the upper Grand Ronde sub-basin in northeastern Oregon that links landscape disturbances to plant communities (habitats), and ecological resources in the area. The boxes represent individual sources, disturbances, habitats, or endpoints, and the lines connecting the boxes indicate that a causal pathway or spatial relationship exists between the different components (reproduced from Anderson and Landis 2012). (Color figure available online.)

Model's Parameterization

The Bayesian network structure consisted of three tiers of nodes: landscape disturbances, habitats, and ecological endpoints (Figure 3). The parent nodes represented the four principal landscape disturbances for the study area: forest management, grazing, insects, and wildfire. These disturbances are major factors contributing to landscape alteration within the study area (Barbour *et al.* 2007). The distribution of risk states for each parent node was based on the likelihood of occurrence within the study area, which was determined from spatial analysis of U.S. Forest Service GIS data (Table 1). The second tier of the model represented the major habitats of plants and animals (spatially defined by the dominant vegetation types) within the watershed: cold forest, moist forest, dry forest, grasslands, riparian, and aquatic systems. A linkage was made from a landscape disturbance to a habitat if the disturbance was known to occur or would likely occur in that habitat based on either spatial analysis data or relationships established in the scientific literature. Habitat nodes were linked to nodes that represented ecological resources or attributes (endpoints) that related to specific management goals for this region. The endpoints

Table 1. Parent node parameters, states, and spatial analysis data sources that were used in the Bayesian network model. All GIS data, except for the Insect and Disease Survey, are available through the U.S. Forest Service online at: http://www.fs.fed.us/r6/data-library/gis/umatilla/index.shtml. The 2007 Insect and Disease Survey data are available at: http://www.fs.fed.us/r6/nr/fid/as/index.shtml.

Model variable	Model variable definition	Variable states	Data sources
Forest management	Intensity of forest management activities	Zero: no management activity (wilderness & backcountry areas) Low: infrequent harvest or thinning (old growth forest) Med: timber harvest and hunting areas (wildlife/timber areas) High: timber production areas (areas allocated for timber production & private timber producing land)	• Spatial distribution of land management plan allocations for Wallowa-Whitman National Forest • Ranks based on defined U.S. Forest Service management areas and associated activities (USFs—Wallowa-Whitman NF)
Grazing	Disturbance related to grazing of native (deer & elk) and exotic (cattle) ungulates	Zero: Rocky slopes & elevation >1350 m (no grazing activity) Low: Areas outside grazing allotments or private timber production areas Medium: Slopes $>14°$ & elevation between 1,270 and 1,350 m (preferred elk grazing areas) High: Slope $\leq 14°$ & elevation $<1,270$ m (grazing areas for cattle and deer)	• Spatial distribution of range allotments and elevation and slope distributions for the Blue Mountain Province • Ranks based on intensity of grazing as defined by slope and elevation preference for cattle and native ungulates (Stewart *et al.* 2002)

Insects	Disturbance from insect (bark beetles & defoliators) damage and related disease	Zero: No damaged trees Low: 0–1 damaged trees/acre Med: 1.01–2.5 damaged trees/acre High: >2.5 damaged trees/acre	• 2007 Insect & Disease Aerial Survey Data form U.S.F.S. Forest Health Protection • Ranks based on the number of damaged trees per acre
Wildfire	Predicted consequences of wildfire derived from the probability of burning and the relative frequency of fire behaviors (USFS—Wallowa-Whitman 2006)	Zero: Non-vegetated land Low: Low risk of severe consequences Medium: Medium risk of severe consequences High: High risk of severe consequences	• Spatial distribution of predicted consequences of wildfires in the Wallowa-Whitman National Forest • Ranks based on predicted wildfire consequences as defined by FIRE RISK

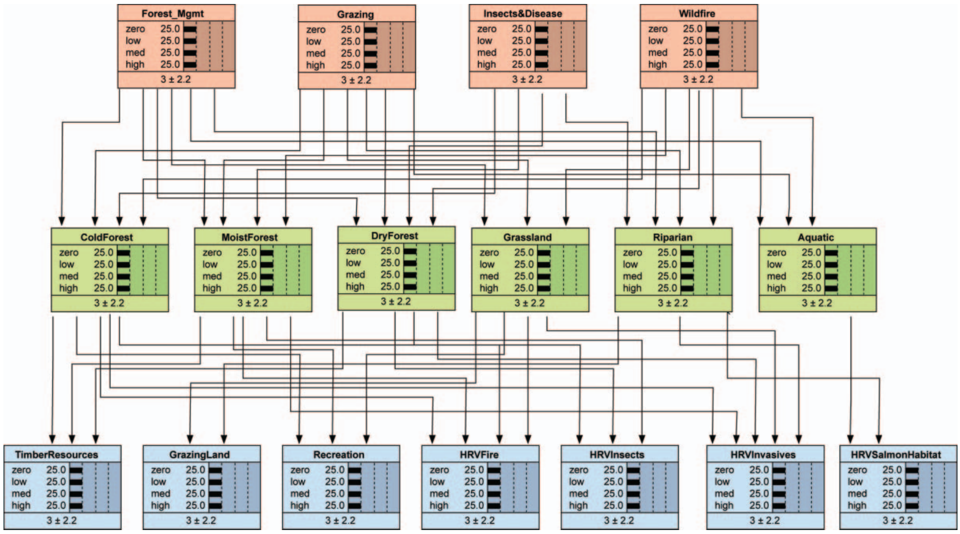

Figure 3. Bayesian network model developed for the analysis of ecological risk from landscape disturbances in the upper Grande Ronde watershed in northeastern Oregon. The top parameter nodes in the diagram represent landscape disturbances that were linked to the habitats where each disturbance occurs (second tier of nodes). The lowest tier of nodes represents the endpoints of interest that reflect desired resources and/or management goals. (Color figure available online.)

for the assessment were: timber resources (productivity and harvest), grazing lands, recreation (specifically hunting wild ungulates), and maintaining wildfire frequency, insect damage, level of invasive species present, and fish (salmonid) habitats within the historical range of variability. These endpoints were chosen because they are among the desired goals and conditions described in the land management plan for the Wallowa-Whitman National Forest (U.S. Forest Service 2010).

Nodes in the lower tiers (habitats and endpoints) were linked to those above if a causal pathway existed. The relationships between nodes are defined by conditional probability tables (CPTs) that describe the likelihood of each state given the states of parent nodes. A CPT consists of every possible combination of parent node states, incorporates the effects of any synergistic or antagonistic interactions, and existing spatial patterns determined by GIS analysis. The conditional probability tables for habitat nodes were based on an analysis of the spatial distribution of each disturbance state among habitats and potential synergistic relationships between disturbance types (Tables 2 and 3A). The likelihood of impacts to each endpoint node was computed based on conditional probability tables developed using a weight-of-evidence approach based on site specific information and an extensive review of scientific publications linking disturbances and habitats to endpoints (Tables 3A and B, respectively). The model's outcome was a probability distribution of node states for each endpoint, which can be interpreted as the likelihood of impact to parameters of interest (Pollino *et al.* 2007b). Because input parameters, relationships between parameters, and the model's outcome are all expressed as probability

Table 2. Habitat variables used in the model (defined by the dominant plant communities) and the relative frequencies of each disturbance state within the habitats (based on GIS analysis). The relative frequencies and information about synergistic effects between disturbance types formed the basis of the conditional probability tables linking disturbance nodes to habitat nodes.

		Relative frequencies of each disturbance state (%)			
Habitat	Rank	Management	Grazing	Insects	Wildfire
Cold Forest	Zero	3.1	24.4	88.3	2.4
Subalpine fir forests at high elevation	Low	3.4	51.2	1.1	0.0
	Medium	39.8	8.7	9.7	92.4
	High	53.7	15.6	1.0	5.2
Moist Forest	Zero	14.1	11.9	97.7	9.2
Grand fir forests	Low	4.9	86.6	0.5	3.1
	Medium	19.8	1.0	1.7	73.5
	High	61.1	0.4	0.1	15.0
Dry Forest	Zero	10.5	24	98.7	9.6
Ponderosa pine & juniper/sagebrush woodlands	Low	0.9	65.2	1.0	4.4
	Medium	47.2	7.8	0.2	72.0
	High	41.4	2.9	0.01	13.9
Grasslands	Zero	33.9	22.1	No causal pathway for impact	11.0
Vegetation with a significant grass component	Low	0.4	34.6		0.0
	Medium	52.6	17.6		77.0
	High	13.1	23.0		12.0
Riparian	Zero	33.9	51.9	97.9	56.6
Riparian areas at all elevations	Low	0.4	34.6	0.2	0.0
	Medium	52.6	0.0	1.9	31.9
	High	13.1	13.5	0.0	11.5
Aquatic	Zero	16.1	35.6	No causal pathway for impact	56.6
All surface waters	Low	5.3	32.4		0.0
	Medium	39.8	1.4		31.9
	High	38.8	30.5		11.5

Table 3. Evidence from published literature that was used in the development of conditional probability tables for habitat nodes (A) and endpoints (B). HRV stands for the historic range of variability, which is the desired condition for several management endpoints used in the model.

A.

Disturbance relationships	Evidence	Source
Forest management & grazing	Forest management and grazing have similar ecological impacts; reduction in understory biomass leading to increased stand density.	Belsky and Blumenthal 1997
Forest management & pathogenic insects	Forest stand thinning decreases the likelihood of insect outbreaks.	Raffa *et al*. 2008
Forest management & wildfire	Forest thinning decreases fire intensity by decreasing the likelihood of crown fires.	Hobbs 1996
Grazing & pathogenic insects	Grazing leads to dense forests, which are more susceptible to insect outbreaks.	Belsky and Blumenthal 1997
Grazing & wildfire	Grazing can increase fire severity by increasing the likelihood of stand density.	Hobbs 1996; Belsky and Blumenthal 1997
	Grazing suppresses regrowth after wildfire in riparian habitats.	Howell 2001
Pathogenic insects & wildfire	Diseased trees increase fire intensity.	Hayes and Daterman 2001; Hummell and Agee 2003
	Decreased fire frequency leads to increased susceptibility to pathogenic insects.	Hemstrom 2001

B.

Endpoints	Evidence	Source
Timber resources	Moist forests contain the greatest percentage of economically important tree species followed by cold and dry forests.	Campbell *et al*. 2004
	The area of moist forest habitats is below historical conditions.	Hemstrom *et al*. 2007
Grazing land	Grazing by cattle preferentially occurs in grasslands and riparian meadows.	Gillen *et al*. 1984
	Cattle are unaffected by timber harvest or road traffic.	Rapp 2006
Recreation (hunting)	Elk avoid roads and areas where cattle graze, and mule deer avoid elk. Elk are more visible and vulnerable to hunting in areas with timber harvests.	Rapp 2006
HRV fire	Fires are less frequent and higher intensity than prior to European settlement.	Hann and Bunnell 2001; Hessburg and Agee 2003
HRV insects	Management activities have increased the number of even aged stands, and an increase in the size and severity of insect outbreaks.	Hummel and Agee 2003; Raffa *et al*. 2008
	Moist and cold forests are most susceptible to impacts because of the vulnerability of Douglas fir and grand fir to western spruce budworm and Douglas fir beetle.	Parry *et al*. 1996
HRV invasive species	Invasive species have been introduced by grazing cattle and timber production activities. Grasslands and dry forests are most susceptible to invasive plants.	Hann *et al*. 1997; Parks *et al*. 2005
HRV salmon habitat	Salmon habitat is impacted by changes in stream temperature and nutrient input from the riparian environment.	Ebersole *et al*. 2003; Rieman *et al*. 2003; Watanabe *et al* 2005

distributions, BN models inherently incorporate and reflect uncertainty (McCann *et al*. 2006).

Model's Evaluation

Evaluation of the model's structure, parameterization, and findings involved a review by a panel of experts and comparison to an earlier risk assessment model conducted for the same area and endpoints using the relative risk model. The model was presented at a meeting in Portland, Oregon that included research scientists from the U.S. Forest Service Pacific Northwest Station, including members of the Corvallis Forestry Sciences Laboratory (Corvallis, Oregon), Portland Forestry Sciences Laboratory (Portland, Oregon), and Western Wildland Environmental Threat Assessment Center (Prineville, Oregon). Also in attendance were land and resource managers from the U.S. Forest Service Region 6, U.S. Bureau of Land Management, and Oregon Department of Fish and Wildlife. Most of the experts in attendance had participated in research and modeling efforts of the study area for many years and as part of the Interior Northwest Landscape System (INLAS) project (Hayes *et al.* 2004). The models and documentation were made available to Dr. Miles Hemstrom (U.S. Forest Service) for review and comment and his suggestions were incorporated.

Sensitivity Analysis

In general, a sensitivity analysis examines how uncertainty in a model's output can be attributed to uncertainty in the model's different input parameters. This is especially important in ecological risk assessments because a sensitivity analysis can identify key drivers in the model and the sources of uncertainty that contribute to overall uncertainty in a model's results. A sensitivity analysis can lead to recommendations for areas of future monitoring or research (Pollino and Hart 2008), and the inclusion of additional data into the model can sometimes reduce uncertainty. This aspect of the model is an important attribute when the risk assessment is intended to assist resource managers in their management decisions, because a key feature of adaptive management is to use information gained from research and monitoring activities to inform future decision-making (Nyberg *et al*. 2006).

Sensitivity analyses for discrete variable nodes were calculated in Netica (Norsys Software Corp.) as the degree of entropy reduction. Entropy reduction is the extent to which an input variable influences the response variable, so that the greater the entropy value the greater the degree of influence (Marcot 2006). We used the information gained from the sensitivity analysis for endpoint variables to determine the input parameters that had the greatest influence on risk estimates and the associated uncertainty.

RESULTS

The BN model for the Grande Ronde watershed produced estimates of the likelihood risk to habitats and the ecological endpoints from natural and anthropogenic

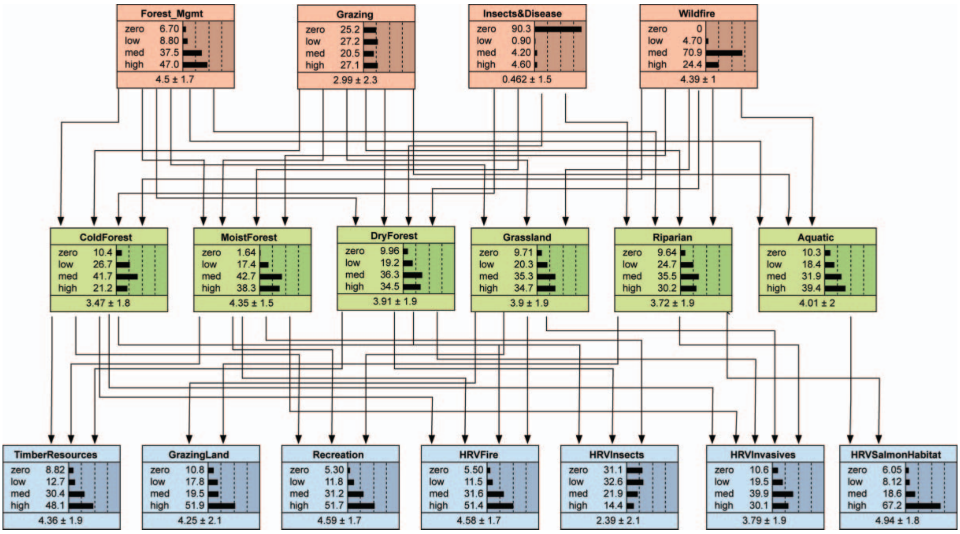

Figure 4. Analysis of ecological impacts from landscape alteration resulting from forest management, grazing, insects and diseases, and wildfire in the upper Grande Ronde watershed in northeastern Oregon. Each parameter (box) had four potential states: zero, low, medium, or high with values of 0, 2, 4, and 6, respectively. The distribution shown in each box is the risk distribution for that parameter with the mean risk score ± the standard deviation shown below the distribution. (Color figure available online.)

disturbances that were consistent to those generated for the same area using a different approach. The model's structure clearly communicated our current understanding of underlying causal relationships, which are not always clear in traditional risk assessments or complex ecological models. While not all possible ecological factors were incorporated into the model, the model represents our current state of ecological knowledge of the major drivers of landscape alteration in this region. The Bayesian approach allowed empirical data to be combined with expert opinion, as revealed in scientific literature, to construct the conditional probability tables; thus, solving one of the primary problems of risk assessments and ecological modeling; a lack of site-specific data.

While it is well known that natural disturbances can substantially alter landscapes, we found that forest management and wildfire were most likely to transform habitats and impact ecological resources in the upper Grande Ronde watershed (Figure 4). Moist forest habitat was at greatest risk of ecological changes from these disturbances. The risk distribution for this habitat was skewed toward medium–high risk states, with only a 20% likelihood of little or no impact. Most of the habitats had distributions with the highest probability of medium risk states; however, the aquatic habitat had an extremely skewed distribution towards higher risk states. Similarly the risk distributions for all of the ecological endpoint except historical range of variability (HRV) insects and HRV invasive species were skewed towards higher risk scores with the highest probabilities associated with the high risk state. The ecological resource with the highest likelihood of impact was HRV salmon habitat, followed by recreation and HRV wildfire.

Evaluation of Model

Our panel of experts reviewed the model by examining the structure, conditional probability tables, and outcomes as well as simulations of how the model could be used to evaluate different management scenarios. Overall there was general agreement that the model's structure, conditional probability tables, and parameter values were appropriate and consistent with ecological patterns, monitoring trends, and results generated from other modeling approaches for the region. Some members of the panel suggested alternate node titles, and slight changes to the endpoint conditional probability tables, yet there were no substantive changes proposed. The recommended changes were made in response to the experts' evaluation.

Sensitivity Analysis

In general the sensitivity analysis indicated that ecological endpoints were most sensitive to risk distributions for habitat reflecting the hierarchal nature of the model, but there was substantial variation in the relative sensitivity of endpoints to each habitat (Table 4). As expected from an examination of the cause–effect pathways, timber resources were most sensitive to impacts to the forested habitat, with greatest sensitivity to moist forests, cold forest, and dry forests, respectively. The risk distributions for recreation and grazing lands were most influenced by the likelihood of impacts to the grassland habitat, consistent with the importance of this habitat to grazing by cattle and native ungulates. The endpoint with the highest sensitivity to habits was HRV Salmon Habitat being sensitive the variable Aquatic

Table 4. Sensitivity analysis for ecological endpoints, showing the percent of calculated entropy for each endpoint attributed to habitat and disturbance nodes. Percentage is expressed relative to the calculated entropy for the endpoint of interest.

Endpoints	Sensitivity to habitats			Sensitivity to disturbances	
Timber resources	Moist forest (3.80)	Cold forest (3.12)	Dry forest (2.06)	Grazing (0.85)	Forest mgmt. (0.80)
Grazing lands	Grassland (8.5)	Riparian (8.24)	Moist forest (0.32)	Grazing (0.91)	Forest mgmt. (0.77)
Recreation	Grassland (5.14)	Moist forest (3.53)	Cold forest (2.54)	Forest mgmt. (1.50)	Grazing (0.99)
HRV wildfire	Cold forest (3.47)	Grasslands (3.54)	Moist forest (3.13)	Grazing (1.33)	Forest mgmt. (1.09)
HRV insects	Cold forest (7.47)	Moist forest (4.96)	Dry forest (3.60)	Grazing (1.41)	Forest mgmt. (0.88)
HRV invasives	Grassland (3.69)	Cold forest (2.24)	Riparian (2.09)	Grazing (1.28)	Forest mgmt. (0.83)
HRV salmon habitat	Aquatic (15.5)	Riparian (4.56)	Grassland (0.37)	Grazing (1.20)	Forest mgmt. (0.52)

Habitat. Sensitivity analysis also suggested that the management endpoints were most sensitive to findings for the grazing and forest management nodes. Grazing was very evenly distributed as far as rank type in the upper Grande Ronde (Figure 4). Forest management was essentially dichotomous with relatively low frequencies of area with ranks of zero or low, and then medium and high rank with a total frequency of 84.5 (Figure 4).

Validation of the Model—Comparison to the Relative Risk Model

The likelihood of impacts to endpoints generated from the BN model was compared to those produced from an application of the relative risk model to the same region (Anderson and Landis 2012). Although the two approaches differ substantially, there were several similarities in risk estimates. In both models the stressors most likely to impact endpoints were forest management and wildfire. Both models predicted a substantial risk to the HRV fire endpoint, yet the BN model estimated the greatest risk to HRV salmon habitat that was not the case for the relative risk model's projections. The relative risk model estimated the greatest risk to HRV fire, HRV insects, timber resources, and HRV invasive species.

Simulations

An important result of this research is that the BN model can be directly used as a management tool simply by setting the state of an endpoint to a desired level and essentially solving the model "backwards." When the risk states for HRV wildfire and HRV invasive species were set to low, reflecting the common management goals for wildfire frequency and severity and invasive species distributions the risk distributions for many of the model parameters were altered (Figure 5). In comparison to the model's results based on current conditions (Figure 4), this simulation showed a change in the risk distribution for grazing from a fairly even distribution to one skewed toward lower risk states, resulting in a lower mean risk score (Table 5). It is important to note that although the standard deviations are presented for sake of comparison, the risk distributions were not normally distributed and should be interpreted accordingly. There were also slight changes in the risk distributions and risk scores for the forest management and wildfire parameters. These modifications translated into changes to the risk distributions for forested and grassland habits so that all had lower predicted risk scores compared to the model's outcome based on current conditions. Interestingly, the conditions predicted to result in low risk to the HRV wildfire and HRV invasive species endpoints also resulted in a more even risk distribution for the grazing land endpoint, and distributions for timber resources and recreation endpoints that were less skewed towards high risk states than the current conditions reflected in the original model. Thus subtle changes in environmental management may result in large changes in the risk distribution for sensitive endpoints. This inherent flexibility in the model's usage makes the model a powerful tool for resource management because alternative management scenarios can be easily evaluated for desired objectives.

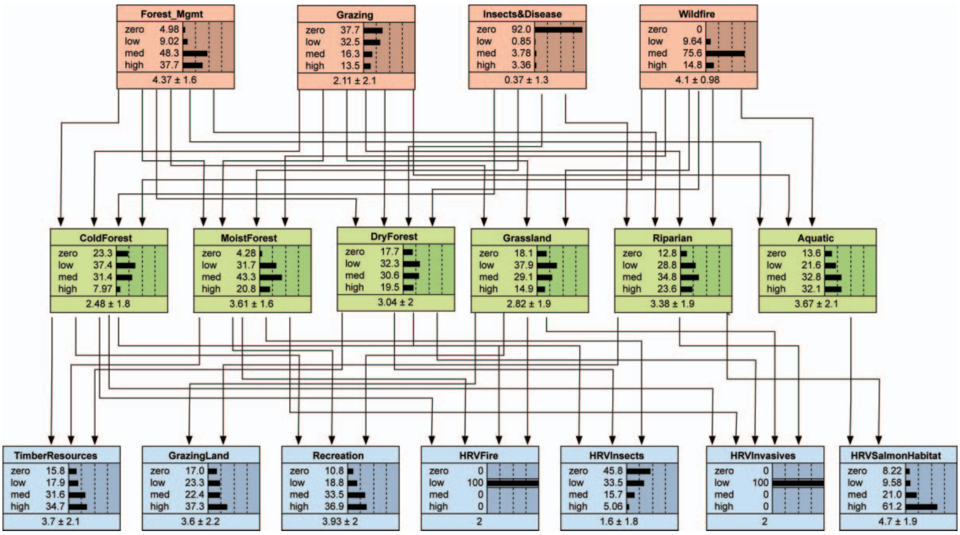

Figure 5. A simulation from the model showing the conditions required to achieve low risk states for the management goals of historical range of variability for wildfire frequency and severity (HRV fire) and invasive species (HRV invasives) distributions. The distribution shown in each box is the risk distribution for that parameter with the mean risk score ± the standard deviation shown below the distribution. (Color figure available online.)

DISCUSSION

Application of Bayesian methods to the framework of the relative risk model for ecological risk assessment allowed us to assess the potential impacts to ecological resources resulting from current management regimes within the INLAS area and wildfire, grazing, and insect outbreaks. There were only slight differences in the level of risk to endpoints predicted from the BN model compared to the analysis using the relative risk model (Anderson and Landis 2012). The differences were likely due to the way the analyses were conducted and the inclusion of a wider variety of data in the BN model. With the BN model we were able to account for potential synergistic effects between landscape perturbations through the conditional probability tables, which allowed complex ecological interactions to be incorporated without increasing the model's complexity. For example, grazing reduces understory vegetation in forests, which can increase fire severity by increasing the likelihood of crown fires (Hobbs 1996), and can also lead to denser forests that are more susceptible to diseases (Belsky and Blumenthal 1997). It is these synergistic effects that may explain why grazing and forest management were the two disturbances that most strongly influenced the level of potential risk to ecological endpoints.

One of the principal advantages of Bayesian network modeling is the fact that uncertainty can be explicitly incorporated into the model and clearly expressed the model's output (Marcot *et al.* 2006a; McCann *et al.* 2006; Pollino and Hart 2008). Uncertainty in the results from the model was reflected in shape of the risk distributions for each node; the broader the distribution, the greater the uncertainty in

Table 5. Risk scores from the simulation based on current conditions versus an alternative management scenario that is necessary to achieve historical range of variability for wildfire and invasive species distributions. Only parameters that had different distributions with the alternative management scenario are presented. Values presented are mean risk scores ± standard deviation for the risk distributions.

	Risk scores based on different management scenarios	
Model-parameter	Current conditions	Alternative management
Landscape disturbances		
Forest management	4.50 ± 1.7	4.37 ± 1.6
Grazing	2.99 ± 2.3	2.11 ± 2.1
Wildfire	4.39 ± 1.0	4.10 ± 0.98
Habitats		
Cold forest	3.47 ± 1.8	2.48 ± 1.8
Moist forest	4.35 ± 1.5	3.61 ± 1.6
Dry forest	3.91 ± 1.9	3.04 ± 2.0
Grassland	3.90 ± 1.9	2.82 ± 1.9
Ecological endpoints		
Timber resources	4.36 ± 1.9	3.70 ± 2.1
Grazing land	4.25 ± 2.1	3.60 ± 2.2
Recreation	4.59 ± 1.7	3.93 ± 2.0
HRV insects	2.23 ± 2.1	1.60 ± 1.8

the risk state. Another advantage of Bayesian networks is that when new information becomes available it can be easily incorporated, and the CPTs and risk distributions are immediately updated. For example when the states for the HRV wildfire and invasive species endpoint nodes were set to low a change in the risk distributions for many parameters was evident; not only due to changing the risk state for those nodes, but due a reduction in the model's uncertainty. Simulations like this can be used to clearly communicate to risk managers and stakeholders that although uncertainty exists in any ecological system, scientific approaches based on current ecological knowledge can be used to evaluate different management scenarios.

It has been proposed that to be most effective all nodes in a BN model, especially endpoint nodes, should be quantifiable so that the model can be updated (Marcot *et al.* 2006b; Pollino *et al.* 2007b). Our model was developed using the framework of the relative risk model for ecological risk assessment that uses a ranking system of zero, low, medium, and high risk. In this analysis the same risk levels were used as discrete node states to facilitate comparison of the output from the two modeling approaches. Each risk state in the model was defined quantitatively to the extent possible (Tables 1 and 2); however, some of the endpoints do not have a quantitative definition. Many of the management goals for the Wallowa-Whitman National Forest, used as endpoints in the model, are defined as an ecological state that is within the historical range of variability (HRV). While the HRV concept is commonly integrated into land and resource management goals it is not easily quantified (Landres *et al.* 1999; Hessburg *et al.* 1999; Agee 2003), which means that there is no way to objectively determine if HRV for a resource has been achieved. This presents a fundamental problem with using HRV endpoints as management goals in BN modeling and adaptive management in general. If one cannot precisely define HRV for an endpoint how can it possibly be achieved?

An alternative to using HRV endpoints would be to use quantifiable parameters that are correlated to our understanding of HRV for specific variables. For example no definition exists for HRV salmon's habitats, yet low sedimentation, cool summer stream temperatures, and availability of pools within a stream channel have been identified as characteristics of "high-quality" fish habitat (Bettinger *et al.* 1996). Incorporating quantitative variables for HRV endpoints would facilitate updating models similar to this one. A transition from loosely defined management goals to quantitative endpoints would allow resource managers to determine whether goals are being met, and incorporating quantitative endpoints into a Bayesian network like the one described here would facilitate adaptive management. The danger of defining management goals by specific parameters is that achieving the desired range of parameter values may not necessarily improve levels of ecologically and socially important resources. Ideally, resource management objectives should strike a balance between specific, quantifiable environmental parameters and resource goals that are culturally defined so that it is possible to assess whether goals have been met or need to be refined.

This research demonstrates that not only can a Bayesian approach be applied to regional scale ecological risk assessments, but that this approach can be effectively used as a tool for land and resource managers. The ability of the model to be used to evaluate alternative management scenarios, coupled with the graphic interface of model results, makes it an invaluable tool for collaborative resource management. The sensitivity analysis can be used to determine where additional information is needed to reduce uncertainty, and once obtained the new information can be used to update the model making the risk assessment model particular well-suited to adaptive management.

Adaptive environmental management requires a feedback loop between management and policy decisions and directed monitoring of ecological effects stemming from management activities (Holling 1978; Walters 1986). Attempts at adaptive management have met with several barriers, including: rejection of uncertainty, conflicting ecological values, and inflexibility among management agencies (Walters 1997; Gunderson 1999). The approach described here may help to overcome these barriers because: (1) the effect of uncertainty is quantifiable and easily communicated, (2) the effects of conflicting ecological values can be observed through the graphic interface of the BN, and (3) once developed this management tool can be easily used and refined by resource managers leading to greater involvement in the adaptive management process.

The goal of this project was to use BN modeling in an ecological risk assessment for multiple stressors across a forested landscape. We found that not only does this approach produce verifiable and tangible results, but it also yields a tool that can be used by resource or risk managers and policy-makers. This approach to ecological risk assessment could be applied to contaminants in natural or urban environments, evaluation of alternative remediation or management strategies, or evaluating the likelihood of impacts from future climate change. Since the completion of this project we have applied the same methodology at a regional scale for large portions of the southwestern United States. Bayesian networks provide the modeling flexibility needed for complex ecological risk assessments while maintaining transparency and clarity so that the risk assessment model itself can be used to communicate quantitative risk estimates to stakeholders and decision-makers.

ACKNOWLEDGMENTS

We thank C. Terry Shaw for his time and effort in facilitating data access. The manuscript benefited from the insightful comments of Andy Bunn, Miles Hemstrom, Margaret Landis, and two anonymous reviewers. Funding for this project was provided by Joint Venture Agreement No. PNW 06-JV-11261900–070 with the U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station.

REFERENCES

Agee J. 2003. Historical range of variability in eastern Cascade forests, Washington, USA. Landscape Ecol 18:725–40

Ager A, McMahan A, Hayes J, *et al.* 2007. Modeling the effects of thinning on bark beetle impacts and wildfire potential in the Blue Mountains of northeastern Oregon. Landscape Urban Plan 80:301–11

Anderson S. 2007. A Pilot Application of the Relative Risk Model to the Upper Grande Ronde Watershed, Oregon. Huxley College of the Environment, Western Washington University, Bellingham, WA, USA

Anderson SM and Landis WG. 2012. A pilot application of regional scale risk assessment to the forestry management of the upper Grande Ronde watershed, Oregon. Hum Ecol Risk Assess 18:705–32.

Barbour R, Hemstrom M, and Hayes J. 2007. The Interior Northwest Landscape Analysis System: A step toward understanding integrated landscape analysis. Landscape and Urban Plan 80:333–44

Belsky A and Blumenthal D. 1997. Effects of livestock grazing on stand dynamics and soils in upland forests of the interior West. Conserv Biol 11:315–27

Bettinger P, Johnson K, and Sessions J. 1996. Forest planning in an Oregon case study: Defining the problem and attempting to meet goals with a spatial-analysis technique. Environ Manage 20:565–77

Borsuk M, Stow C, and Reckhow K. 2004. A Bayesian network of eutrophication models for synthesis, prediction, and uncertainty analysis. Ecol Model 173:219–39

Campbell S, Azuma D, and Weyermann D. 2004. Forests of eastern Oregon: An overview. US Department of Agriculture, Forest Service, Pacific Northwest Resarch Station, General Technical Report PNW-GTR-578

Cortner HJ. 2000. Making science relevant to environmental policy. Environ Sci Policy 3:21–30

Ebersole JL, Liss WJ, and Frissell CA. 2003. Cold water patches in warm streams: Physiochemical characteristics and the influence of shading. J Am Water Resour As 39:355–68

Gibbs M. 2007. Assessing the risk of an aquaculture development on shorebirds using a Bayesian belief model. Hum Ecol Risk Assess 13:156–79

Gillen RL, Krueger WC, and Miller RF. 1984. Cattle distribution on mountain rangeland in northeastern Oregon. J Range Mange 37(6):549–53

Gunderson L. 1999. Resilience, flexibility and adaptive management antidotes for spurious certitude? Conserv Ecol 3(1):7. Available at http://www.consecol.org/vol3/iss1/art7
Hann WJ, and Bunnell DL. 2001. Fire and land management planning and implementation across multiple scales. Int J Wildland Fire 10:389–403
Hann WJ, Jones JL, Karl MG, *et al.* 1997. Landscape dynamics of the basin. In: Quuigley TM and Arbelbide SJ (eds), An Assessment of Ecosystem Components in the Interior Columbia Basin and Portions of the Klamath and Great Basins, vol 2. General Technical Report PNW-GTR-405, pp 337–1055. US Department of Agriculture, Forest Service, Pacific Northwest Research Station, Portland, OR, USA
Hann W, Wisdom M, and Rowland M. 2003. Disturbance Departure and Fragmentation of Natural Systems in the Interior Columbia Basin. Research Paper, USDA Forest Service, Pacific Northwest Research Station, Portland, OR, USA
Hart B, Burgman M, Grace M, *et al.* 2006. Risk-based approaches to managing contaminants in catchments. Hum Ecol Risk Assess 12:66–73
Hart Hayes E and Landis W. 2004. Regional ecological risk assessment of a nearshore marine environment: Cherry Point, WA. Hum Ecol Risk Assess 10:299–325
Hayes JL, Ager AA, and Barbour JR. 2004. Methods for integrated modeling of landscape change: Interior Northwest Landscape Analysis System. General Technical Report PNW-GTR-610. US Department of Agriculture, Forest Service, Pacific Northwest Research Station. Portland, OR, USA.
Hayes J and Daterman G. 2001. Bark beetles (Scolytidae) in eastern Oregon and Washington. Northwest Sci 75:21–30
Hemstrom MA. 2001. Vegetative patterns, disturbances and forest health in eastern Oregon and Washington. Northwest Sci 75:91–109
Hemstrom M, Mezenich J, Reger A, *et al.* 2007. Integrated analysis of landscape management scenarios using state and transition models in the upper Grande Ronde River Subbasin, Oregon, USA. Landscape Urban Plan 80:198–211
Hessburg PF and Agee JK. 2012. An environmental narrative of inland United States forests, 1800–2000. Forest Ecol Manage 178:23–59
Hessburg P, Smith B, and Salter R. 1999. Detecting change in forest spatial patterns from reference conditions. Ecol Appl 9:1232–52
Hobbs N. 1996. Modification of ecosystems by ungulates. J Wildlife Mange 60:695–713
Holling C. 1978. Adaptive Environmental Assessment and Management. John Wiley & Sons, New York, NY, USA
Howell P. 2001. Effects of disturbance and management of forest health on fish and fish habitat in eastern Oregon and Washington. Northwest Sci 75:157–65
Hummel S and Agee J. 2003. Western spruce budworm defoliation effects on forest structure and potential fire behavior. Northwest Sci 77:159–69
Johnson C. 1994. Forest Health in the Blue Mountains: A Plant Ecologist's Perspective on Ecosystem Processes and Biological Diversity. General Technical Report. US Department of Agriculture Forest Service, Pacific Northwest Research Station, Portland, OR, USA
Landres P, Morgan P, and Swanson F. 1999. Overview of the use of natural variability concepts in managing ecological systems. Ecol Appl 9:1179–88
Landis W and Wiegers J. 1997. Design considerations and a suggested approach for regional and comparative ecological risk assessment. Hum Ecol Risk Assess 3:287–97
Landis W and Wiegers J. 2005. Introduction to the regional risk assessment using the relative risk model. In: Landis W (ed), Regional Scale Ecological Risk Assessment Using the Relative Risk Model, pp 11–36. CRC Press, Boca Raton, FL, USA
Leuschner W. 1984. Introduction to Forest Resource Management. John Wiley & Sons, New York, NY, USA

Lubowski R, Vesterby M, Bucholtz S., *et al*. 2006. Major uses of land in the United States, 2002. U.S. Department of Agriculture Economic Research Service, Washington, DC, USA

Marcot B, Holthausen R, Raphael M, *et al.* 2001. Using Bayesian belief networks to evaluate fish and wildlife population variability under land management alternatives from an environmental impact statement. Forest Ecol Manage 153:29–42

Marcot BG. 2006. Characterizing species at risk I: Modeling rare species under the Northwest Forest Plan. Ecol Soc 11:10. Available at http://www.ecologyandsociety.org/vol11/iss2/art10/

Marcot B, Hohenlohe P, Morey S, *et al.* 2006a. Characterizing species at risk II: Using Bayesian belief networks as decision support tools to determine species conservation categories under the Northwest Forest Plan. Ecol Soc 11:12. Available at http://www.ecologyandsociety.org/vol11/iss2/art12/

Marcot B, Steventon J, Sutherland G, *et al.* 2006b. Guidelines for developing and updating Bayesian belief networks applied to ecological modeling and conservation. Can J Forestry Res 36:3064–74

McCann R, Marcot B, and Ellis R. 2006. Bayesian belief networks: applications in ecology and natural resource management. Can J Forestry Res 36:3053–62

Nyberg J, Marcot B, and Sulyma R. 2006. Using Bayesian belief networks in adaptive management. Can J Forestry Res 36:3104–16

Obery A and Landis W. 2002. A regional multiple stressor risk assessment of the Codorus Creek watershed applying the relative risk model. Hum Ecol Risk Assess 8:405–28

Oregon Department of Fish and Wildlife. 2006. Oregon Conservation Strategy. Oregon Department of Fish and Wildlife, Salem, OR, USA

Parks CG, Radosevich SR, Endress BA, *et al.* 2005. Natural and land-use history of the Northwest mountain ecoregions (USA) in relation to patterns of plant invasions. Perspectives in Plant Ecology, Evolution and Systematics. 7:137–58

Parry DL, Filip GM, Willits SA, *et al.* 1996. Lumber recovery and deterioration of beetle-killed Douglas fir and grand fir in the Blue Mountains of eastern Oregon. General Technical Report PNW-GTR-376. US Department of Agriculture, Forest Service, Pacific Northwest Research Station, Portland, OR, USA

Pollino C and Hart B. 2008. Developing Bayesian network models within a risk assessment framework. In: Forth Biennial Meeting of iEMSs, pp 372–9. International Environmental Modelling and Software Society, Barcelona, Cantelonia, Spain

Pollino C, White A, and Hart B. 2007a. Examination of conflicts and improved strategies for the management of an endangered Eucalypt species using Bayesian networks. Ecol Model 201:37–59

Pollino C, Woodberry O, Nicholson A, *et al.* 2007b. Parameterisation and evaluation of a Bayesian network for use in an ecological risk assessment. Environ Model Softw 22:1140–52

Powell D, Johnson C, Crowe E, *et al.* 2007. Potential vegetation hierarchy for the Blue Mountains section of northeastern Oregon, southeastern Washington, and west-central Idaho. General Technical Report PNW-GTR-709. US Department of Agriculture, Forest Service, Pacific Northwest Research Station, Portland, OR, USA

Raffa K, Aukema B, Bentz B, *et al.* 2008. Cross-scale drivers of natural disturbances prone to anthropogenic amplification: The dynamics of bark beetle eruptions. BioScience 58:501–17

Rapp V. 2006. Elk, deer and cattle: The Starkey project. Science Update 13. US Department of Agriculture, Forest Service, Pacific Northwest Research Station,.Portland, OR, USA

Regan H, Colyvan M, and Burgman M. 2002. A taxonomy and treatment of uncertainty for ecology and conservation biology. Ecol Appl 12:618–28

Rieman, B, Lee D, Burns D, *et al.* 2003. Status of native fishes in the western United States and issues for fire and fuels management. For Ecol Manage 178:197–211

Rowland M, Wisdom M, Johnson D, *et al.* 2003. Evaluation of landscape models for wolverines in the interior northwest, US of America. J Mammal 84:92–105

Stewart K, Bowyer R, Kie J, *et al.* 2002. Temporospatial distributions of elk, mule deer, and cattle: Resource partitioning and competitive displacement. J Mammal 83:229–44

Taylor G and Bartlett A. 1993. Climate Zone 8 Northeast Area. Oregon Climate Service, Oregon State University, Corvallis, OR. USA

Torgersen T. 2001. Defoliators in eastern Oregon and Washington. Northwest Sci 75:11–20

USEPA (US Environmental Protection Agency). 1992. Framework for Ecological Risk Assessment. EPA/630/R-92/001. Risk Assessment Forum, Washington, DC, USA

USEPA. 1998. Guidelines for ecological risk assessment. Fed Reg 63:26846–924

US Forest Service. 2010. Blue Mountains Revised Land and Resource Management Plan: Proposed Action. US Department of Agriculture Forest Service, Pacific Northwest Region, Portland, OR, USA

Walters C. 1986. Adaptive Management of Renewable Resources. MacMillan Publishing Company, New York, NY, USA

Walters C. 1997. Challenges in adaptive management of riparian and coastal ecosystems. Conserv Ecol 1:1. Available at http://www.consecol.org/vol1/iss2/art1/

Watanabe M, Adams RM, Wu J, *et al.* 2005. Toward efficient riparian restoration: Integrating economic, physical, and biological models. J Environ Manage 75:93–104

Wiegers J, Feder H, Mortensen L, *et al.* 1998. A regional multiple-stressor rank-based ecological risk assessment for the fjord of Port Valdez, Alaska. Hum Ecol Risk Assess 4:1125–73

Wisdom M, Holthausen R, Wales B, *et al.* 2000. Source Habitats for Terrestrial Vertebrates of Focus in the interior Columbia Basin: Broadscale Trends and Management Implications. General Technical Report. USDA Forest Service, Pacific Northwest Research Station, Portland, OR, USA