BAYESIAN BELIEF NETWORKS: A CONCEPTUAL APPROACH TO ASSESSING RISK TO HABITAT

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ABSTRACT

BAYESIAN BELIEF NETWORKS: A CONCEPTUAL FRAMEWORK FOR ASSESSING RISK TO HABITAT

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I developed an integrated application of Bayesian belief networks with Geographic Information Systems to provide a framework for assessing risk relative to wildlife habitat in the southern Wind River landscape of southwestern Wyoming. The Bayesian belief network applied in this research is a graphical, probabilistic model representing cause and effect relationships (Pearl 1988; Jensen 1996). Further explanation of Bayesian statistics and of Bayesian belief networks is discussed in the "Methods" section on page 42.

Specifically, I conducted an assessment of risk(s) to mule deer (*Artiodactyla cervidae),* sage grouse (*Centrocercus urophasianus*) and mink (*Mustela vison*) habitat from anthropogenic activity based on professional opinion. Local wildlife and habitat expert opinion was vital in compiling and ranking risks. In an informal interview process, experts were asked to rank risk as being either 'high', 'medium', 'low' or as having 'no' risk. The rankings were used to develop the Bayesian belief network that

provided probabilities of risk. The probability values were then used to in a Geographic Information System to create a spatial representation of landscape risk. As a decision-making tool, the Bayesian network models may provide a tool for adaptive land-use planning and management strategies.

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INTRODUCTION

Land managers and planners have the challenging task *and* opportunity of determining appropriate and compatible land uses within the confines of political or management unit boundaries. In the western U.S., these boundaries are drawn: 1) along public agency land management units, or 2) to define political districts such as counties or state borders; or, 3) as property boundaries segmented into varying public and private ownership patterns with oftentimes conflicting management mandates and multiple use objectives, or some combination of the above.

Prior to coordinating land management plans for either private or public lands, land managers and planners need to consider the cumulative impacts and outcomes that may result from proposed management strategies. Environmental risk assessments can provide a framework for evaluating the potential risks or impacts that new land uses may pose to ecological components such as vegetation, water quality, soil stability, air quality, and wildlife populations and habitat. These risk assessments are valuable for making informed resource management decisions, and for identifying alternative action plans within appropriate spatial and temporal scales that often transcend traditional management or political boundaries.

Risk assessment has been applied to conservation planning strategies that include representation of data that may signify anthropogenic and/or natural environmental stressors (Stoms 2001). The Sierra Nevada Ecosystem Project, the California Gap Analysis Project, and planning for the Columbia Plateau are examples of how researchers have used measurements of stress attributed to roadedness, population growth, and invasive plant species to identify potential “train wrecks” where biodiversity and stressors converge (Stoms 2001) at a landscape scale.

Furthermore, environmental assessments are conducted as mandated by the National Environmental Policy Act (NEPA) and the President’s Council on Environmental Quality (CEQ) to determine direct, indirect, and cumulative effects of proposed actions on federal lands. This process is also used to revise forest and resource management plans. In general, these assessments address the biological and socioeconomic impacts of an action at regional and site-specific scales.

In the public and private planning process, multidisciplinary teams are assigned to determine the impacts that proposed actions or group of actions will have on environmental resources. These assessment processes are almost always hindered by a lack of empirical data at the appropriate scale or resolution (Stoms 2001). While these processes typically include some level of public involvement, differing opinions of the type and quality of scientific data, personal and professional biases and opinions often complicate the decision-making process. These uncertainties and differences in opinion can frustrate traditional land management decision-making processes.

How then do we account for uncertainty and differences in expert opinion? Is it important to account for the deficiencies in landscape-specific empirical evidence?

Research Purpose and Scope

In few other places are planning challenges more evident than in and around the Greater Yellowstone Ecosystem. The Greater Yellowstone area is one of the largest "intact" ecosystems remaining in the temperate zones of the world (Reese, 1984; Keiter and Boyce 1991). According to Knight (1994), the Greater Yellow Ecosystem is one of the world's foremost natural laboratories in landscape ecology and geology and is a world-renowned recreational site. Concerns for public land managers and interest groups include eroding ecological integrity, maintaining the unique plant and animal communities, wildlife migration corridors, and seasonal ranges critical to the well-being of wildlife, and the overall fragmentation of the Yellowstone ecosystem (Hansen et al. online). Managing diverse and sometimes conflicting and competing land uses in the region are daunting tasks for public and private land managers, area residents, and advocacy groups. Public and private groups have organized in the last decade to address the multitude of conflicting uses in the region.

The Southern Wind River Landscape (SWRL) is the southern most extension of the Greater Yellowstone Ecosystem located in west central Wyoming. Despite its proximity to the more populated and faster growing Yellowstone region, the nearly three million acre SWRL remains largely intact. As part of the ecoregional planning process, the Nature Conservancy recently has completed a preliminary conservation plan for the SWRL. A goal of the planning process is to develop an integrated ecological conservation strategy that restores and/or maintains linkages between habitat as well as buffer key habitat patches, i.e., to identify relatively intact, contiguous patches of landscape that ensure a measure of biodiversity (TNC 2001).

As part of the planning process, a risk assessment may identify conservation priorities in the context of large ecological systems and human use of the landscape (personal communication, TNC 2002). As an example of this planning strategy, a central planning component includes ranking threats and stressors relative to biodiversity and landscape connectivity.

Risk assessment, as applied to this project, is defined as the probability of a specific undesired effect resulting from the existence of a hazard and uncertainty about its expression (Suter 1996). The assessment addresses some present or future impact(s) or an estimation of the probabilities of outcomes. Estimating relative risk is important to any assessment process. Selecting a means of quantifying risk represents some challenges. Some commonly used criteria for ranking risks include determining areas of risk, estimating the severity and magnitude of effects, understanding the temporal aspects of impacts, such as reversibility, or quantifying the ecological "value" of the system (Varis 1995).

The ranking process is built upon existing scientific knowledge, databases, literature, and expert opinion but often ignores uncertainty or professional disagreements (Morgan and Henrion 1990). Data and information is often extrapolated from dissimilar research sites and geographic regions. Inferences and decisions are then made that relate threats, risk, and effects of disturbance events on the landscape of interest. As a result, assessment conclusions can be misleading. This uncertainty begs the questions: 1) Is a landscape level, standardized methodology of quantifying threats or risk for a particular landscape, ecosystem, eco-region, or habitat(s) appropriate; and 2) If not, what alternative method would be appropriate for quantifying or ranking relative risk?

Some progress has been made in predicting impacts on species and habitat using urban growth simulations (White et al. 1997, Landis et al. 1998, Duane 1999). However, definitive empirical research required for completing a landscape level habitat risk assessment is usually lacking in determining conclusive risk potential. As a result, uncertainty leaves many decision-making processes with informational gaps. Specific data about the effects of anthropogenic activities on habitat in the SWRL, in particular, is inadequate with respect to quantifying many types of risk. Inferences can be made from the scientific literature and from personal observation of local land managers. Considering that site-specific and relevant landscape data are not available, a probabilistic approach to the planning process may provide an appropriate method for ranking or establishing risk.

This research is intended to illustrate the applicability of the Bayesian belief network (BBN) as a means by which multi-scale habitat risk assessment may be accomplished. The BBN is a useful communication tool for representing influences on wildlife habitat that combines in a graphical model empirical data with expert judgement (Heckerman et al. 1994). It can be used to express the likelihoods of risk where uncertainty or bias in expert judgement and where deficencies in empirical data exists There are several primary assumptions required to construct a BBN according to Marcot (2001). First, a BBN represents a “causal web” of ecological influences and can further reflect cumulative risks to habitat and ecological function. Marcot further states that it is not intended to replace empirical research but rather offers a method for “analyzing planning alternatives". Unlike other types of ecological risk assessments, this method accounts for subjectivity and uncertainty in the data.

When addressing the ranking process in an assessment, it is dangerous to assume that definitive empirical knowledge exists with respect to a particular landscape’s ecological processes and how some proposed action or set of actions will impact or “stress” the system. Some measure of uncertainty exists in this evaluation process. In their 1990 book *Uncertainty: A Guide to Dealing with Uncertainty in Quantitative Risk and Policy Analysis,* Morgan and Henrion (1990) note that historically the most common approach to uncertainty in policy analysis and in risk assessment has been to ignore it. In a section titled ``Why Consider Uncertainty?" they advance three primary reasons, all of which are especially relevant to risk assessment. They suggest that it is important to worry about uncertainty when: a) one is performing an analysis in which people's attitude toward risk is likely to be important, for example, when people display significant risk aversion; b) one is performing an analysis in which uncertain information from different sources must be combined. The precision of each source should help determine its weighting in the combination; and c) when a decision must be made about whether to expend resources to acquire additional information. In general, the greater the uncertainty, the greater the expected value of additional information.

The objective of this project is to provide a conceptual model or framework for assessing risk in the study area using this probabilistic approach that accounts for uncertainty. Within the context of a Bayesian belief network, I intend to develop a methodology for assessing risk to wildlife habitat attributed to human activities.

In this project, I have used a Bayesian belief network approach to quantify qualitative information and expert opinion of risk(s) to habitat. I integrated this information and adapted it to a GIS environment to provide a spatial illustration of risks from anthropogenic activities across the landscape. The activities identified are not an exhaustive list but present a workable subset of parameters likely to have implications for habitat quality. This project is not intended to assess the stressor(s) effects but, rather, identify and rank probabilities of risk from local and regional habitat stressors to mule deer, mink and sage grouse habitat. The stressors included in this study involve land development in or near critical wildlife habitat, oil and natural gas development, and roads across the landscape.

Three steps provide a framework for assessing risk to habitat from human-related activities: 1) collection of spatial data; (2) modeling risk probability using a Bayesian belief network; and (3) integration of GIS data with the risk models to spatially represent risk across the landscape.

As a central element to the model development, spatial analysis and quantification of cumulative disturbance(s) were assessed using GIS to illustrate multi-scale disturbance patterns. Recognition of present risks and potential risks to habitat across the landscape can inform a methodology for better habitat planning (Marcot 2001). This process may also provide a decision support tool given the limited scientific data available to land managers, wildlife managers and the interested public.

Key Definitions

The following terms will be used throughout the project.

Cumulative Risk: The combined risks from aggregate exposures to multiple agents or stressors (USEPA 2003)

Cumulative risk assessment: An analysis, characterization, and possible quantification of the combined risks to health or the environment from multiple agents or stressors (USEPA 2003).

Disturbances: are events that disrupt ecological systems; they may occur naturally [e.g., wildfires, storms, or floods or be induced by human actions, such as clearing for agriculture, clear-cut in forests, building roads, or altering stream channels (ESA Committee on Land Use).

Habitat: is based on the WYGAP analysis GIS habitat layers at a coarse scale anda finer data taken from the Wyoming Department of Game and Fish. A less formal definition of habitat is provided by Begon et al. as the place where a microorganism, plant or animal lives (1996).

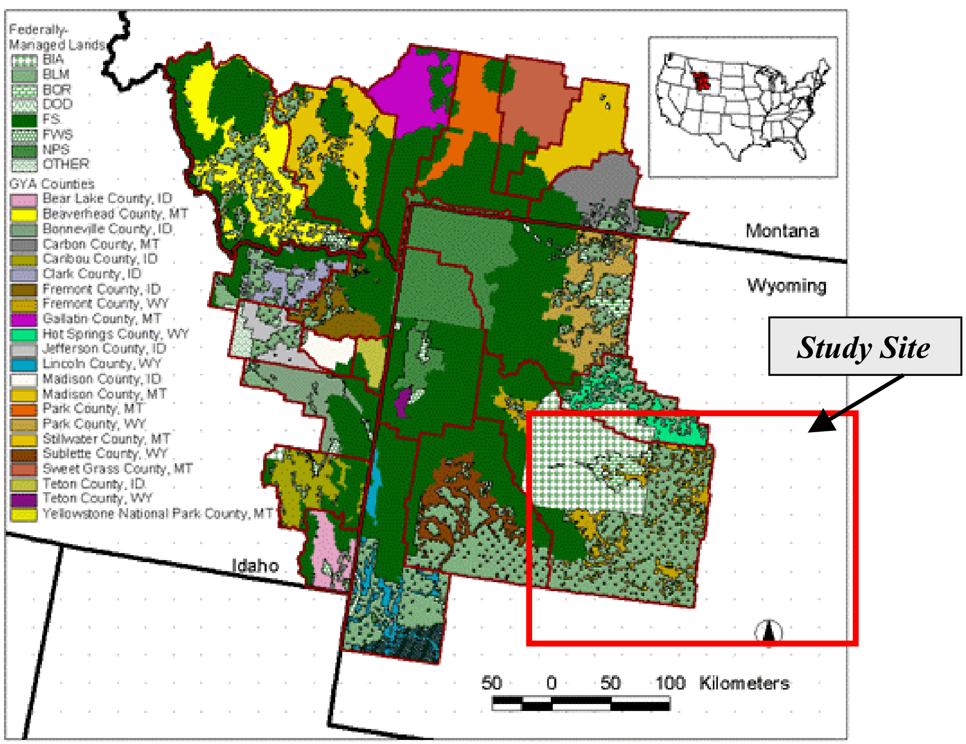
Multiple stressor assessments: Exposures can be accumulated over time, pathways, sources, or routes for a number of agents or stressors. These stressors may cause the same effects (e.g., a number of carcinogenic chemicals or a number of threats to habitat loss), or a variety of effects. A risk assessment for multiple stressors may evaluate the risks of the stressors associated health effects or ecological impacts, one effect or impact at a place (USEPA 2003).

Stressor: is a physical, chemical, biological, or other entity that can cause an adverse response in a human or other organism or ecosystem. A stressor can be exposure to a chemical, biological, or physical agent (e.g., radon), or it may be the lack of, or destruction of, some necessity such as a habitat. A socioeconomic stressor, for example, might be the lack of needed health care, which could lead to adverse effects (USEPA 2003).

STUDY SITE

The Southern Wind River Landscape

As part of the southern segment of the Greater Yellowstone Ecosystem (Figure 1.), the SWRL encompasses approximately three million acres of public and private land. Portions of five Wyoming counties comprise the study area including Fremont, Sweetwater, Sublette, Natrona and Carbon (Figure 2.). Fremont County as well as a large portion of the Wind River Indian Reservation make up at least a quarter of the total acreage of the Landscape (Figures 2 & 3).



(Image Provided Courtesy of the USGS)

Figure 1. A map of the Greater Yellowstone Ecosystem with a portion of the Southern Wind River Landscape

The diversity of topographic features include sand dunes and pocket conifer island, granitic outcroppings of Green Moutain and Crooks Mountain along the Landscape's southern boundary. The Landscape's western border follows the Continental Divide and the southern portion of the Wind River Moutain range. Moving eastward along the Sweetwater river, the eastern boundary area includes Pathfinder Reservoir (see Figure 3).

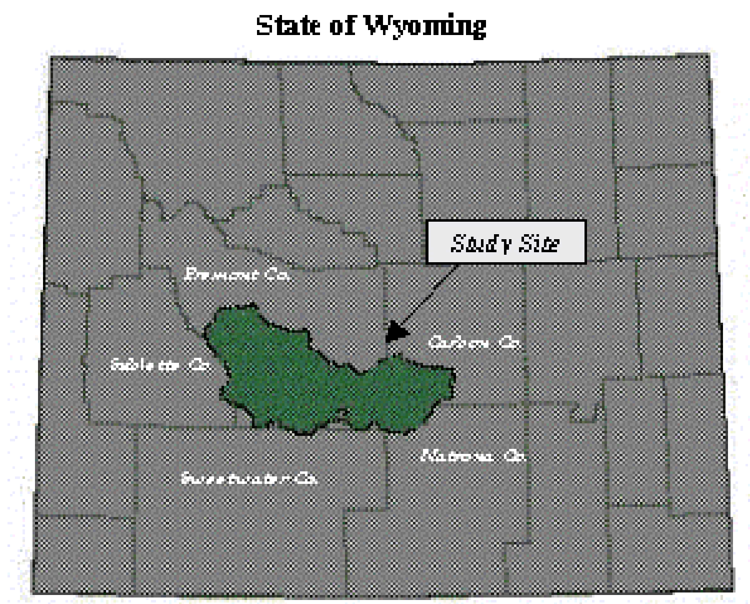


Figure 2. The State of Wyoming and the Southern Wind River Landscape study area

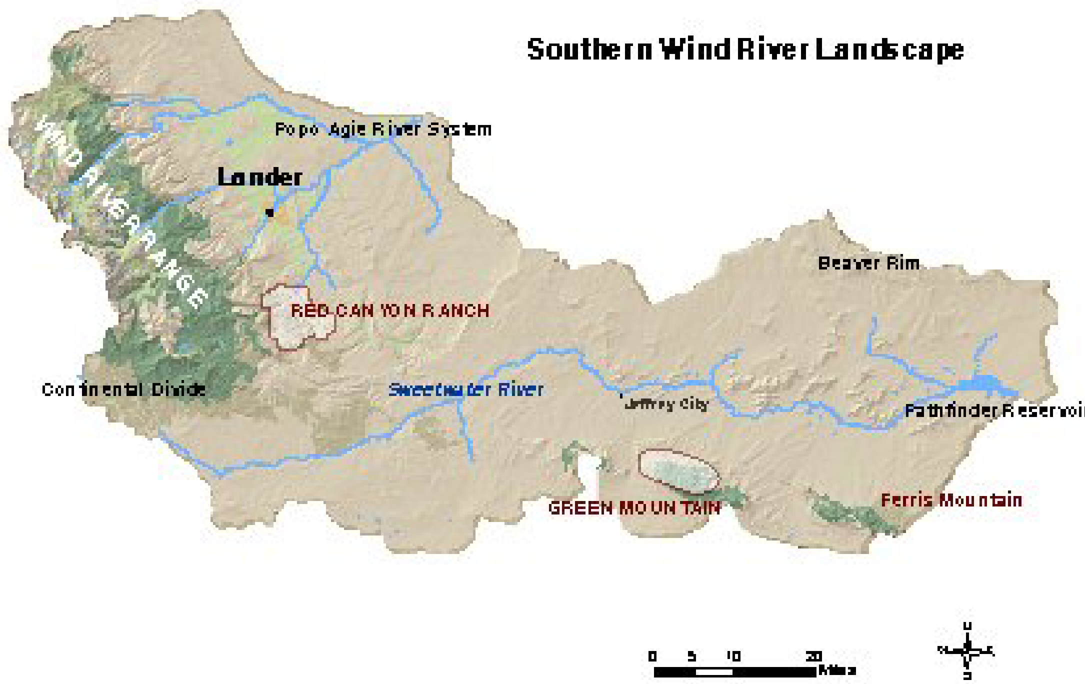


Figure 3. The Southern Wind River Landscape Study Area and significant landmarks.

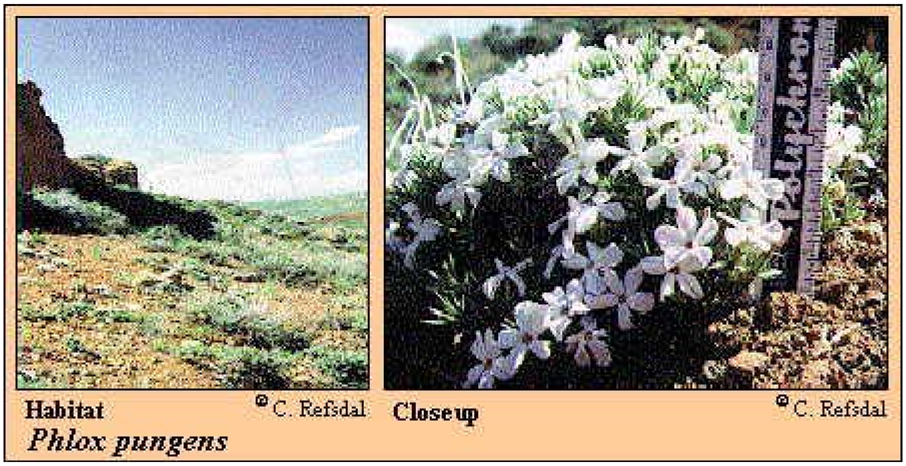
Biophysical Overview

Physically, the region consists of plains at elevations of 6,000-8,000 ft (1,800-2,400 m) broken by isolated hills and low mountains 1,000-2,000 ft (300-600 m) higher. The higher overall elevation allows for slightly lower average temperatures and precipitation than on the plateaus. Winters are cold, and summers are short and hot (Knight 1994). Average annual temperature range from 40 to 52 F˚ (4 to 11C˚) and the average growing season has fewer than 100 days in the south and 140 days in the north and east (Knight 1994). Average annual precipitation ranges from 5 to 14 in (130 to 360 mm), and is fairly evenly distributed througout the year (Knight 1994).

Three major fourth order watersheds including the Popo Agie River complex, the Sweetwater River, the Little Wind River and their related tributaries compose the Landscape (Appendix A, Map #1). Major river systems and stream systems remain undammed with the exception of some small high-elevation lake projects located along first order streams. Much of the water is diverted for irrigation purposes throughout the Landscape (TNC 2002). Large expanses of cropland along riparian corridors are irrigated for winter feed and hay (TNC 2002).

Diversity among plant and animal communities is substantial. The "ecoregion" of the Intermountain Semidesert (Bailey 1995) is comprised primarily of a sagebrush steppe ecosystem dominated by *Artemisia tridentata* and *A. nova* grasslands consisting of mostly bunchgrasses including *Koeleria macrantha, Poa secunda, Elymus spicatus, Oryzopsis hymenoides,* and *Festuca* (Fertig 1994). Of special concern to the BLM and The Nature Conservancy are higher elevation, endemic and, particularly, cushion plant communties located along the west and north slope of the Ferris Mountains and those located in the Red Canyon area and the foothills of the Rattlesnake Mountains (Figure 4). Some examples of these cushion plants include *Yermo xanthocephalus* (G1), *Trifolium barnebyi* (G1), *Cirsium aridum* (G2), and *Phlox pungens* (G2) (Wyoming Natural Diversity Database). For example, Wyoming's only endangered plant species, Blowout penstemon (*Penstemon haydenii*) are located along the southeastern boundary of the Ferris mountains (WYNDD) in the study area (Figure 3).

A wide variety of willow and graminoid meadow communities exist along much of the Sweetwater river and its tributaries (Fertig 1994). Alkali wetlands and subirrigated ephemeral meadow plant communities are abundant throughout the landscape. *Scirpus* *pungens/Distichlis stricta, Antennaria arcuata* (G2) *and Scirpus nevadensis* (G4/S2) are good examples of the rarer plants found in these unique areas.



(photo ourtesy of USGS)

Figure 4. An example of vegetation representing the cushion plants found in the study area.

Other regions of interest identified for their unique vegetation communties include the woodlands of limber pine and juniper along the Wind River Mountains and foothill areas. Advances of pine blister into these important areas of critical deer and elk wintering habitat are of particular concern as well as increased land development including subdivisions around the Lander area. (Fertig 1994).

Additional important vegetation habitats include greasewood playas, the calcareous grasslands in the southeastern portion of the Wind River Range, and the sand dune system located near the Ferris mountains (Fertig 1994).

In addition, the granite desert mountains dotting the Sweetwater Plateau and include the Ferris, Granite, Rattlesnake, Green and Grooks Mountains contain small coniferous forest patches that are critical stopover sites for migrating birds and provide seasonal habitat for other species.

Diversity in topographic features and vegetation contribute to a wide variety of wildlife populations including the Townsend's big-eared bat(*Corynorhinus townsendii)* , swift fox *(Vulpes Velox)*, Grizzly bear *(Ursus arctos)*, American peregrine falcon *(Falco peregrinus)*, Sage grouse, common species including elk and mule deer, and recent residents like the grey wolf (*Canis lupis*) (WYNDD). River otters are found in the Sweetwater river and its tributaries as well as mink. These waterways are also important areas for several water bird species including the American avocet.

SocioEconomic Overview

Rough estimates for regional population place numbers at approximately 40,000 residents with 35,840 people residing in Fremont county alone (Bureau of Economic Analysis 2000). Overall regional census data recorded an average 8.0 % increase in the population from 1990 to 2000 for the five counties. The city of Lander is the most populated community in the region with approximately 7,500 residents (Lander 2020 2000).

Primary land use in the region such as mining and ranching have deep historic roots (TNC 2001). Agriculture, for example, contributes to the economic base for the region and is the dominant land use on both public and private land, however, retail and mining activity is by far the fastest growing industry (U.S. Census Bureau, Census 2000). A 17.1% increase in Fremont County resident income was attributable to the mining industry, for example (Wyoming State Department of Administration and Information – Economic Analysis Division online). Mining activities like oil and gas development, coal mining and support activities contribute to local economies but also to the state as well.

In addition, the service sector provides a significant proportion of the overal earnings in the region. 25.7% of earnings in Fremont County are associated with the service sector (Bureau of Economic Analysis 2000). Some of those services include those associated with tourism and recreation including hunting, fishing, hiking and backpacking.

Like most of the west, demographics in the intermountain west are changing. According to the Lander Valley 2020 report cosponsored by the area Chamber of Commerce, in 1994 18% of Lander's population had arrived in the past three years. According to the U.S. Population Census, Census 2000, 11.9% of Fremont County residents had moved to the county from other states since 1995. In 1999, the Chamber had reported a 600% increase in requests for information about Lander since 1990.

These changes in the social landscape are thought to be impacting the ecological landscape. According to the American Farmland Trust (online), ranchland lands that provide economic bases for rural communities are disappearing. Fremont County, in particular, has been listed by the AFT in their report on Strategic Ranchlands as being of their 25 "at risk" counties. As defined by AFT, strategic ranchlands at risk are those most vulnerable to low density housing development by the year 2020. Fremont County was targeted because of it's projected growth in suburban density in the next twenty years. The AFT methodology included identifying high quality agricultural land with desirable wildlife characteristics including proximity to publicly owned lands, year-round water availability, rural development densities and high diversity in vegetation cover types.

LITERATURE REVIEW

Applications of Bayesian statistics to risk assessment are found in medical research and diagnostics and in ecological toxicology. Its applicability to wildlife management occurs less frequently, but is no less appropriate. The following section examines current literature addressing risk assessment, its applications, and the current research and applications of Bayesian statistics and Bayesian networks to estimate risk in light of scientific uncertainty. The terms Bayesian networks, Bayesian belief networks, knowledge maps and probabilistic causal networks may be used interchangeably but imply methods of reasoning using probabilities (Charniak 1991).

Risk Assessment

Ecological risk assessments are common methods of quantifying effects or the likelihood of impacts from disturbance events and human related activities with respect to ecosystem integrity. These analyses seek to identify, characterize or order a variety of consequences that impact various ecological components, systems and/or functions. According to Wilson and Crouch, risk assessments in general present a method of examining risks "…so that they may be better avoided, reduced, or otherwise managed" (1987: p. 268).

The Society for Risk Analysis (SRA) broadly characterizes the discipline of risk analysis as including issues pertaining to risk assessment, risk characterization, risk communication, risk management, and policy relating to risk (SRA online). Furthermore, the analysis of risk considers threats from physical, chemical and biological agents and from various human activities and natural events.

According to Hoffman et al. (1994), there are important differences between risks that are voluntarily assumed and those that people are subjected to involuntarily. Voluntary risks include those associated with activities we engage in linked with known risk (e.g. driving a car, riding a motorcycle, smoking cigarettes). Involuntary risk are those that may occur either to us or around us without prior consent including acts of nature such as flood events, lightning strikes and exposure to environmental contaminants. In addition, risks can be either statistically verifiable or nonverifiable. Statistically verifiable risks can include either voluntary or involuntary activities that are determined by direct observation. Statistically nonverifiable risks are only associated with involuntary occurrences that are based on limited data sets, mathematical equations and models (Hoffman et al. 1994).

Considerable research and applications of risk assessments have been completed in a wide variety of disciplines where there is some level of uncertainty and limitations to empirical data. In medical research, for example, a model derived empirically from epidemiological studies is used to estimate the probability of a woman's developing breast cancer over the next ten years. An initial assessment requires some level of data collection to determine the “stressors" (Hoffman et al. 1994). Here, certain factors are known to be correlated with that form of cancer, such as the woman's age at first childbirth, age at menarche, having a previous biopsy with atypical hyperplasia, and others. However, not all stressors are the same type (e.g. chemical or genetic) and not all data is available to quantify the risk (US EPA 2003).

Ecological risk assessment research, in particular, has been an important duty of the U.S. Environmental Protection Agency. Substantial research conducted by the agency pertains to toxicology and associated risks to the human health and to natural and built environments. Chemical, biological, radiological, other physical, and even psychological stressors can cause a variety of human health or ecological health effects. Environmental related research include determining the measurable impacts from flood events, point and non-point source pollution and erosion, all of which can provide data that assist to guide scientists and land use managers in future land use planning (US EPA 2003).

Other efforts are directed towards community-based watershed risk assessments; where, according to the *EPA's Guidelines for Ecological Risk Assessment* (US EPA 1998b), three phases are necessary for risk assessment, including problem formulation, risk analysis, and risk characterization. The agency's overall approach to risk analysis involves understanding risk, the sources of risk and the development of risk policy and decision-making processes (Serveiss 2002).

Assessing the risk for these situations is quite methodological complex and computationally challenging (EPA 2003). Probability-based assessments provide a scientific process for estimating, with measurable *degrees of certainty*, anthropogenic effects on the integrity of natural ecosystems (Cairns and McCormick, 1992). Suter (1993) more clearly addresses the "certainty" issues with his definition of ecological risk assessment as the determination of the *probability* of adverse effects on humans and nonhuman biota resulting from an environmental hazard.

Russell and Gruber (1987) argue, however, that the EPA is placed in a difficult position of assessing risks when a complete understanding of outcomes and risks are not fully known. The National Research Council has stated that in any risk assessment, inferences are derived from subjective scientific judgements and policy choices (National Research Council 1983). Risk assessments provide guidelines but are not intended to give certainty in a scientific sense (Gruber and Russell 1990). However, quantification of risk is useful in approximating the magnitude of effect(s), to set conservation priorities and to make comparisons (Gruber and Russell 1990).

Uncertainty is widely recognized and usually stated or assumed in research. The American Heritage Dictionary (Morris 1978) defines uncertainty as "the condition of being in doubt". MacIntosh et al. (1994) defined the major types of uncertainty as knowledge uncertainty and stochastic variability. Knowledge uncertainty is due to incomplete understanding or inadequate measurement of system properties and is a property of the analyst. Stochastic variability is due to unexplained random variability of the natural environment and is a property of the system under study (Hession et al. 1996).

Uncertainty is acknowledged in risk assessments of population viability, in methods of determining conservation status, in land management decisions and in conservation of biodiversity. Akcakaya and Raphael (1998) conducted a risk assessment where the viability of the northern spotted owl was estimated with respect to human impacts. The authors demonstrate the effect of uncertainty resulting from a lack of information and measurement error on the assessment. The research parameters or measurements consider the risk of decline in the metapopulation and the estimated time to extinction. According to Akcakaya and Raphael, if uncertainty is incorporated in the research, parameterized and used to estimate upper and lower bounds of species viability, assessing human impacts is reliable. The results, they concluded, are sensitive to large uncertainties related to habitat loss as well. Overall, the predictions were affected by the uncertainties in inputs and were relative to the sets of assumptions or scenarios.

According to Todd and Bergman (1998), assessing threat(s) to a species does not account for the "underlying uncertainty inherent in the data". They consider that uncertainty in the parameter estimates of the biological variables can be used within reasonable bounds to make plausible determinations of species status.

Bayesian Statistics and Bayesian Networks

Bayesian networks model uncertainty by "explicitly representing the conditional dependencies between different knowledge components. It provides an intuitive graphical visualization of the knowledge including the interactions among the various sources of uncertainty" (Pearl 1988). The Bayesian approach to incorporation of expert belief, probabilistic inference, prior knowledge and numeric information (Varis 1995) allow for a risk assessment to account for uncertainty.

Uncertainty arises in a variety of situations such as: (1) uncertainty in the experts themselves concerning their own knowledge; (2) uncertainty inherent in the domain being modeled; (3) uncertainty in the knowledge being translated; and, (4) uncertainty of the accuracy and actual availability of knowledge. Bayesian networks use probability theory to manage uncertainty by explicitly representing the conditional dependencies between the different knowledge components (Varis 1995). This provides an intuitive graphical visualization of the knowledge including the interactions among the various sources of uncertainty.

Applications

The essence of Bayesian statistics and Bayesian belief networks is Bayes' Theorem. Bayes' Theorem is the fundamental law governing the process of logical inference-determining degrees of confidence we have in various possible conclusions, based on a body of available evidence. This is exactly the process of predictive reasoning; therefore, to arrive at a logical defensible prediction one must use Bayes' Theorem (Bayesian Systems, Inc. online). The difference between what Bergerud and Reed (1998) call frequentist statistics and Bayesian statistics is the way parameters are defined. A frequentist's approach would have one or more unknown parameters and the Bayesian approach assigns probabilities to parameter values before the study is conducted.

In forest management, for example, Bergerud and Reed (2002) contend that managers would like simple answers to practical questions from traditional scientific methods of experimental and/or observational sampling. For example, frequentist statistical methods can not "directly" provide an assessment of the probability that one or more hypotheses are true, or the probability that an estimate of a parameter is close to its unknown true value. Such results are of limited use to managers. However, a Bayesian method can provide precisely this type of information (Bergerud and Reed 1998).

In it's essence, Bayes' Theorem provides a basis to assess how people use empirical observations or experience to update the probability that a hypothesis is true (Bergerud and Reed 1998) . This is also called "posterior odds" and can be represented as the following mathematical statement.

$P(H)$ = The probability you would have assigned to the hypothesis before you made the observation, called the "prior probability" of the hypothesis.

$P(O|H)$ = The probability the observation would occur if the hypothesis were true.

P(nonH) = The prior probability the hypothesis is not true, 1-P(H)

P(O|nonH) = The probability the event would have occurred even if the hypothesis were not true.

$$P(H|O) = P(H) \times P(O|H) / [P(H) \times P(O|H) + P(nonH) \times P(O|nonH)]$$

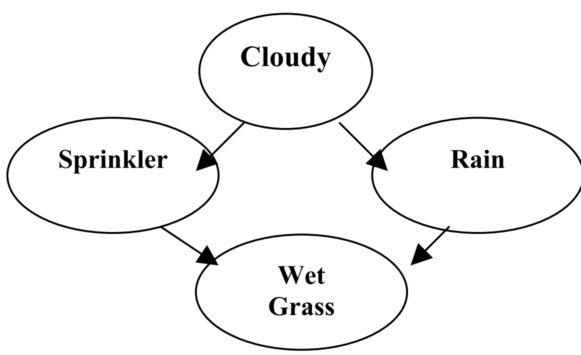
Variations of Bayesian statistics are used in ecological research. For example, Dilks et al. (2002) used the Bayesian Monte Carlo (BMC) analysis to quantify uncertainty in a water quality model for Lake Okeechobee located in south Florida. Bayesian inference has been combined with Monte Carlo analysis to generate improved estimates of parameter uncertainty by considering the variations in parameter values to describe the observed data (Dilks et al. 1992). By combining prior information (prior probabilities) derived from literature reviews with available site-specific data set ranges, the BMC was used to describe a given model simulation output. The results fell within the 95% confidence interval of the observed total data (Dilks et al. 1992). Additional analysis included projections for model uncertainty given different future scenarios.

Additional, applications of Bayesian statistics in ecology include modeling of neotropical bird habitat. Vitale (online) applied GIS with landscape variables and Bayesian statistics where multiple hypotheses are represented as probabilities rather than accepted or rejected. The output was a map of probability of species occurrence that was similar to habitat suitability and association maps (Vitale online). The assertion in this project is that stakeholders can easily understand the creation of a map using Bayesian statistics; and, that rather than being a definitive determination of habitat, the estimates are probabilities or likelihoods of habitat presence. This is an implicit statement of uncertainty and allows for stakeholder input for management development (Wade 2000 in Vitale online).

Further adaptation of Bayesian statistics to environmental analysis includes work in the development of Bayesian belief networks (BBN). Bayesian networks or Bayesian belief networks adhere to Baye's rule for probabilistic inference (Murphy 2003). They provide a representation of uncertainty and complexity using probability theory with directed graphical representations among random variables (nodes) (Pearl 1988). The directed models of a BBN illustrate a causal relationship among variables, indicating that A "causes" B, for example. The following example adapted from Murphy's (2003) *A Brief Introduction to Graphical Models and Bayesian Networks* illustrates the graphical model of a Bayesian belief network.

P(C = F)	P(C=T)
0.5	0.5

C	P(S=F)	P(S=T)
F	0.5	0.5
T	0.9	0.1



C	P(R=F)	P(R=T)
F	0.5	0.5
T	0.9	0.1

S	R	P(W = F)	P(W=T)
F	F	1.0	0.0
T	F	0.1	0.9
F	T	0.1	0.9
T	T	0.01	0.99

Graph 1. A graphical representation of a Bayesian belief network (Murphy 2003)

The application of Bayesian belief networks in ecology has proven useful in assessing and managing wildlife species (Cohen 1988, cited in Marcot et al. 2001) and for forests (Crome et al. 1996, cited in Marcot et al. 2001). Researchers in the U.S. Forest Service's Pacific Northwest Research Station have applied Bayesian belief networks to evaluate fish and wildlife population viability under various land management alternatives (Marcot et al. 2001).

Important elements contributed to the thoroughness of this multi-level analysis including access to significant data sources, participation of numerous experts and the various extents to which the analyses were conducted. The first element included the geographic extents at which the analyses were conducted. These included a basin-wide level (specifically the Columbia River basin) a subwatershed level, and a site-specific analysis. For example, at a subwatershed level, GIS data depicted wildlife habitats at 1 km^2 pixel resolution and key environmental correlates (Marcot et al. 2001) such as specific species-environment relations and expert review. At a basin-wide extent, the analysis outcomes represented the potential population(s) responses to the management strategy. Empirical data was readily available through two substantial databases, one developed for the Interior Columbia Basin Ecosystem Management Project and the other published databases. The research team also had extensive multi-year input from a large panel of experts (80+) who collaborated in a Delphi process (Marcot, personal communication 2002).

In this particular application of BBN's, influence diagrams using conditional probability tables represented the causal relations among ecological factors that influence likelihood outcomes or effects given some land management strategy (Marcot et al.

2001). According to Marcot et al., (2001) the BBN species models provide a method for expressing the ecological cause and effect relationship influencing a species and the uncertainty inherent in that relationship. Uncertainty in the BBN is found in the probability distributions for each node (variable), the error denoted by the mean standard deviation and the sensitivity of nodes to another. Finally, according to Marcot et al., (2001) the BBN models should provide synthesis of expert opinion and experience with solid data. "They should also provide a basis for understanding the types, sources, degrees, and implications of uncertainties in existing data and expert understanding."

Other work in BBN applications has been completed by Hass and Cleaves (online) to model waterbody eutrophication and by Kuikka and Varis (1997) to assess the Baltic salmon. Kuikka and Varis (1997) utilize a Bayesian meta-model as a diagnosis and forecasting method for allowing "fusion" of other analyses such as regression and Virtual Population Analyses that facilitate probabilistic predictions in a Bayesian belief network. Their work provides a complete description of how the BBN is created (e.g. what the nodes contain, prior and posterior probability distributions, and the links between nodes), how the network is propagated, and how uncertainty and contradictory information are contained in an analytic framework (Kuikka and Varis 1997).

Kuikka and Varis continue to assert that the three most crucial properties of this approach are: (1) the advanced handling of uncertainties that include network propagation and presentation, objectives and structure; (2) the ability to include modeling techniques from many methodologies typically considered divergent such as metric and linguistic; and, (3) support for the acquisition of expert knowledge and structure of a model. Final recommendations suggest that expert opinion and knowledge should be handled more formally as they are often important sources of information.

Lynam et al. (2002) applies Bayesian belief models to adaptive resource management strategies in Zimbabwe. The model was adapted to incorporate natural and social dynamics with environmental research to improve community involvement in the decision-making process. Spatially and temporally complex variables such as the dynamics in land change were a key component of the Bayesian network model. Local village representatives offered their feedback about the cause and effect relationships between the model variables and their management actions in relation to the subsequent impacts on the community. By identifying problems in the system dynamics modeling, the local community took direct action to stop particular activities including illegal allocation of lands (Lynam et al. 2002).

Conclusion

Two general conclusions can be made from the literature on both risk assessment and Bayesian belief networks: scale and extent matters and uncertainty must be formally accounted for. Risk assessments are established to further our management objectives. In applying assessment results to land use and ecological management and decision-making, risk assessment "is often characterized by a large number of uncertain, interrelated quantities, attributes and alternatives based on information of highly varying quality" (US EPA 2003: p. 129). When dealing with ecological risk assessment, particularly those concerned with population viability and habitat-species associations, there are often problems in the geographic extent, the physical and temporal scales as well as the amount and quality of observation data, purely physical or data-based models to be used as effective decision-making tools. Available data is either too broad or fine for the question at hand. Furthermore, the collection of statistically valid data may often prove impossible, or at least highly impractical, due to the nature and extent of the problems and with the resources available for research. Bayesian statistics seems to provide a reasonable method to parameterize input variables given inconsistencies in existing data sources with an opportunity to apply expert knowledge.

Futhermore, the process of environmental decision-making does not support quantification of decision inputs and inference, bias and opinion is typically assumed (Serveiss 2002). Bayesian approaches to risk assessment and environmental management may provide a method of accounting for expert and stakeholder knowledge (Serveiss 2002).

METHODS

The project was conducted in three stages. In the first stage, relevant spatial data were collected and processed for risk assessment integration. In the second stage, the Bayesian network-based risk models derived from expert opinion were developed to provide the framework and rationale for the final risk maps. The third and final stage was the integration of GIS with the BBN risk models to create the risk maps.

Project Parameters

Spatial and temporal considerations were identified as parameters for creating a risk network. First, data availability was a limiting factor. Both spatial and empirical data were limited for the study area. As a result, not all variables, particularly temporal data influencing habitat such as climatic fluctuations were considered. Available spatial data representing human activity were limited in the study area; therefore, data layers, in general, are coarse and were often adapted to characterize broad anthropogenic influence patterns and species' seasonal habitats.

The project sought to represent the spatial distribution of risk with respect to habitat at two spatial extents illustrating the application of the BBN framework to both landscape and site-specific risk assessments. Two approaches to spatial data assessment were conducted. 30-meter GIS data were adequate for illustrating the landscape or regional extent of risk with respect to habitat for the entire study area. A second approach identified two sites nested within the Landscape that are representative of unique vegetation associations.

The second parameter was time availability. As a result, risk effect analyses were not completed as part of the risk assessment. Therefore, the assessment is broad and solely addresses the spatial patterns of risk at landscape and site-specific levels.

Data Collection

GIS data were collected for the study site from numerous public sources including the Bureau of Land Management, the State of Wyoming Geographic Information Center, The Wyoming Natural Diversity Database, and The Nature Conservancy. Relevant data included land ownership, a 30- meter digital elevation model, mineral development potential and other surface feature information including pipelines, oil and gas well sites, mine sites, roads and fences.

Habitat data layers were critical to the assessment. Standard 30-meter data were readily accessible. At a landscape or regional extent, these course resolution data are sufficient to represent generalized landscape pattern, habitat distribution, and the spatial dispersion of human-related features.

Those data associated with human activities or disturbances were buffered to portray the relative spatial disturbance of particular features (Figure 3.) This determination was based on expert knowledge of the features, impacts on habitat and known understanding of avoidance behavior of a particular species. Well pads were given three concentric buffers with distances of 0 – 100 meters from the well pad, 100 – 300 meters and 300 – 500 meters. Linear features such as roads, fences, and pipelines were buffered 30 meters on either side.

Coarse level

The coarse resolution habitat data were obtained from the Wyoming GAP analysis completed in 1996. Thirty-meter land cover classification assessment delineated habitat potential for the three species of interest. Potential habitat for mule deer and sage grouse covered the entire study area while mink habitat was located primarily along riparian corridors and extending into the uplands.

The following GIS data layers (Table 1.) were utilized as the human disturbance factors and input variables for the risk models.

GIS Data Layer	Buffer	Data Source
All roads types	**30 m**	**Tele Atlas**
Fences	**30 m**	**Bureau of Land Management**
Land Development Potential	**30 m**	**WY Data Clearinghouse**
Oil & Gas Wells	**0-30 m** **30-100 m** **100-300 m** **300 – 500 m**	**WY Data Clearinghouse**
Oil & Gas Pipelines	**30 m**	**WY Data Clearinghouse**
Mine sites	**0-30 m site** **30-100 m** **100-300 m** **300 – 500 m**	**WY Data Clearinghouse**

Table 1. Available GIS data, their sources and buffer extents.

Fine Level

The site specific or fine level assessment included identifying species' seasonal habitat. The Wyoming Department of Game and Fish (WYGF) provided the finer scale seasonal habitat information for both mule deer and sage grouse, while mink seasonal habitat spatial data were not available. The site-specific data provided a finer level of detail relative to the disturbance. Often, differentiation in habitat type (e.g. sage grouse reproduction areas such as leks and nesting sites vs. winter habitat) may require unique treatment in a GIS environment. For instance, the buffer of a given seasonal habitat may be larger compared to another seasonal habitat site for the same species.

Seasonal habitats for mule deer habitat (map #4) were categorized as the following: spring/summer/fall/year long habitat, winter/crucial winter, out of range, and migration routes. No spatial data were available for mule deer within the boundaries of the Wind River Indian Reservation (Appendix A, map #4)

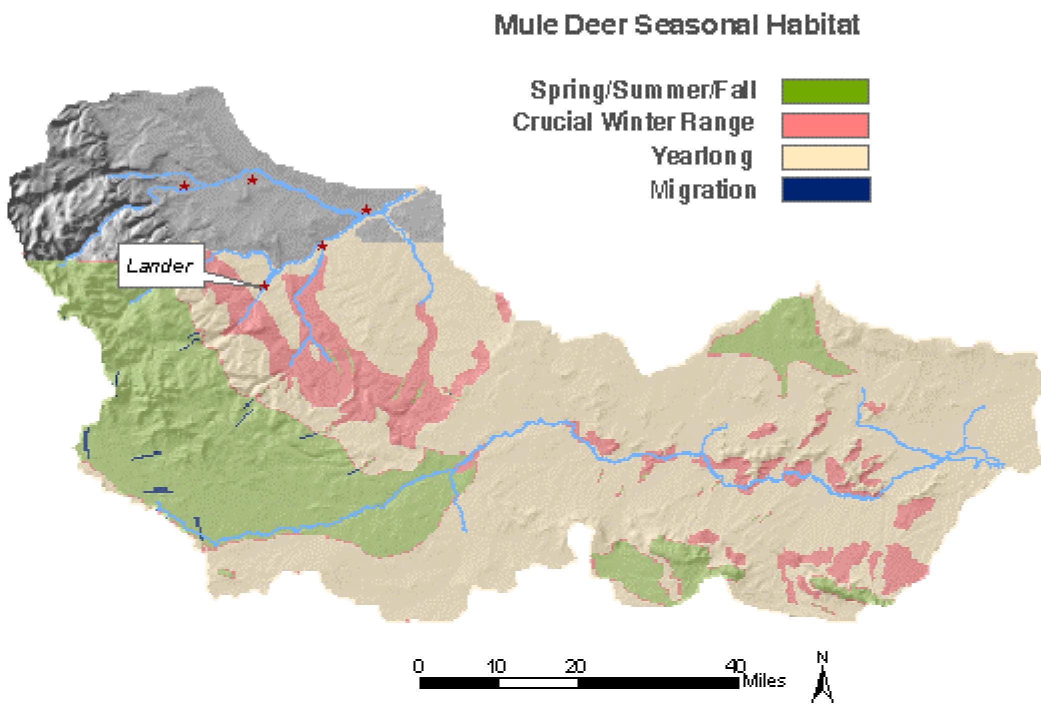


Figure 5. Mule Deer Seasonal Habitat. Source: Wyoming Game & Fish Dept.

The Wyoming Game and Fish Department had collected sage grouse point data over a twenty-year time span. Dates associated with each data point were subset to establish seasonal habitat data layers including winter, reproduction areas (e.g., leks and breeding areas), as well as early brood-rearing and late brooding rearing habitats. The data subdivision was based on local expert knowledge and current species literature. All seasonal sage grouse habitats were buffered as follows: each point site was 30 meters squared in area and three concentric buffers ranging from 30 – 100 m, 100-300 m, and 300 – 500 m distance from the center. The reproduction point data, however, were an exception to this rule. Each point was buffered 3000 meters or approximately 2.5 miles. Again this information is based on literature and local expert knowledge as to the potential avoidance zones for this species.

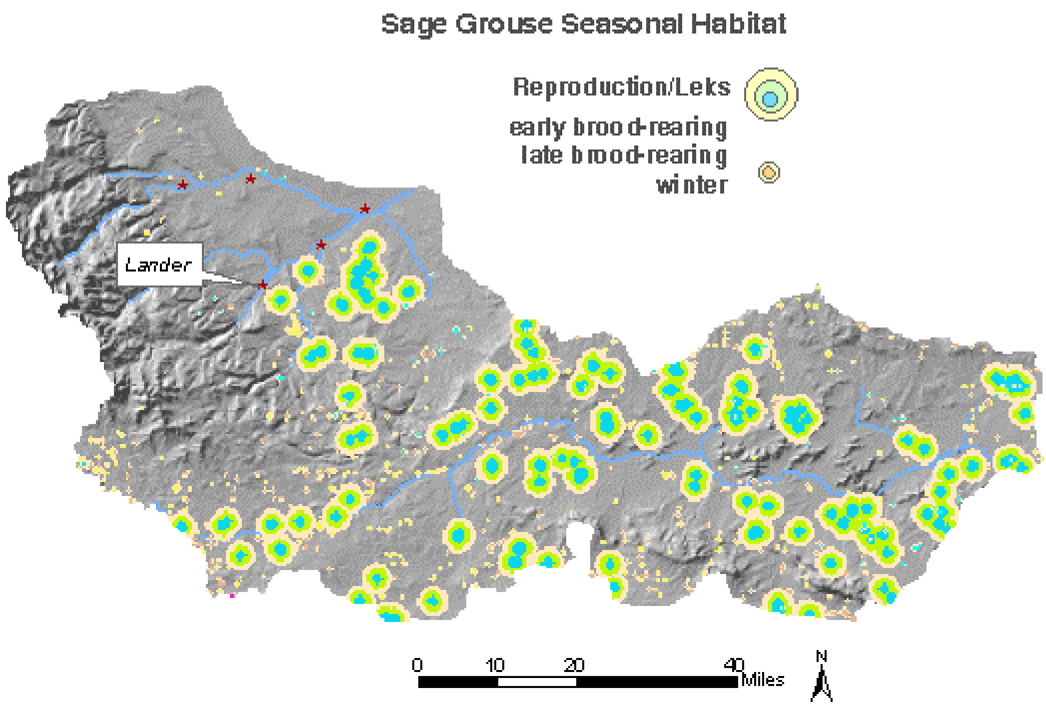


Figure 6. Sage grouse point data adapted to represent seasonal habitat areas.

Additional point data taken from telemetry was available for the Nine-mile Basin area. However, I determined that given my time constraints, these data would not be applied to this research.

Representative spatial data for mink (Figure 7) was limited to the Wyoming GAP analysis from 1996. Very little is known about this regional population. In general, its home range includes most major watercourses, riverine systems, and associated uplands as identified in the GAP data.

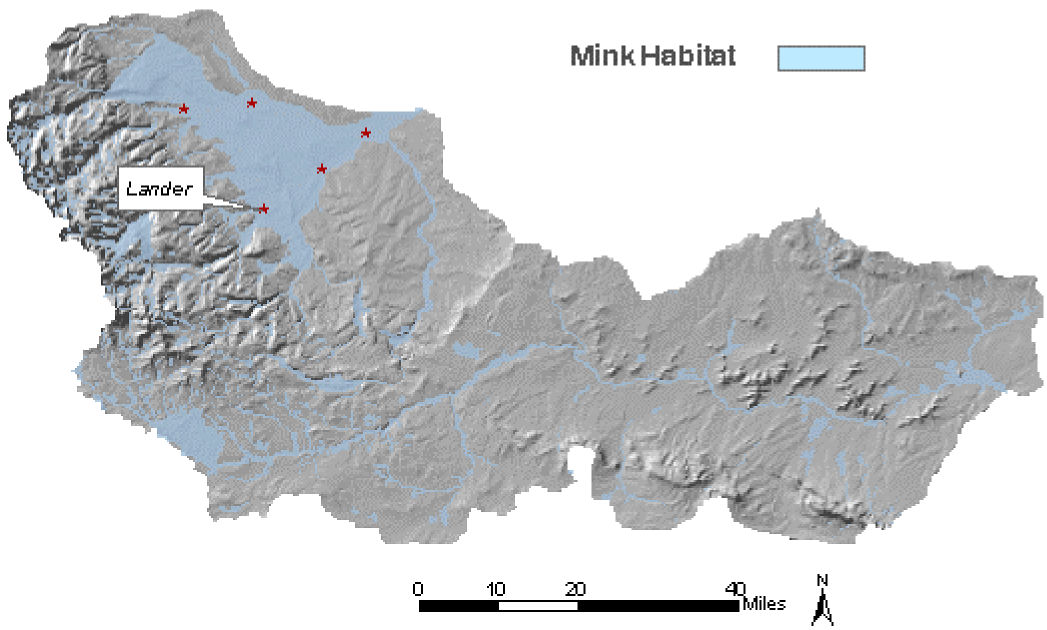


Figure 7. Mink habitat map. Source: WY GAP Analysis 1996.

Two areas were chosen within the study area for site-specific risk assessment: Green Mountain and Red Canyon ranch.

Green Mountain

Green Mountain was chosen as a good example of public land managed for multiple uses. The Bureau of Land Management administers use of the approximately 8 km^2 area. Current activities include: grazing, off-highway vehicle recreation, hiking and riding on the historic Oregon Trail, hiking trails including a planned extension of the Continental Divide Trail, management of historic mine sites including a uranium mine, activity at several capped natural gas wells, and current seismic exploration.

Red Canyon Ranch

Red Canyon Ranch is an ~4,600 acre property owned by The Nature Conservancy with an additional 30,000 + acres of federally permitted land and state wildlife management inholdings. Like Green Mountain, the Red Canyon area is unique in its plant and animal diversity. Significant aspen stands, rare plant communities, and wildlife populations occupy the site. Surrounding land conversion from traditional large agricultural production to smaller, subdivided ranchettes are of concern and impact local biodiversity. The site is representative of the larger regional pressures from rural land development activities including further road development and off-highway vehicle access into more remote areas, domestic pets that may threaten wildlife populations, and general degradation of habitat through the loss of food and water sources, cover and loss of adequate space required for reproduction and survival.

GIS is intended to visually represent patterns of disturbance in the landscape relative to habitat. With the addition of identification of risk areas using Baysean Belief Networks, the maps can be used to illustrate habitat/wildlife experts understanding of risk and to graphically depict that understanding. The benefit of this process is intended for regional planning and management efforts. Using maps and models, collaborative planning groups can confirm or reject the expert knowledge or understanding of risk as well as determine how to plan for future development and identify needs for further analysis.

Bayesian Networks

The use of the term Bayesian belief network as applied to this research refers to a probabilistic model connecting independent variables with conditional statements that define variable interdependence or a causal links between variables. In this case, BBN's will be used to model the probabilities of risk from human disturbance to wildlife habitat. Two stages in the risk modeling process were completed to attain the habitat risk assessments. The first stage was to build the model by determining the prior probabilities using available GIS data and expert knowledge. The second involved interviewing experts to rank risk for determination of the posterior probabilities. The posterior probability in this case is an estimation or approximation of risk probability given the presence of habitat type and the rankings of risk relative to a surface feature or disturbance type. For example, the probability of risk being 'high' is determined by the presence of a sage grouse lek site in proximity to a road or well pad. The prior probability would be if habitat or a feature is present conditioned by the expert judgement estimation of risk or called the conditional probability.

The belief network is designed to illustrate the believed relations between sets of variables relevant to some question (Norsys, online). Relevancy is based on observations, knowledge or empirical evidence. The first step in building the network for this risk assessment was determining the variables believed to influence or pose risk to wildlife habitat and those data that are spatially represented. Those activities include:

1. Land ownership. Land use development includes proposed or established housing and commercial developments, and management or changes of agricultural lands.

2. Oil and gas development and associated pipeline and pad systems.

3. Roads and road density including those classified as either primary, secondary, two-track, off-road vehicle or trails.

Risk Model Development:
Application of the Bayesian network

A risk assessment can be divided into three critical steps. Formalizing the process includes: 1) risk identification, 2) risk estimation and 3) risk evaluation. For this project, risk identification uses local expert knowledge to identify the human-related activities within the study area that pose risk to either mule deer, sage grouse or mink habitat. In an interview, those same experts are asked to rank or estimate the risk relative to a particular habitat. The third and final step includes both landscape and site-specific risk evaluations using a Bayesian belief network that are subsequently spatially represented.

Netica

The belief networks for each species were built using the Netica software package by Norsys, Inc.. These networks model an outcome of disturbance defined in terms of an ordinal scale of high, medium , low, unsure, or no. To build each model, prior (unconditional) probabilities must be established. That is, what is the likelihood that an input parameter (e.g., roads or habitat) is in a particular state (e.g., present or not present). My selected variables represented available spatial information but not all possible variables contributing to a risk model . In this case, prior probabilities were established in the initial phase of the interviewing process where experts are asked to determine which human-related activities pose risk to a particular habitat.

The GIS proxies such as habitat, roads, and wells are quantified or ordinally-scaled variables portrayed as nodes within the network. Sets of nodes represent distinct model elements such as seasonal habitat and selected human activities. Prior probability and conditional probability nodes describe the cause and effect relationship between variables that influence habitat (Marcot 2001). Additional information for determining the state of a variable was taken from literature and by regionally-based species' experts through an interview process.

Conditional probability is the likelihood of the state of a parameter given the condition of another states. A range of probabilities (e.g. .32 - .67) are generated and applied to the model based on the questionnaire outcomes establishing the posterior probabilities of risk. The prior probabilities are Dirichlet functions (Spieglehalter et al., 1993 in Marcot et al. 2001) meaning that probabilities are continuous and bounded between 0 and 1 (Castillo et al. 1997 in Marcot et al. 2001). These are used as a prior distribution for binomial proportions in Bayesian analysis (Evans et al. 2000). The power of the networks lie within the conditional probability tables associated with the discrete state of each variable/node (Table 2). The conditional probability tables was based in large part on expert opinion. The CPT's power is that updates are easily constructed as new information is obtained.

Node: risk

Chance

Apply Okay Load Close

Deve...	Well_P...	Road	PipeLine	none	low	medium	high
present	dist0	present	present	0.000	5.000	20.000	75.000
present	dist0	present	present	0.000	5.000	20.000	75.000
present	dist0	present	present	0.000	5.000	20.000	75.000
present	dist0	present	present	0.000	5.000	20.000	75.000
present	dist0	present	present	0.000	5.000	20.000	75.000
present	dist0	present	present	0.000	5.000	20.000	75.000
present	dist0	present	present	0.000	5.000	20.000	75.000
present	dist0	present	present	0.000	5.000	20.000	75.000
present	dist0	present	present	0.000	5.000	20.000	75.000
present	dist0	present	present	0.000	5.000	20.000	75.000
present	dist0	present	notpres...	0.000	14.000	24.000	62.000
present	dist0	present	notpres...	0.000	14.000	24.000	62.000
present	dist0	present	notpres...	0.000	14.000	24.000	62.000
present	dist0	present	notpres...	0.000	14.000	24.000	62.000
present	dist0	present	notpres...	0.000	14.000	24.000	62.000
present	dist0	present	notpres...	0.000	15.000	23.000	62.000

Table 2. An example of a conditional probability table for mink.

Expert Knowledge

The primary objective in the interview process is to determine, from resource professionals, a cause and effect relationship between human-related activities and species habitat. The process was adapted from Marcot et al.'s (2001) research in Bayesian belief network modeling of wildlife population viability in the Columbia River Basin. Their research utilized a Delphi process in which wildlife professionals estimated a causal web influencing wildlife populations given an environmental impact statement's land management alternatives. This process resulted in probabilities of population viability and likelihood of management effects (Oliver and Smith 1990). Over 80 wildlife professionals were available for the Delphi and "selected at-risk fish and wildlife species" (Marcot 2001). I determined that due to time constraints and logistics associated with travel and commitments with wildlife experts, that an informal, personal interviews would provide sufficient baseline data for establishing model variables and ranges or states for the variables.

Interview Selection criteria

Two experts per species were selected to establish a-priori probabilities for the risk assessment. These individuals were recognized among their peers as having significant species and-or habitat specific knowledge and experience. They were either state or federal resource professionals identified as having a working knowledge of the region or had worked within the region of interest. Because the majority of the land is managed by federal and state resource agencies, these professionals were selected because of their familiarity with agency management issues and specific wildlife populations in the region.

Interview Methodology

A semistandardized (Berg 2001) approach was used for the personal interview with selected wildlife professionals. According to Berg (2001), a semistandardized method, as compared to a standardized approach, allows for a freer discourse between interviewer and interviewee. In a standardized format of interviewing, the questions are rigidly outlined and therefore do not allow for clarification or probing of answers. The interviewer's use of language and terminology may differ from that preferred and utilized by these particular professionals. The semistandardized approach allows the researcher to further delve into subject material or to digress to previous issues so as to supplement and improve the understanding of the content of information obtained.

In this research, the semistandardized method was particularly useful because the prior probabilities and marginal probabilities of the model are established by the initial interview session. For example, establishing whether or not sage grouse habitat is at risk from road networks depended on interview responses. Depending on the response, the researcher may continue to probe regarding: a) what the professional believes or understands the causes of risk to sage grouse habitat to be; or b) what specific aspects of roads and road networks create risk to sage grouse habitat.

Freeform probing can allow for clarification of interpretations of observations and of scientific literature. Due to the probabilistic nature of the BBN habitat risk model, it is important that information is clearly represented within the model and in the model structure. How and to what degree interpretations of information that includes personal observations, anecdotal information and scientific literature is articulated is critical to risk modeling. It is the wildlife professionals' responses to these questions and the information they provide that reflect the basis on which land managers rely when creating and updating land and wildlife management plans.

The semistandardized interviewing method was comprised of scheduled questions leading to unscheduled or probing questions, whereby a professional's perceptions were more fully detailed (Berg 2001). (See appendix B).

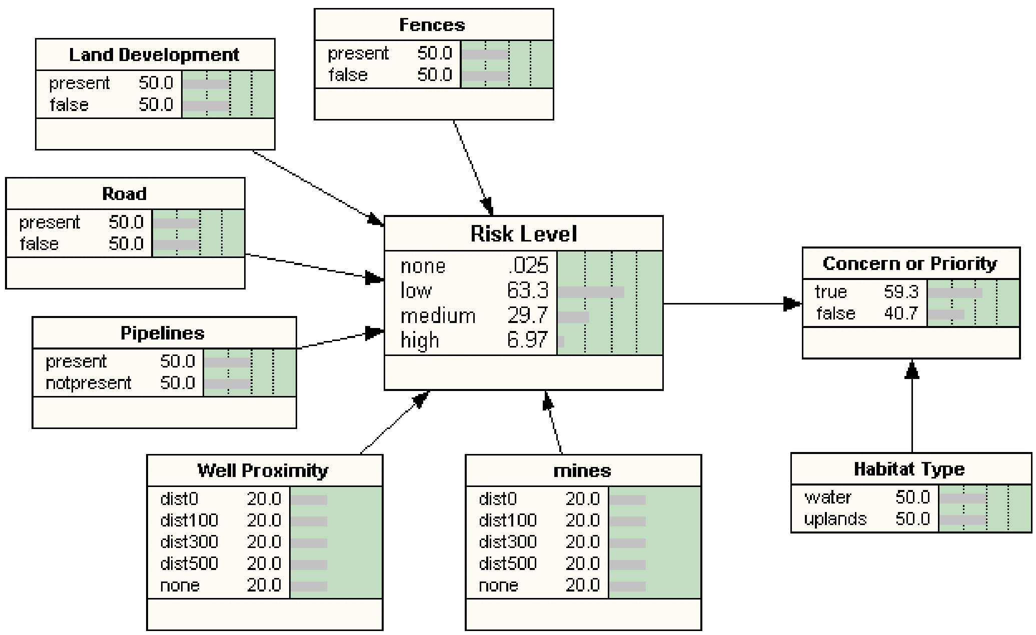
Risk Models

Three steps occur in the development of the risk models. First, following the interview process, expert responses are rated on a numerical scale. For instance, 'High' risk ranged in value from .68 - 1; 'Medium' risk = .34 - .67; 'Low' risk = .17 - .33; and, a 'None' risk ranking = 0 - .16.

One challenge in this process is to combine multiple expert opinions for a ranking range. To meet this challenge, Marcot et al. (2001) used a consensus building process to establish risk rankings. In this project, ancillary data were used to weight individual responses and to establish a relative average value. For example, current literature that supports or counters the respondent rankings would influence the final value. In addition, respondent qualification of rankings such as dependency on activity location, utilization and age would also influence the final value.

The second step applies these values in establishing the conditional probability tables (CPT) within the Netica software. An influence diagram is created that symbolizes the variables that pose risk to habitat (Graph 2). For example, given the presence or absence of a particular activity (e.g. well pad), the probability of risk is established from the combined expert responses. The individual rankings are then combined in a CPT that evaluates all combinations of given or conditional variable rankings (Table 2).

The final step in the risk model development is to determine levels of "concern" based on the overall probability of risk given the states or rankings relative to habitat type. Concern is rated as being either true (present) or false (absent). The concern ranking is then integrated into a GIS.



Graph 2. An example of the Bayesian belief network for Mink.

Risk Maps
Risk Model and GIS Integration

The risk maps are intended to visually represent concern based on the probability of risk across the Southern Wind River Landscape. Two types of maps were created: one that represents concern to a particular species' overall habitat and one that represents concern to that species' seasonal habitat. The following section describes in the step-by-step process of how the risk model outcomes or concern rankings are integrated in a GIS environment.

First, each of the existing data layers are converted to a grid format. Each grid cell is given a value. For example, in the mink habitat grid, habitat presence = 1 and habitat absence = 0. Sage grouse data and mule deer habitat are unique in that each habitat type is given a value based on seasonal habitat delineation. There are five habitat types identified for mule deer: crucial winter habitat = 5, migration routes = 4, yearlong = 3, spring/summer/fall = 2, out-of-range (Wind River Indian Reservation) = 1 and no data (outside of the study area) = 0. Sage grouse habitat types are distinguished similarly: lek/reproduction areas = 4, early brood-rearing = 3, late brood-rearing = 2, wintering habitat = 1 and no data = 0.

An empty grid is created with the same spatial extent as the study site boundary. A computer program or "risk program" written in Visual Basic "steps through" each of the existing habitat grid cells and identifies the state of each disturbance or range of risk probability in that particular cell. For instance, if a habitat grid cell = 4, the risk probability state may equal .57. The risk program will take those states and enter them as evidence in the Bayesian network. The program will then compute the following ranges using the BBN and probability distribution of the risk node yielding:

1. P(C=H*)* *(the probability of Concern = high)*
2. P(R=M) *(the probability of Concern = medium)*
3. P(R=L) *(the probability of Concern = low)*
4. P(R=none) *(the probability of Concern = none)*

The risk program will store the concern rankings in the grid cells of the new grid. The final step is to convert the grids to images with color schemes that signify the ranges of concern relative to risk probability. Maps of concern will be generated at a landscape level and for the two sites of interest: Green Mountain and Red Canyon Ranch.

RESULTS

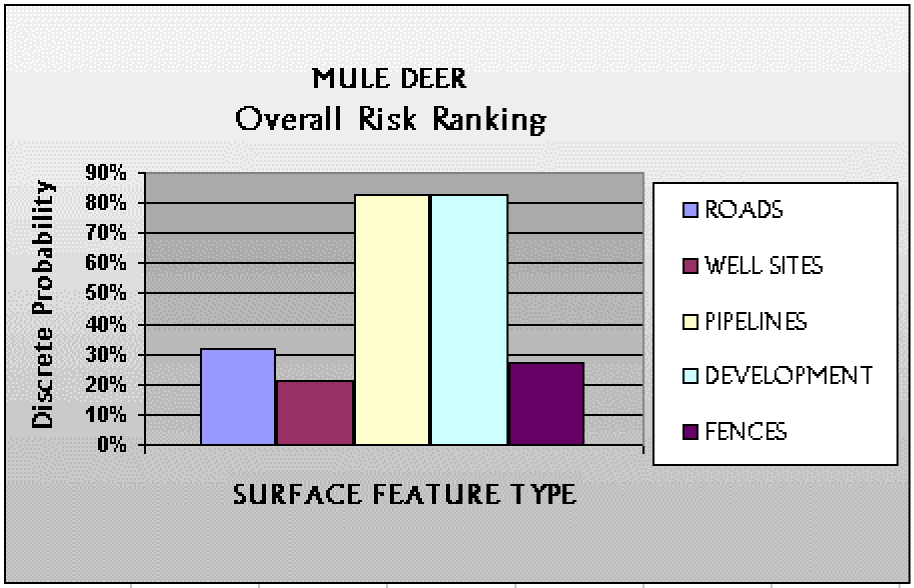
The following examples are of expert responses and risk rankings from the interviews. Similarly, the resulting risk maps reflect discrete probability rankings produced from the BBN models and interview results. Interpretation of species-specific BBN model outcomes and risk maps are also included in this section.

The Interviews

Respondents were asked to rank risk from human-caused disturbances relative to a particular species' habitat. Two experts per species were interviewed and their responses were used to develop risk model parameters and probability value ranges defining the Baysian belief network. Each response fell within a range of probability: 'High' risk ranged in value from 1 - .68; 'Medium' risk = .34 - .67; 'Low' risk = .17 - .33; and 'None' risk ranking = 0 - .16. Probability values within these ranges were applied to the conditional probability tables.

Interviews with six regional species' experts, two per species, were conducted over the course of two days. Individuals included three from the Bureau of Land Management, one from the U.S. Forest Service and two from the Wyoming Game and Fish Department. Four individuals were Wildlife Biologists and two were Range Conservationists. The average number of years in their chosen field and within this particular region was approximately 17 years.

The following graphs illustrate some but not all results from the interviews. Overall risk rankings were averaged to reflect the combined interview responses or risk rankings by species. Graph 3 illustrates combined results of the averaged risk ranking of the two experts given a particular surface disturbance for mule deer habitat, for example.



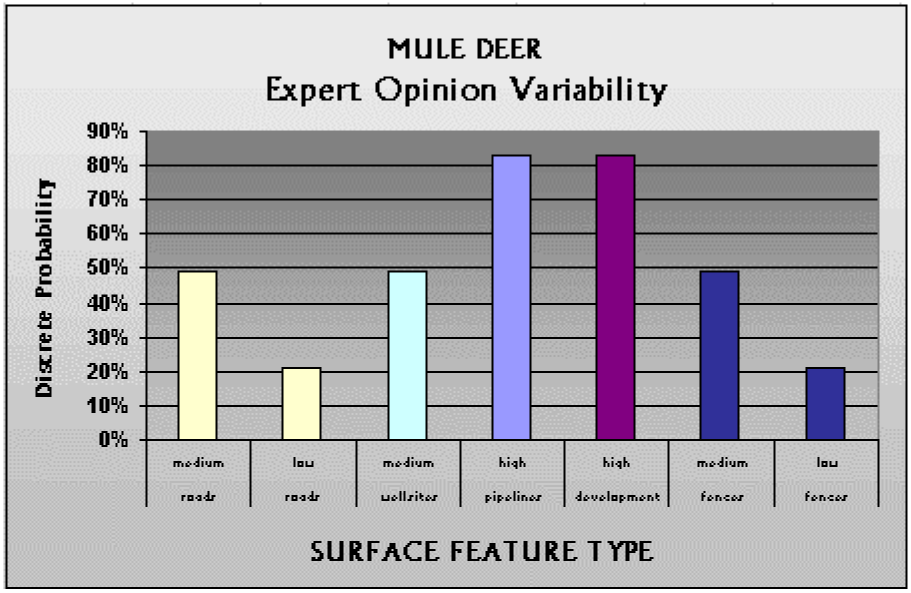
Graph 3. Representation of expert opinion probability averages for surface disturbance risks.

The initial question "Is there risk to mule deer habitat?" was used to establish justification for the Mule Deer BBN risk model; and, that in fact, the mule deer habitat is at risk. The experts agreed that there were risks to habitat and ranked it as 'Medium'. In an open-ended question of what poses risk to mule deer habitat, both suggested that rural land uses such as subdivisions fragment habitat and other issues of concern were drought, irrigation practices and other municipal uses. Neither, however, suggested that energy development and features of this type of development posed risk to habitat; and, yet, pipelines ranked as posing one of the highest risks overall when asked directly if pipelines posed risk later in the interviewing process. Specifically, as is noted in a latter segment of this section, these types of inconsistencies in risk rankings most likely exemplify the notion that most experts maintain that while habitat is a concern, the risk ranking is dependent on the disturbance locale and temporal elements.

Interestingly, the sage grouse results reflect the perceived risk relative to the disturbance frequency, activity level and extent across this particular landscape. That is, there is relatively little, new energy development occurring in the region but more historic inactive and active sites. Initial effects of the energy development pose risk such as construction, increases human activity and road traffic. After the first three years of site development, activity levels drop off tremendously according to one expert. Therefore, risk could be considered temporally as well as spatially explicit.

General risk factors and various habitat-altering activities of concern include detrimental grazing practices and management on both public and private lands, vegetation treatments and fire suppression. The experts also stated the conflicting wildlife management and land use planning practices might degrade habitat quality. Specifically, excessive elk and wild horse numbers as well as increased off-highway vehicle use and incompatible recreation management decisions result in poor habitat quality. Habitat fragmentation and loss resulting in the subsequent reduction in overall forage, fewer insects and increased susceptibility to predation have led to a downward trend in the regional sage grouse population.

There were fewer differences in the responses from the mink experts. Overall, the experts risk rankings were more similar than those of the other species' experts; however, both individuals admitted to having had less direct experience with the species but were still considered the primary regional specialists. Their primary source of information was derived from literature sources and from experience with similar species



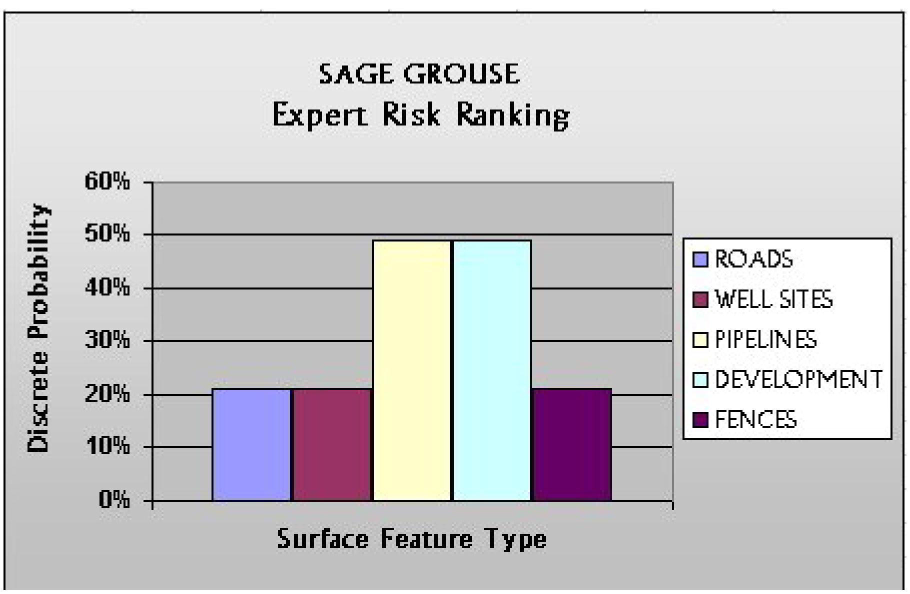
Graph 4. Representative graph of expert opinion variability. Similar colors are diverging rankings for surface feature risk relative to habitat.

Again, the sage grouse experts' responses to ranking risk also illustrate the complexity and uncertain nature of habitat risk assessments at a landscape level (Graph 4). Both individuals agreed that sage grouse habitat was at risk and rated it as "medium"; however, ratings for specific anthropogenic disturbance risks were less definitive. For example, both experts agreed that there was risk associated with energy development.

However, one individual rated it as being low while the other rated the risk as being high intimating that the ranking was dependent on the particular locale of the development. Rankings were averaged where divergent opinions existed.

As was notably apparent in the sage grouse responses, experts concurred that well pads posed risk but ranked it as being low and as possibly "improving habitat". Other disturbances related to energy development such as pipelines posed a medium (49%) risk Experts noted that pipelines and pipeline development are related to habitat fragmentation potential as well as associated disturbances with pipeline-related roads and road expansion, road maintenance, human activity and access-related consequences. Moreover, one expert qualified the risk from pipelines as being particularly high at lower elevations where vegetation recovery following the initial disturbance is slower. One might infer that determining risk could be contingent on multiple factors, on a site-specific basis and individual bias and/or experience.

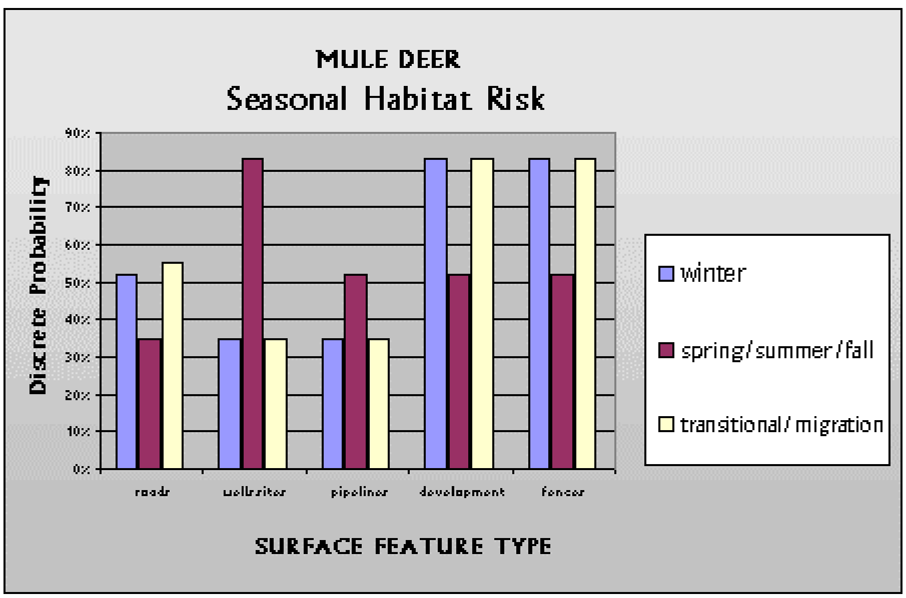
Responses from the sage grouse experts to assessment of land development or conversion not related to energy development were contradictory. In one case as to the question of whether or not land development posed risk, both experts ranked risk as 'low'. The follow-up question of as to ranking risk from subdivisions specifically, the experts ranked the risk as 'high' (graph 5).



Graph 5. Representation of expert opinion averages for ranking surface disturbance risk.

Seasonal habitat – fine level assessment

Each respondent was asked to consider disturbance relative to seasonal habitat type. Expert variability was apparent in these responses. Dissimilar responses in the mule deer experts' responses were interesting, for instance. The rankings of risk relative to roads and winter range were contrary to one another. One ranked risk from roads in winter range as low and the other ranked it as being high citing habitat disturbance due to increased snowmobile access. However, both agreed that energy development, specifically well pads, in winter range and around migration corridors posed a high risk, but overall the risk to habitat was low.



Graph 6. Representation of expert risk ranking averages for seasonal mule deer habitat.

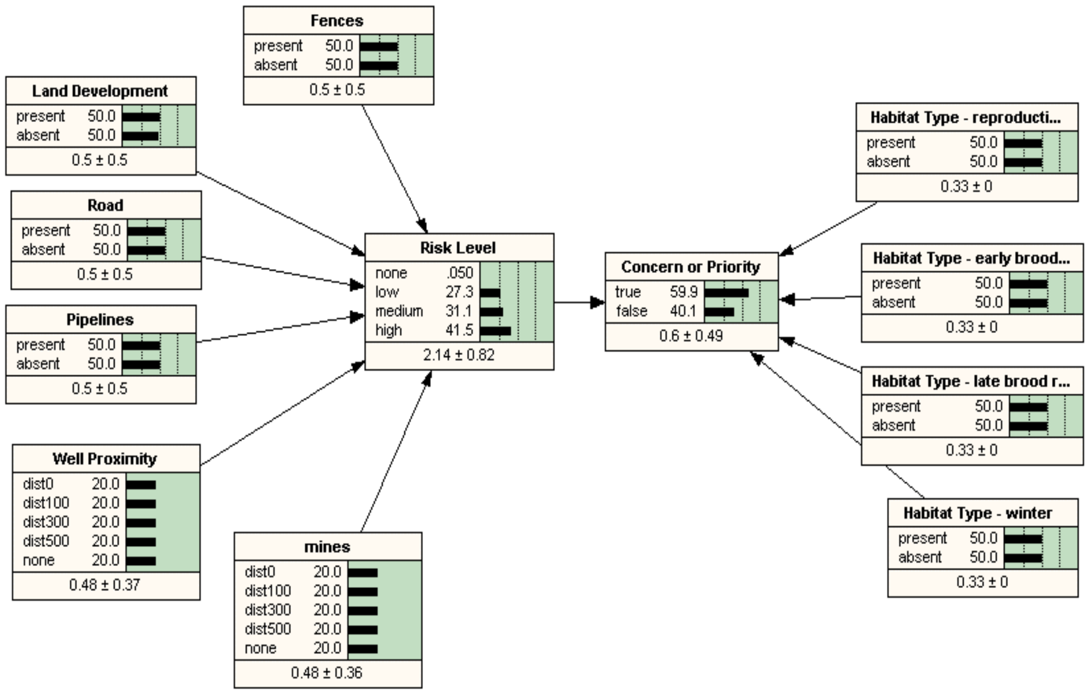
A BLM expert, for example, manages and is familiar with, more actual available mule deer habitat than that located in either private or any other public lands within the SWRL study area as well as having more disturbance activity or presence within their region. As compared to the responses of a Forest Service Range Conservationist, mule deer habitat is limited to spring/summer and some fall ranges. As well, this particular segment of National Forest has very limited oil, gas and land development and, similarly, fewer roads and fences. Therefore, the Forest Service's Range Conservationist responses compared to that of the BLM's Wildlife Biologist ranked risk lower with respect to roads and fences, in particular.

At the conclusion of each interview, the respondents were asked from where their knowledge of habitat risk was attributed. All six experts relied on personal observation and experience in the region. Five of the six experts referred to literature although never cited specific sources during the interview. All referred to their reliance on their peers for sharing knowledge and information, from within the region and from within their professional disciplines. And, finally, all often prefaced their rankings by stating that risk from a particular disturbance was "site specific"; noting that landscape-level risk determination for a single habitat was challenging.

The interview also included determining rankings related to more specific disturbance types such as road density and road type. However, this information was eliminated from the application within the BBN models for a number of reasons. Road classification information was not available. Road density calculations, however, would have been applicable and may be used in future research given more time.

BBN Models & CPT's

The Belief Network models are intended to represent knowledge. Each node represents discrete random variable values whereas the arcs represent the causal relationship among variables (Figure 9). Together, the nodes and arcs with their associated conditional probability tables (CPT) exemplify a one to one relationship in the graph (Graph 6).



Graph 6. Netica software belief network example developed for sage grouse.

Develop	Well_Prox	Road	PipeLine	fences	mines	none	low	medium	high
present	dist0	present	present	present	dist0	0.0500	5.000	20.000	74.950
present	dist0	present	present	present	dist100	0.0500	5.000	20.000	74.950
present	dist0	present	present	present	dist300	0.0500	5.000	20.000	74.950
present	dist0	present	present	present	dist500	0.0500	5.000	20.000	74.950
present	dist0	present	present	present	none	0.0500	5.000	20.000	74.950
present	dist0	present	present	absent	dist0	0.0500	5.000	20.000	74.950
present	dist0	present	present	absent	dist100	0.0500	5.000	20.000	74.950
present	dist0	present	present	absent	dist300	0.0500	5.000	20.000	74.950
present	dist0	present	present	absent	dist500	0.0500	5.000	20.000	74.950
present	dist0	present	present	absent	none	0.0500	5.000	20.000	74.950
present	dist0	present	absent	present	dist0	0.0500	14.000	24.000	61.950
present	dist0	present	absent	present	dist100	0.0500	14.000	24.000	61.950
present	dist0	present	absent	present	dist300	0.0500	14.000	24.000	61.950

Table 3. Conditional probability table example for sage grouse.

Each response is applied to the CPT's for the BBN model development. Each response was given a value within a range and discretized to signify the probability of risk state. Probabilities are read from the CPT as "given the presence of roads, for example, there is a 74.95% chance that the risk will be 'high', a 20% chance the risk will be 'medium', a 5% chance the risk will be 'low' and a .05% chance that there will be 'no risk.' In this example, the table suggests that when disturbance is present (e.g. a road) and the risk is 'high', there is a very strong likelihood that the concern for habitat will be 'high'.

These values within the risk node are evidence that allow us to make inferences and qualify the probability of concern given a particular disturbance or set of disturbances. The probability values were used, in this example, as input for the BBN model development with the output probability ranges signifying areas as being of concern, either high, medium, low, none or unsure. As new evidence and new knowledge comes available, propagation or updating of the probabilities is possible.

Risk Map Results

The following maps are the output created with the risk program based on the Netica software belief network. Figure 7 is the resultant mink habitat risk map. In the legend, red represents 'high' risk, orange represents 'medium – high' risk and yellow represents 'low to medium' risk.

At the landscape level, it would appear that the highest risk follows the WY GAP mink habitat GIS layer (Figure 8), a finer representation of risk probabilities are seen at the finer level. In this case, Red Canyon Ranch is highlighted (see Figure 8) and it becomes more apparent that probability estimates are most sensitive to habitat and land development potential. In Figure 8, mines and pipelines were excluded as they had little influence at Red Canyon Ranch.

The fine level risk maps for sage grouse and mule deer at Red Canyon Ranch clearly illustrate how the expert estimations influence the model output (see Figures 13 and 15). The sage grouse model output illustrates the sensitivity of probability estimates for early brood-rearing and reproduction sites relative to land development potential and pipelines.

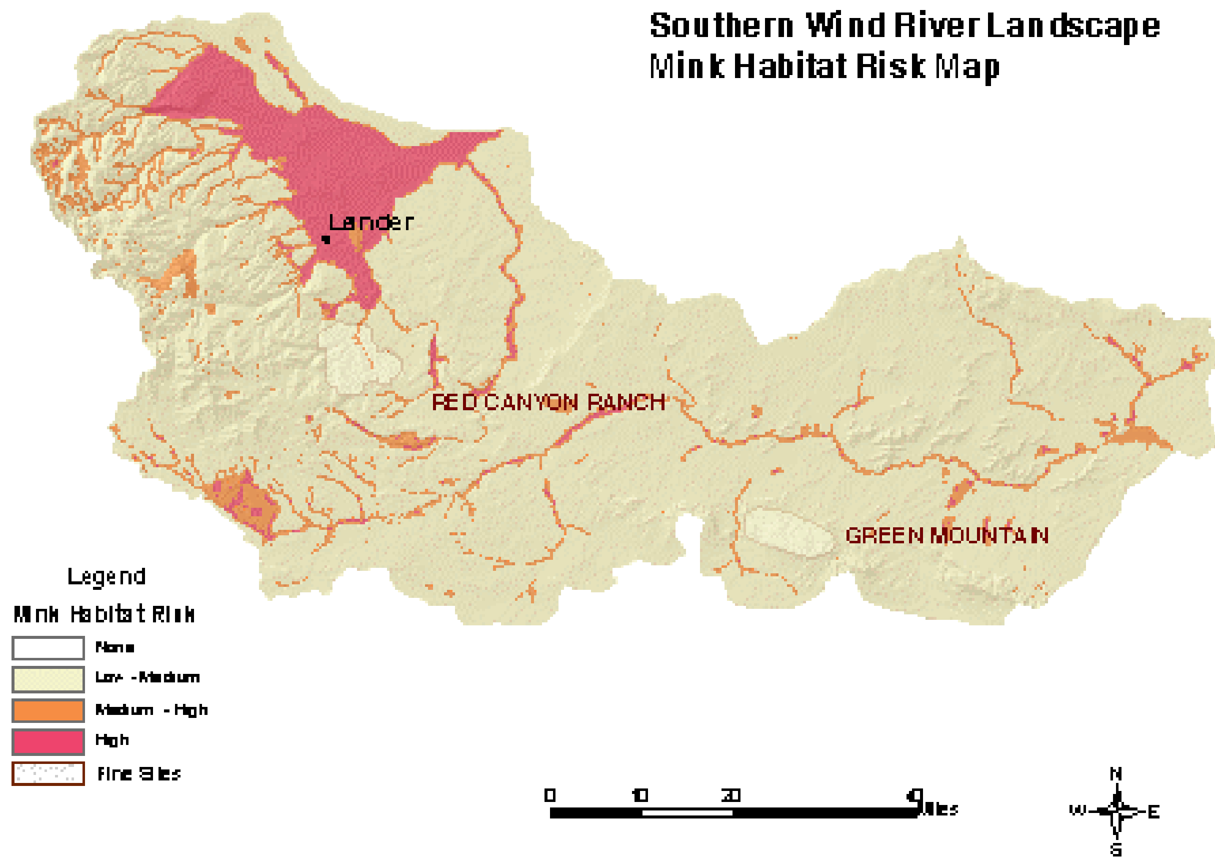


Figure 8. Risk map for mink habitat based on the Mink BBN model.

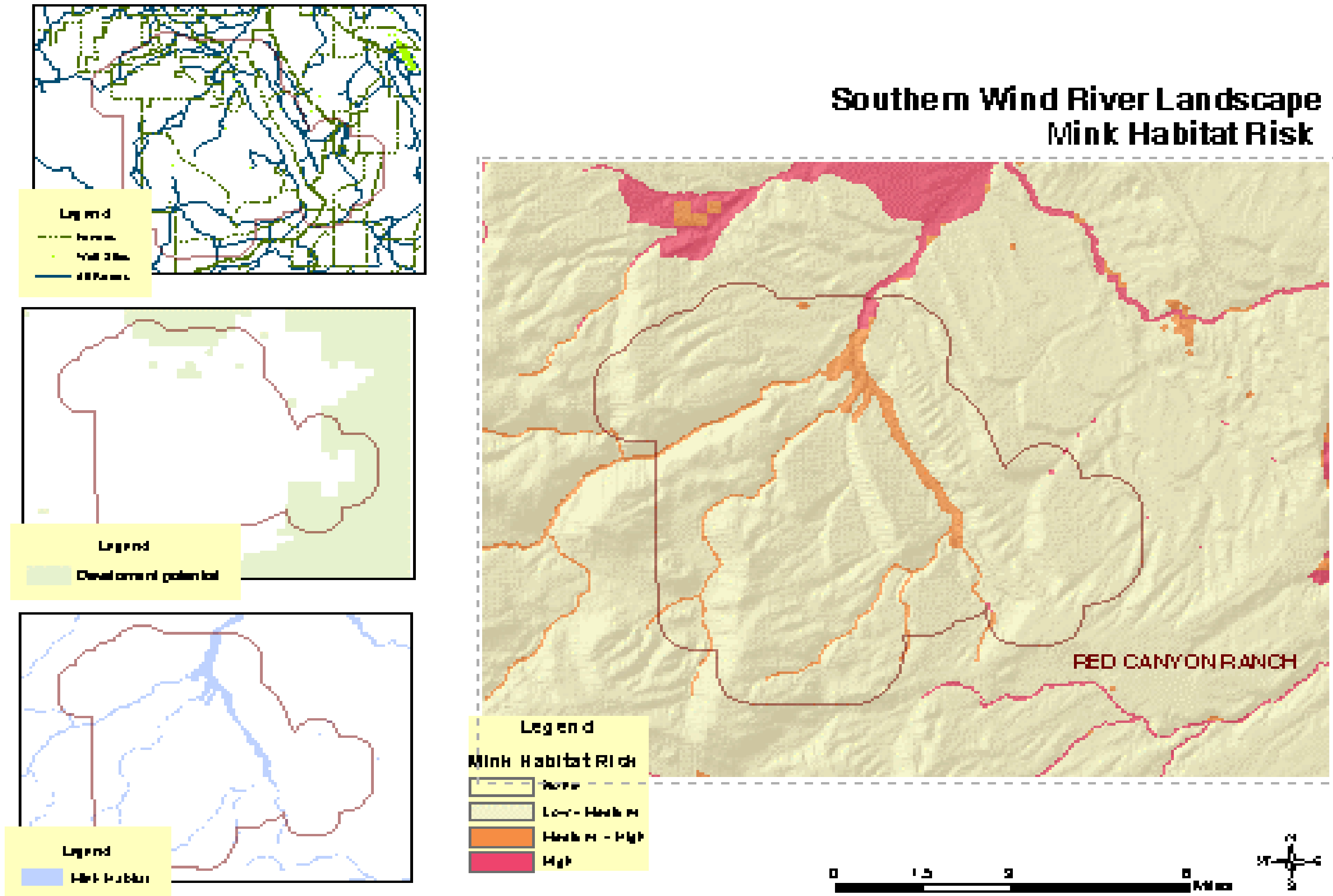


Figure 9. The risk map for mink at Red Canyon Ranch illustrating surface feature and habitat to output.

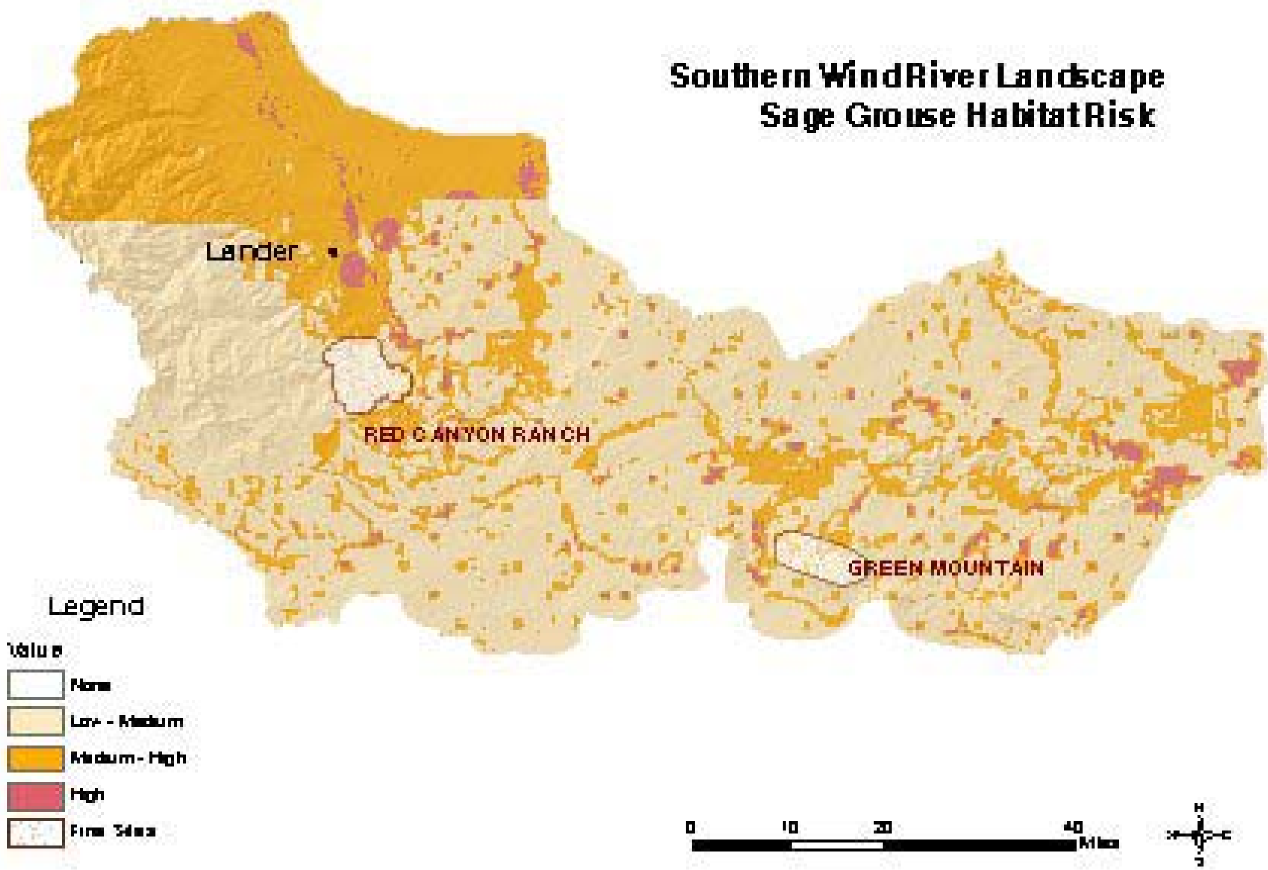


Figure 10. Sage grouse landscape level risk map.

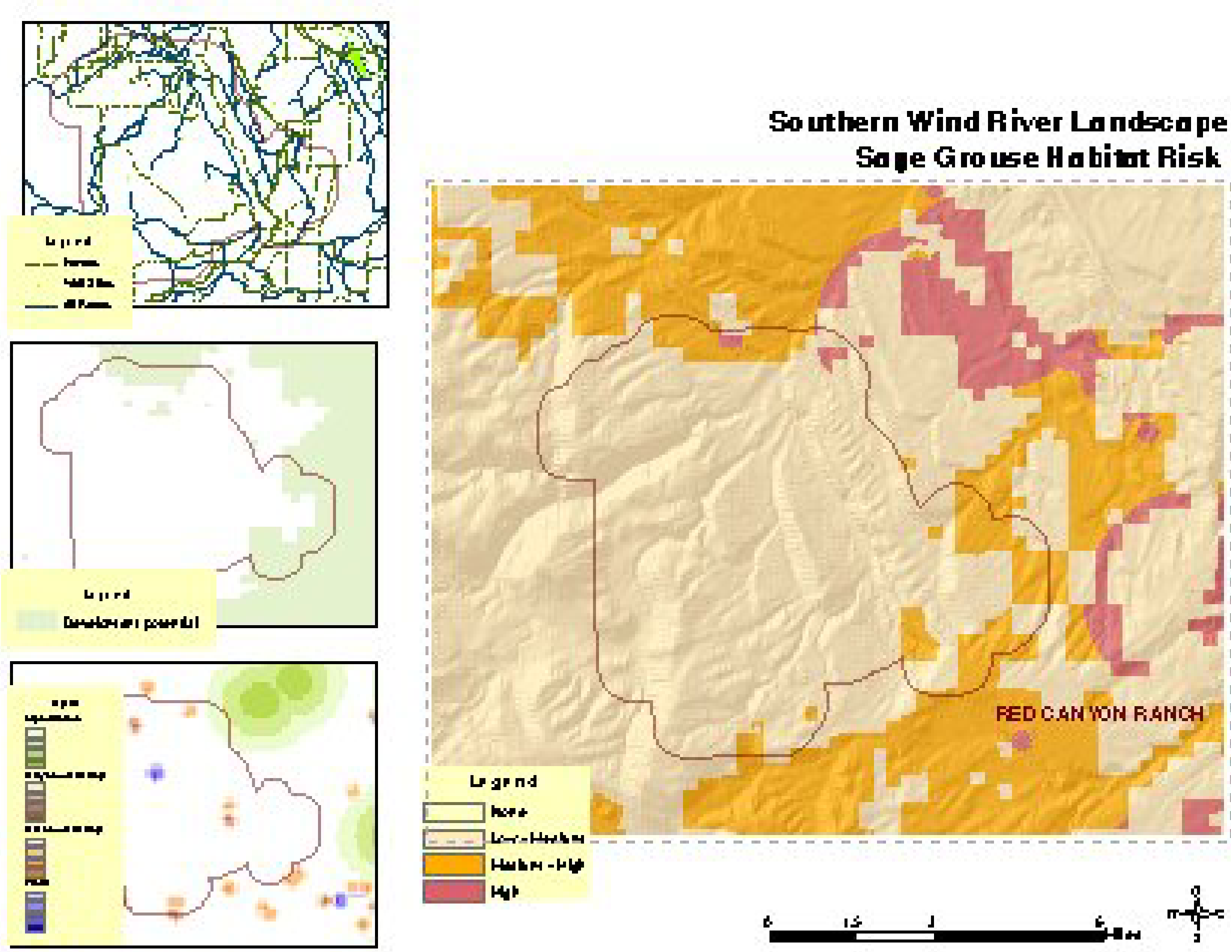


Figure 11. Sage grouse seasonal habitat risk map at Red Canyon Ranch with surface features.

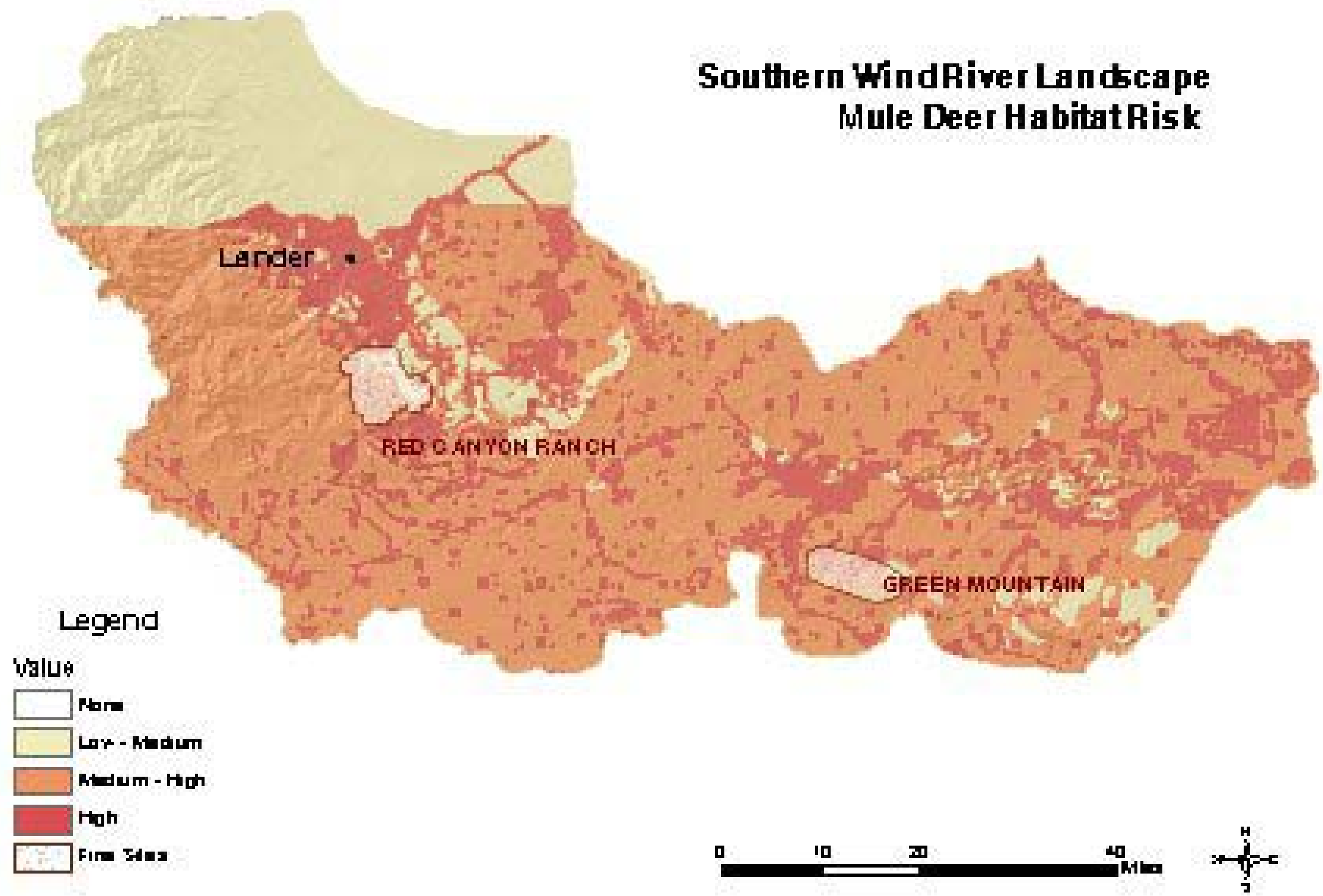


Figure 12. Mule deer habitat risk map at the landscape level.

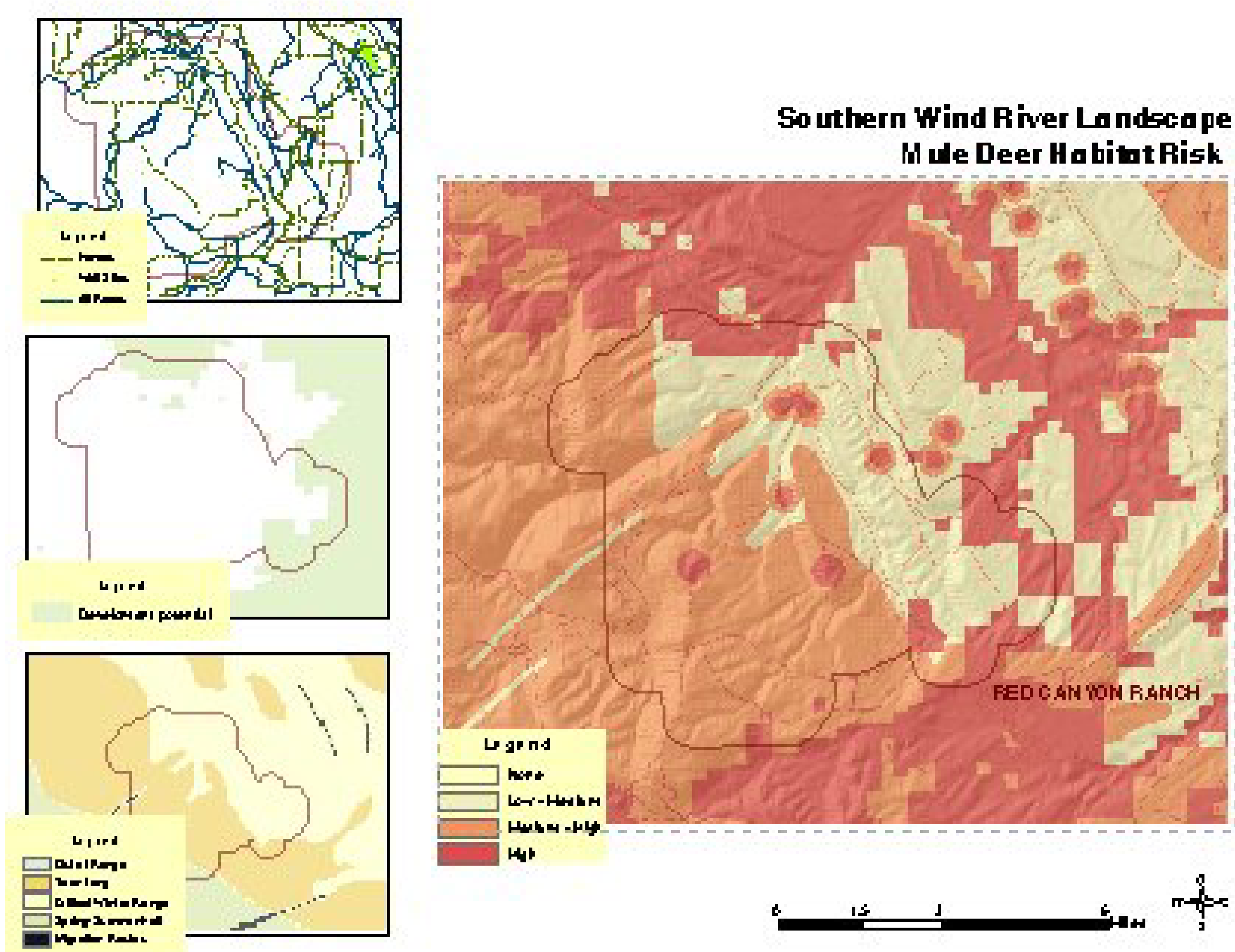


Figure 13. Mule deer seasonal habitat risk map at Red Canyon Ranch with surface features.

DISCUSSION

It's critical to acknowledge the uncertainty that exists in the natural world. In essence "*the reality and uncertainty of nature tells us that there will be instances when the predicted… does not agree with the observed..*" *(Ames 2000).* In the Belief Network approach to risk assessment, modeling qualitative evidence of risk as probabilities allows us to account for the uncertain nature of an ecological system and disturbance within the system and incorporate expert and public opinion. Spatially representing risk in a GIS environment and as maps further assists in the decision-making and public involvement process.

The results of this project illustrate the variability in expert knowledge and demonstrates the difficulty in applying a risk assessment where there is inherent uncertainty in the data. The interview results, depict divergent viewpoints of risk. Differences in responses are indicative that the knowledge base of the variable in question and is dependent on the individual expert's experience with and perception of disturbance types. Furthermore, in this process, experts are challenged to connect habitat, population viability and disturbance factors at multiple spatial levels to create what Marcot et al. refer to as the "ecological causal web" (2001).

Marcot et al. (2001) recommends full exploration of what they term as "key environmental correlates" influencing habitat. In this research, some of those key environmental correlates such elements such as slope, erosion potential, soil type, fire regimes as well as grazing systems were not evaluated. This data may have allowed for a clearer synthesis of quantifiable hypotheses rather than basing the models solely on ambiguous opinion. Given more time to add these variables and to reach consensus of expert opinion would provide a more accurate picture of the physical processes across that landscape contributing to habitat “risk”.

Accounting for response variability within the BBN exemplifies both the power of the conditional probability tables used to establish risk rankings and the drawbacks and error associated with applying the discrete variables based on the operator’s own subjectivity.

Initially, expert responses were averaged. For instance, if one ranked risk as ‘high’ whereas the second expert ranked risk as being ‘medium’, one would expect that averaging to establish a discrete ‘risk ranking’ was reasonable. However, in populating the CPT’s of the model, that discrete value was not useful. The very basis of the BBN is that there is some probability that there is either ‘no’, ‘low’, ‘medium’, or ‘high’ risk. Therefore, in applying multiple expert opinions to the CPT, the operator is required to determine, however subjectively, a discrete value for each ranking of probability. Therefore, one would conclude that a failing in this approach is the estimation of applied discrete variables.

Additionally, further meetings and follow-up with the professionals would have been appropriate to determine if they concurred with the mapped results. Multiple meetings would have also provided the research with true-to-life group decision-making dynamics and ultimately consensus regarding risk. It also would have been appropriate to include more individuals. Throughout the interviews, in fact, the experts recommended that both retired nature resource professionals as well as lay people be involved in the interviews.

Overall, the BBN and GIS program represented expert-based opinion of risk to habitat relative to the available spatial data. However, factors not included such as road type, road densities, active and non-active well sites and proximity to water course and riparian systems may have allowed for clearer representation and determinations of risk.

Further adaptations to the Netica models such as 'utility' representing optimal population numbers and 'decision' nodes representing land management options may have provided a cost-benefit type analysis. And, finally, a cummulative assessment of all disturbance relative to all habitats would have been interesting.

The BBN provides an opportunity for improving and adding to the decision-making process; and providing quantifiable method for the determining either site specific or landscape level risk aiding the planning process. Specifically, this approach can be an effective tool in adaptive management strategies.

Model Validation

Three validation opportunities may be applied to the Bayesian belief models created in this project.

One may include an extensive ground-truthing process that entails multiple years of observational studies of risk attributes at selected locales across the landscape. A blind study, in this case, may be an appropriate validation method whereby field crews are not aware of the current risk rankings. Their assessment may include a questionnaire designed to capture a particular species' presence and/or persistence at the selected sites. Their independent, observational assessments will allow you to compare the computed risks. A summary of these independent assessments and ranking the risks would allow you to evaluate the estimates relative to the modeled results.

Two more immediate validation opportunities would include a second interview with either the selected experts or different experts to assess the model and map results. Again, interviewees would be asked a series of questions designed to ascertain whether they agree or disagree with the modeled results at selected sites. The information provided through a second interview would either verify or contradict the probabilities weighting the model results and map output.

A final approach to validation used in this research was to utilize the built-in Netica software sensitivity analyses function to determine which node/disturbance most influenced the model results.

Sensitivity Analysis

Sensitivity analyses were conducted for each of the three models to explain the variability in risk outcomes stemming from uncertainty about stressors and habitats. According to Marcot et al. (2001), sensitivity is defined as the expected reduction in variation of some query variable due to the conditional probability structure of the BBN and the specific value of the parent nodes.

The sensitivity analysis is used to determine which nodes most influence the outcome. Two sensitivity analyses were produced that reflect variance in the 'Risk' nodes and in the 'Concern' nodes. The risk node input are probabilities of risk based solely on disturbance value. The concern node inputs are from both the risk node output and the seasonal habitat node(s) (Appendix E).

The disturbances having the greatest influence on risk and concern levels are development. For the sage grouse and mink, in particular, a manager or planner may seek to focus their efforts on the effects of development with respect to these habitat types. The sensitivity analyses can help identify priority areas and as new data is added, the models can assist in determining areas of conservation, protection or rehabilitation value, for example.

The Broader Implications

Adaptive management is a melding of acknowledgement of uncertainty with sustainable land management (Lee 1986). It is a process in which there is:

1) a recognition of boundary management problems and constraints;
2) a representation of existing knowledge and one that models dynamism, assumptions and predictions so continued learning is experienced;
3) representation and acknowledgement of uncertainty and alternative hypotheses; and finally,
4) policy adaptation which allows for productivity and learning opportunities (Walters 1986).

It is an iterative, decision-making process, based on present or a priori knowledge (prior probability) which allows for the acceptance of new information in the evolution of management objectives. In recent years, adaptive management strategies have been applied to management of public lands and resources where public and private cooperators have made attempts to manage for highly competitive resource demands including fisheries, water and timber resources and for biodiversity.

In theory, adaptive management's basic assumptions are probabilistic in nature. In application, a Bayesian decision framework for the planning or management process seeks to establish or quantify sets of all possible actions and outcomes. Adaptive management methodology simply suggests that an individual or, in this case, a planner will continue to revise his/her plans as new information becomes available. They can adjust as ecological or societal "values" change. Humans will make decisions based on current understanding of the world, but an adaptive management allows for knew information to be accepted (Bergerud 1998).

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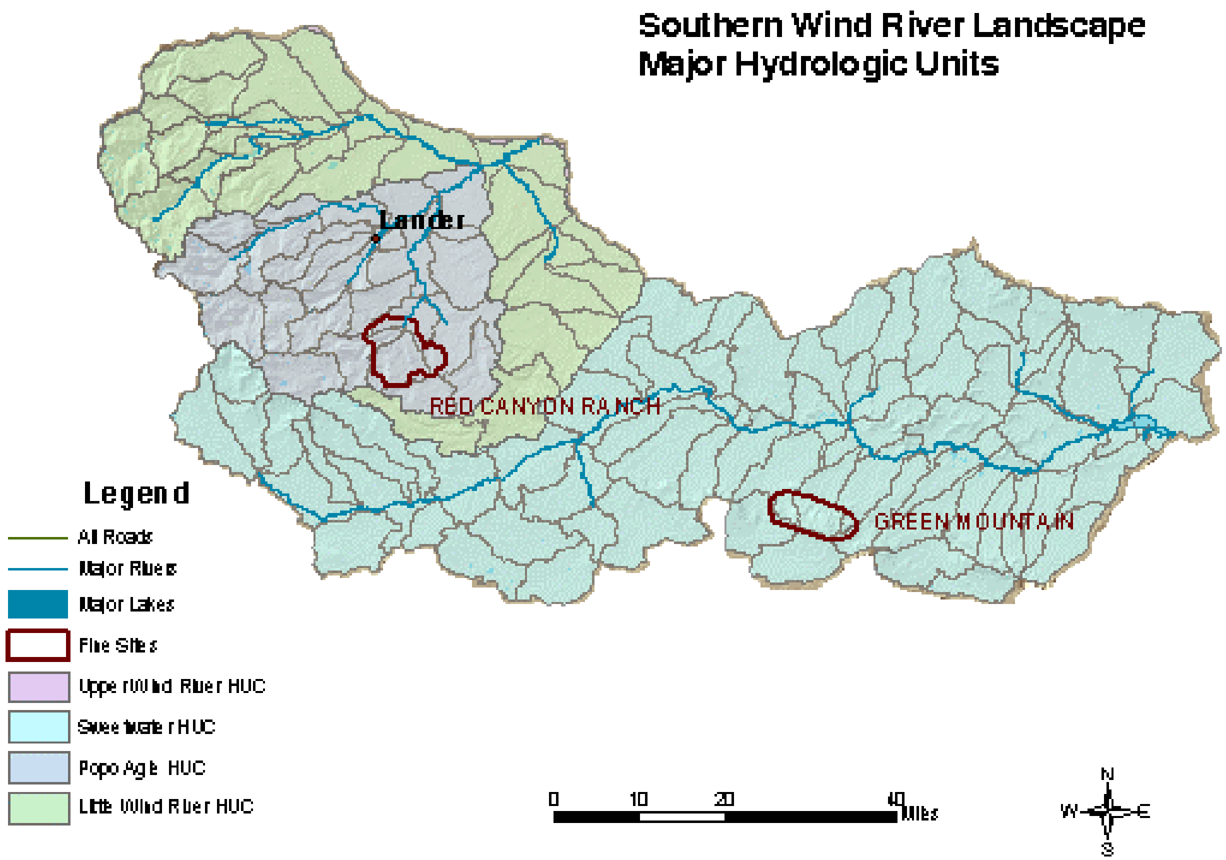
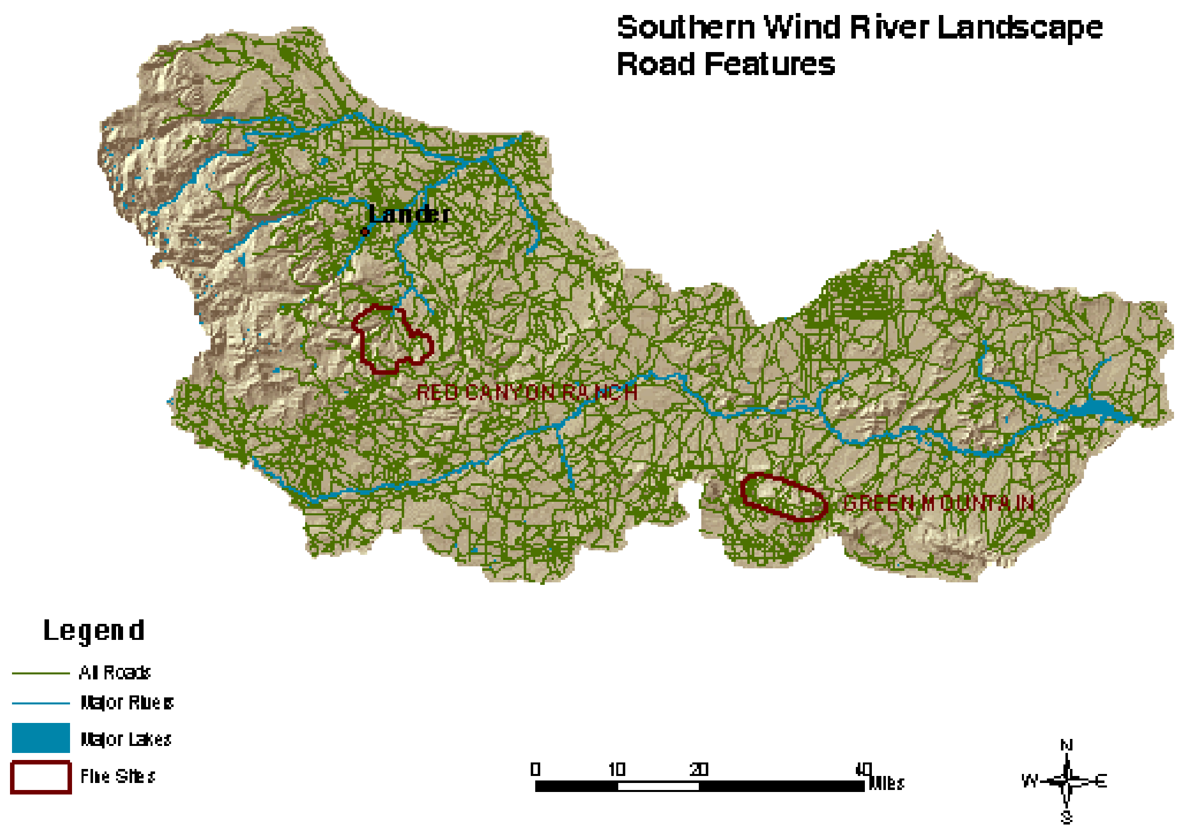
APPENDICES

Appendix A.
Maps

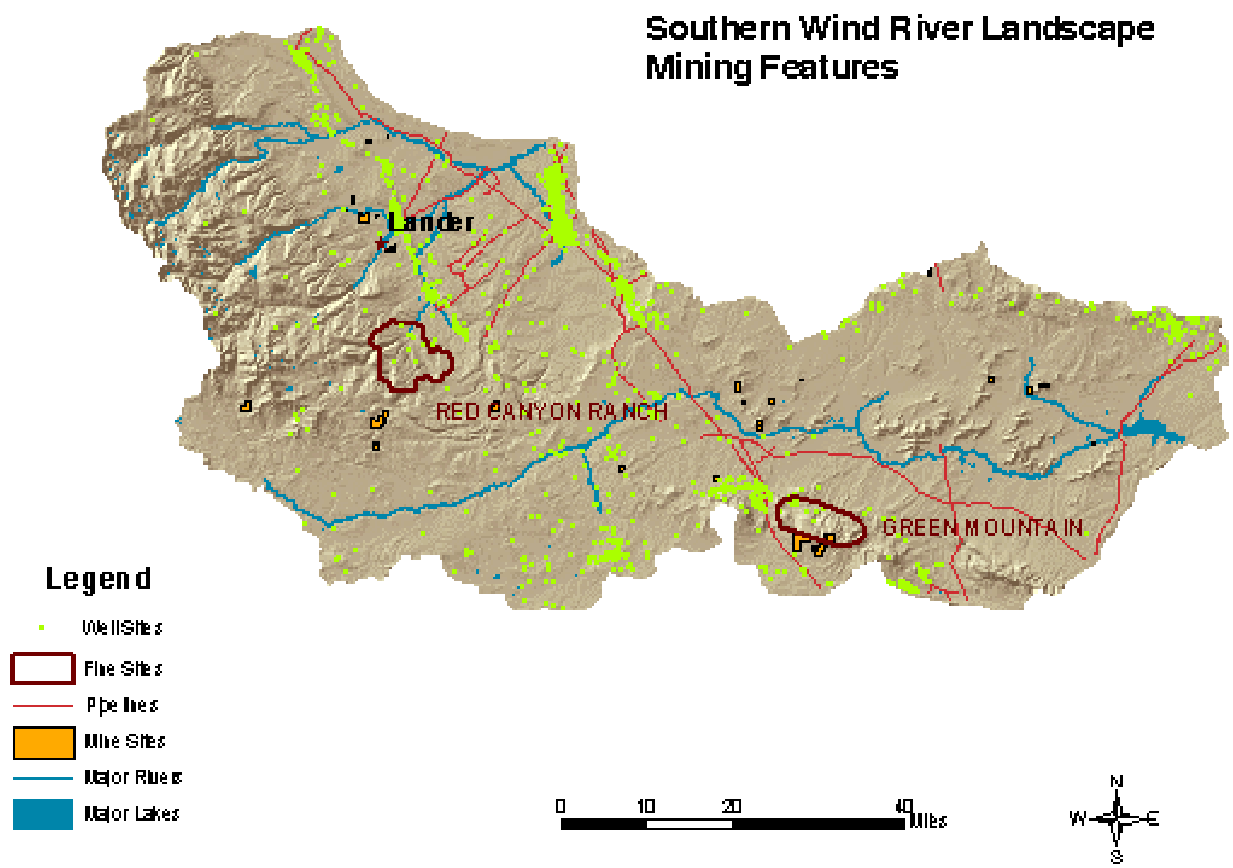
Appendix A.
Maps



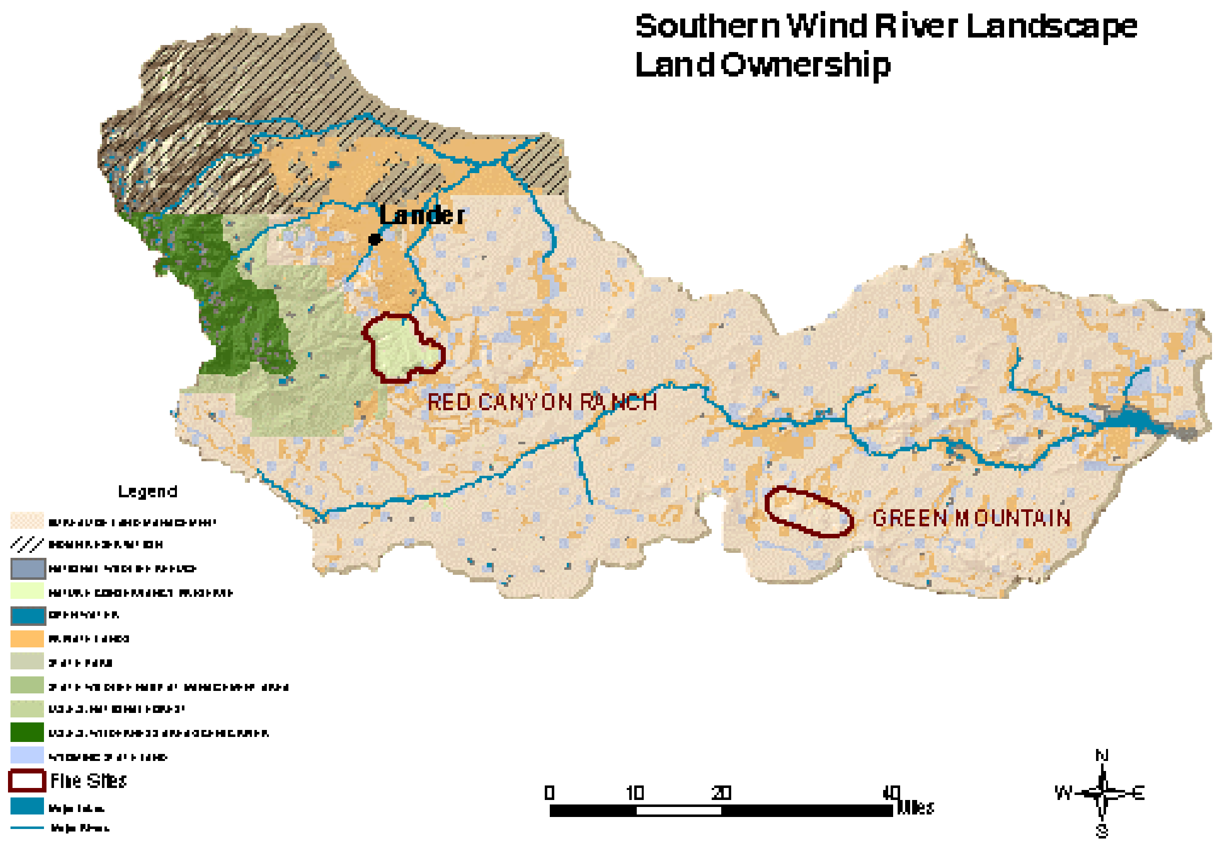
Map 1. Southern Wind River Landscape Hydrologic Units – major, fourth order watersheds.



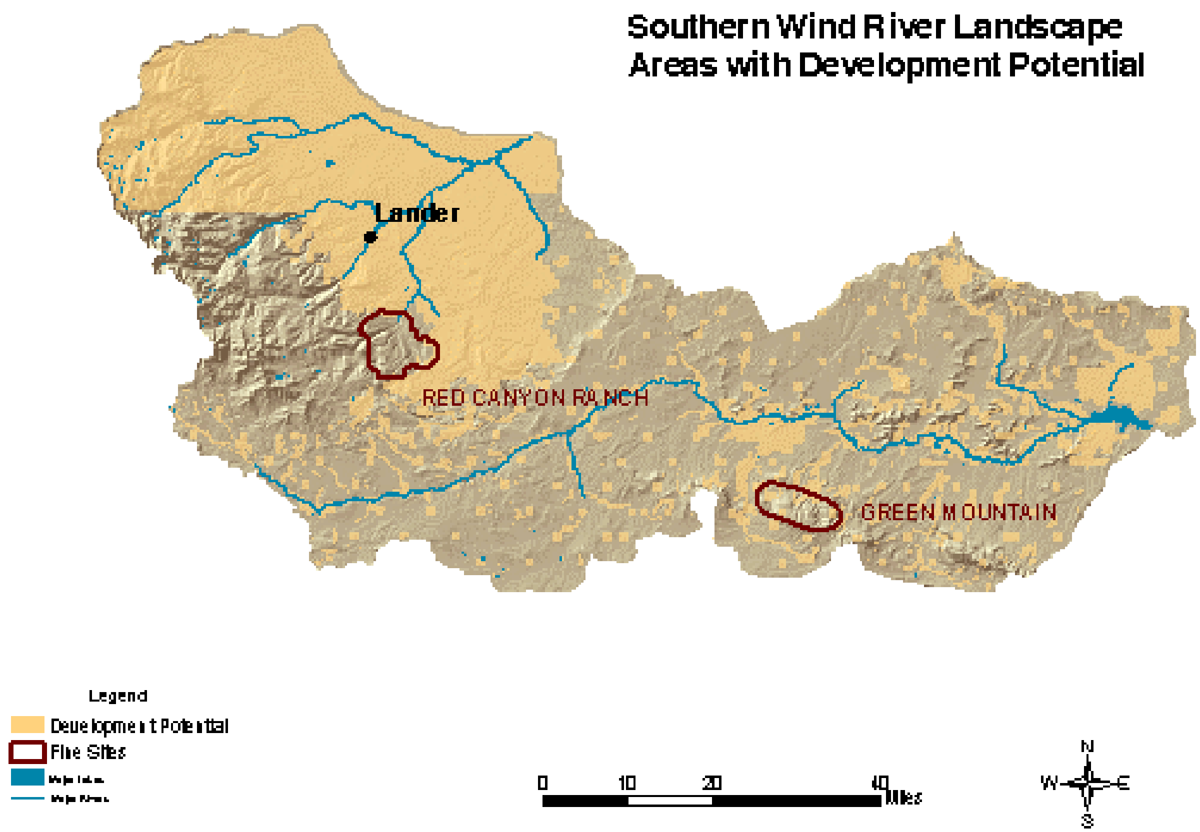
Map 2. Southern Wind River Landscape Surface Features – Roads.



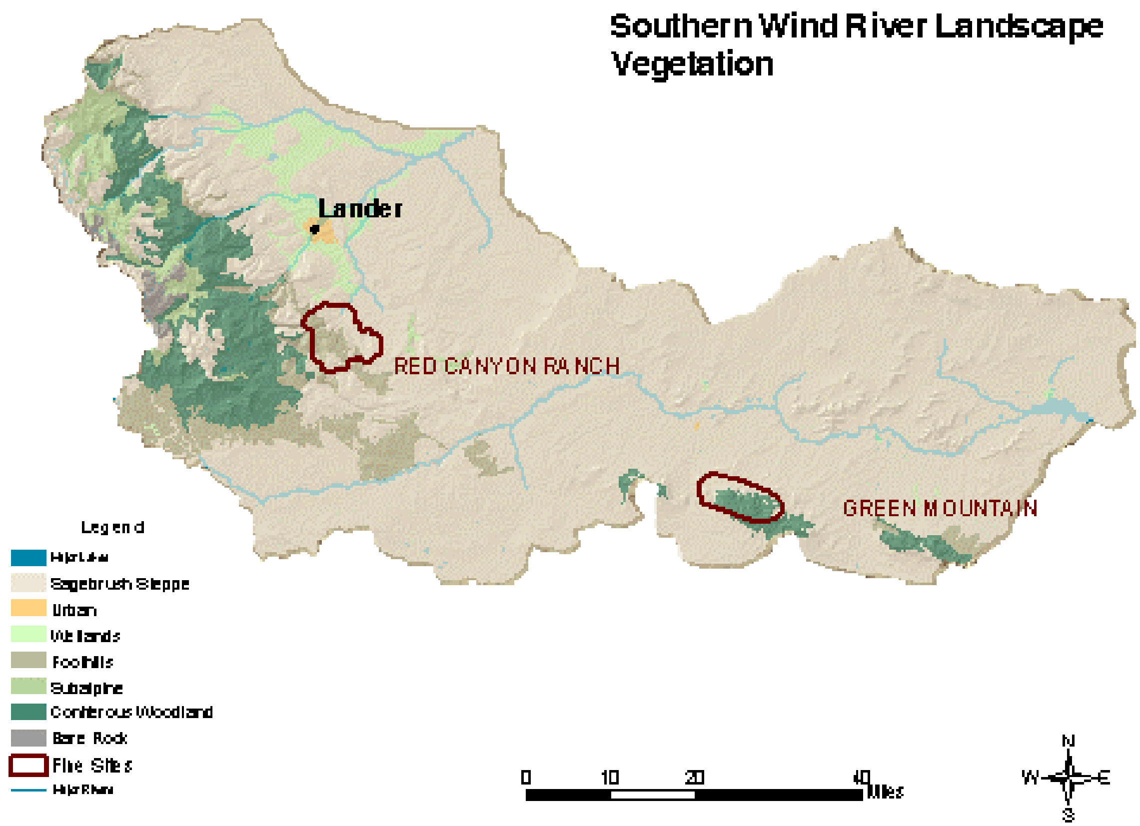
Map 3. Southern Wind River Landscape Surface Features – Mining Features



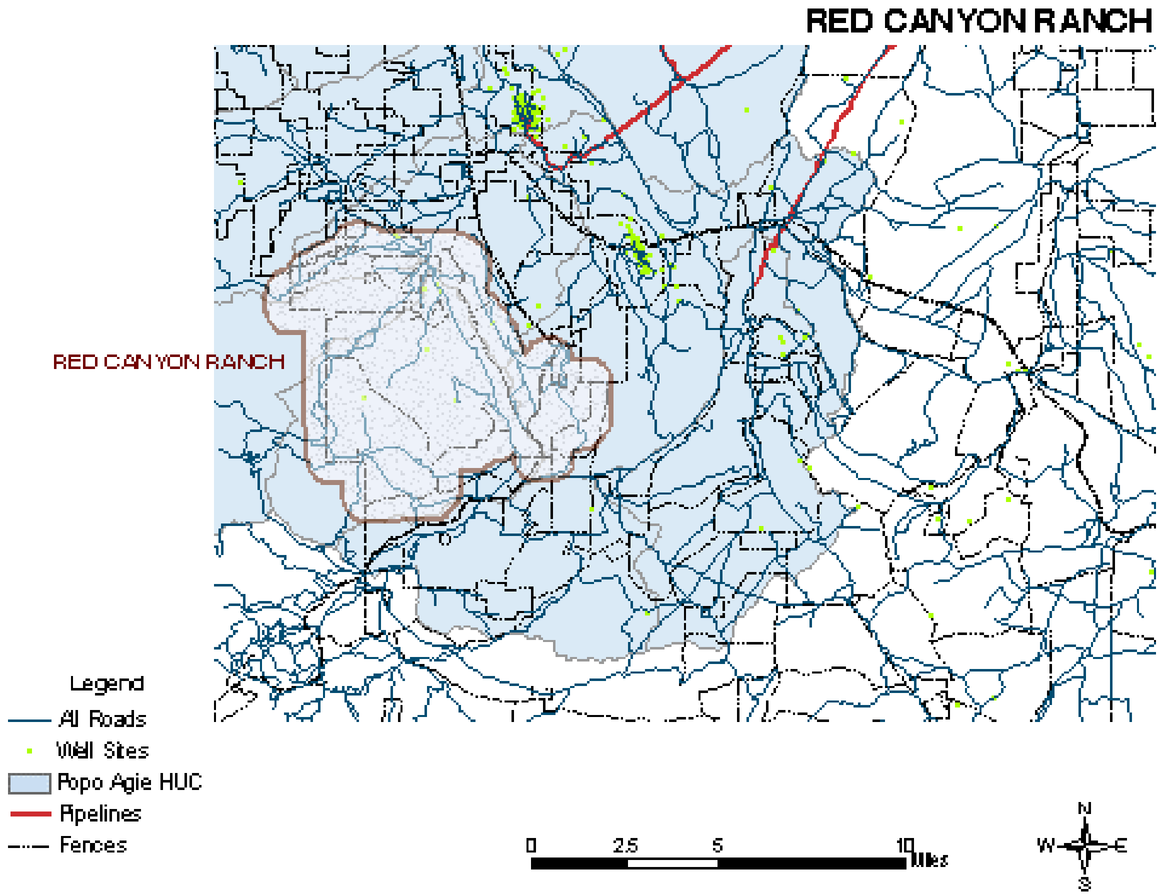
Map 4. Southern Wind River Landscape Land Ownership



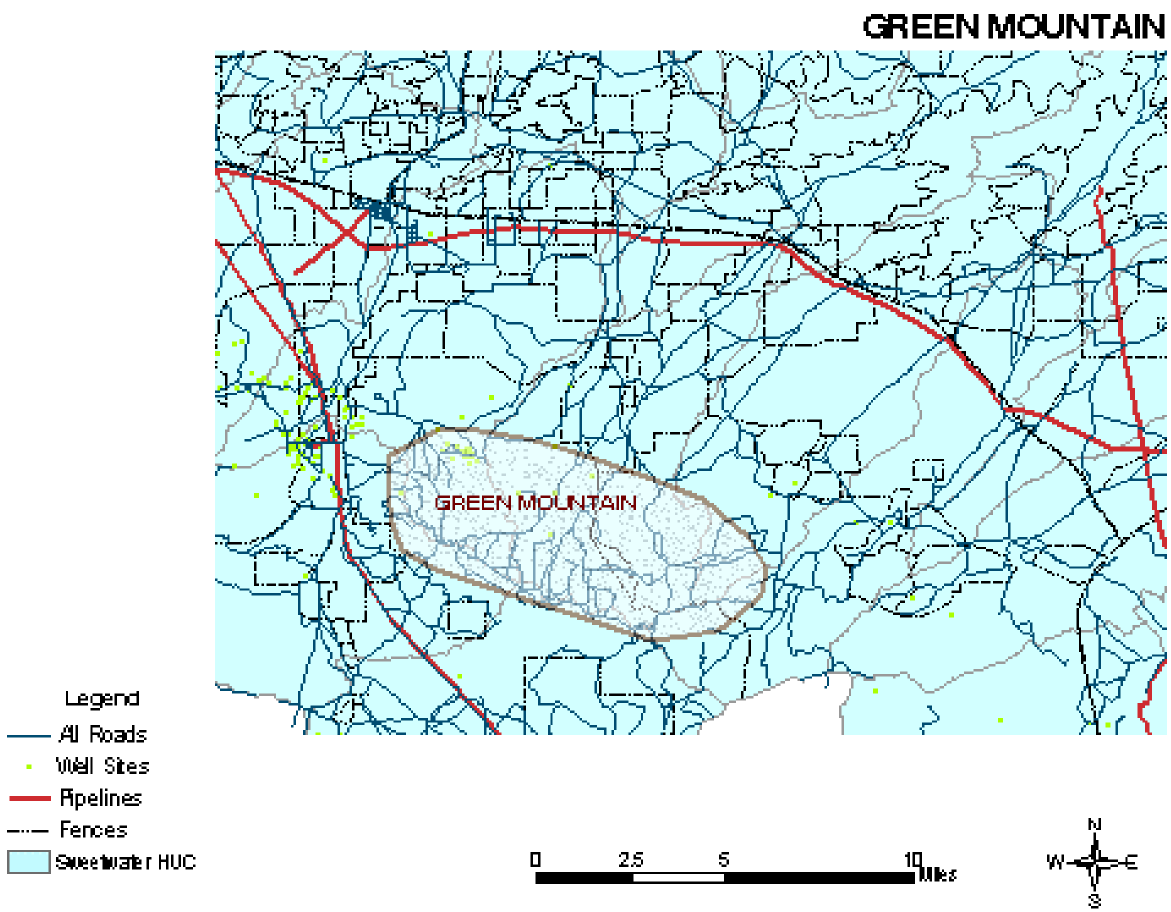
Map 5. Southern Wind River Landscape – Areas with land development potential



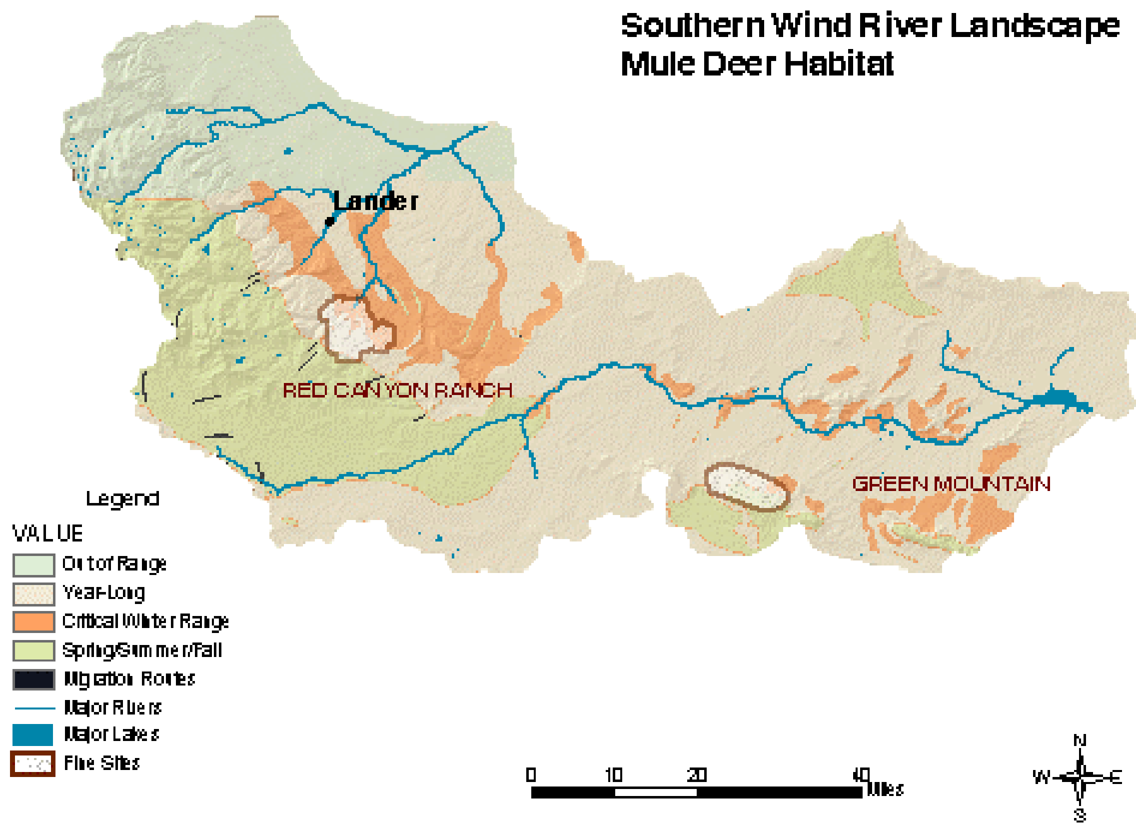
Map 6. Southern Wind River Landscape – Vegetation



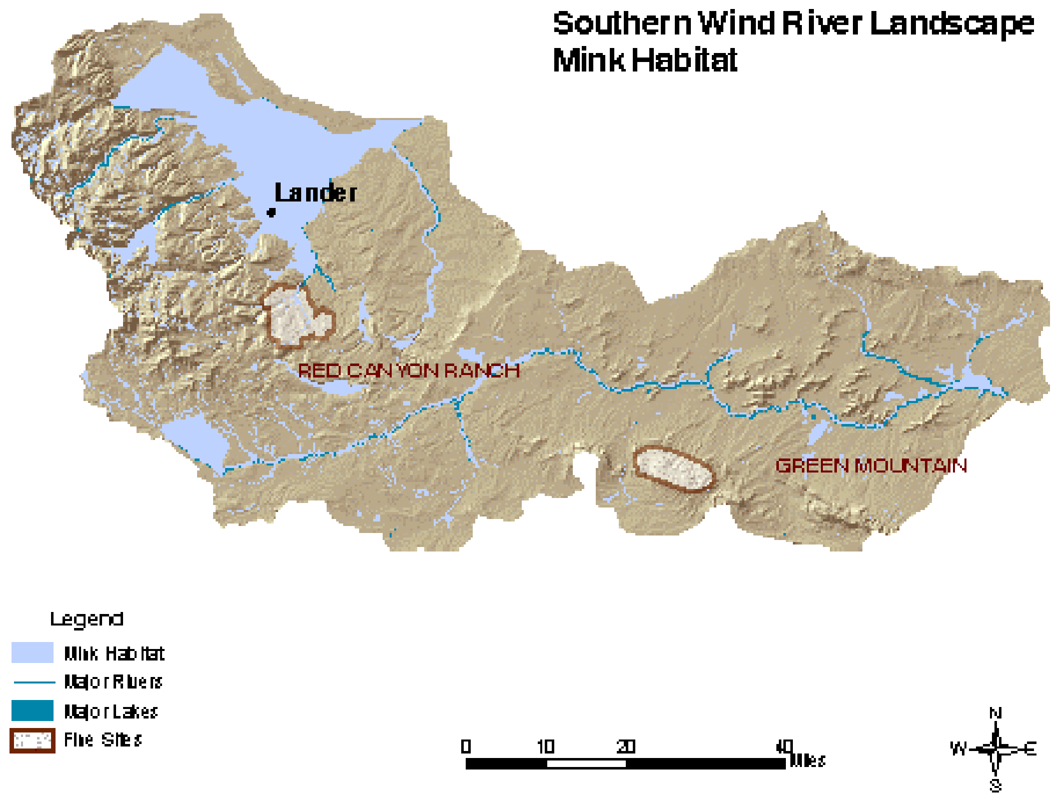
Map 7. Red Canyon Ranch – Surface Features



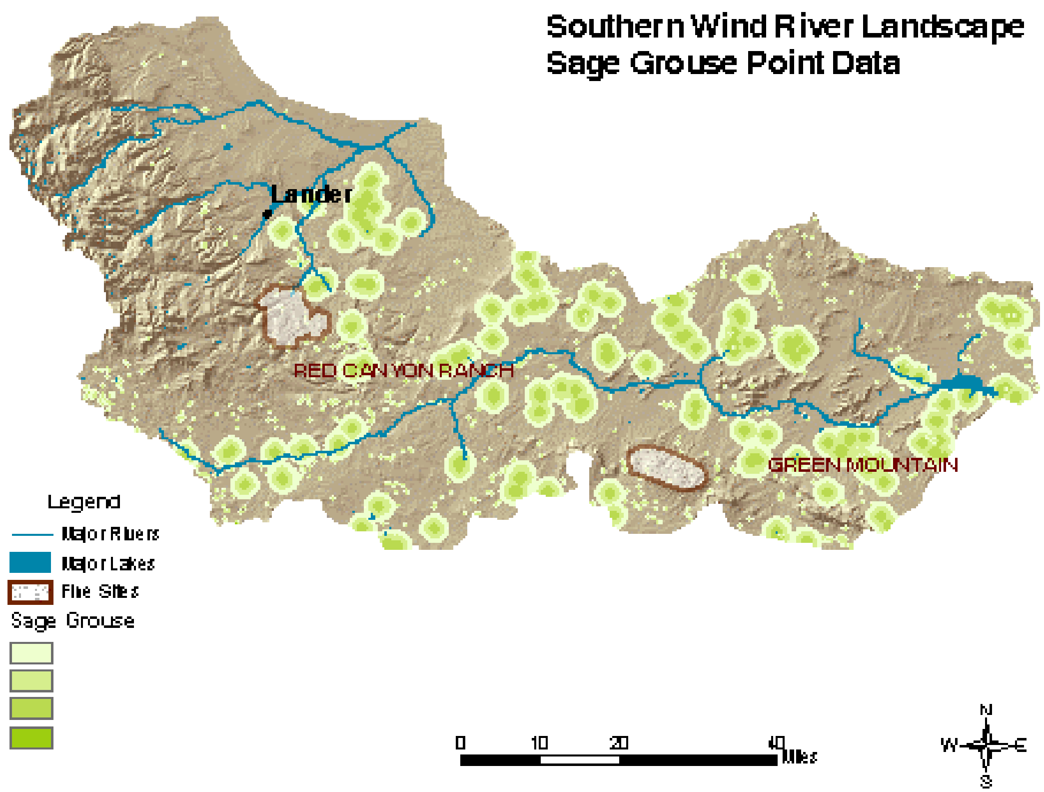
Map 8. Green Mountain – Surface Features



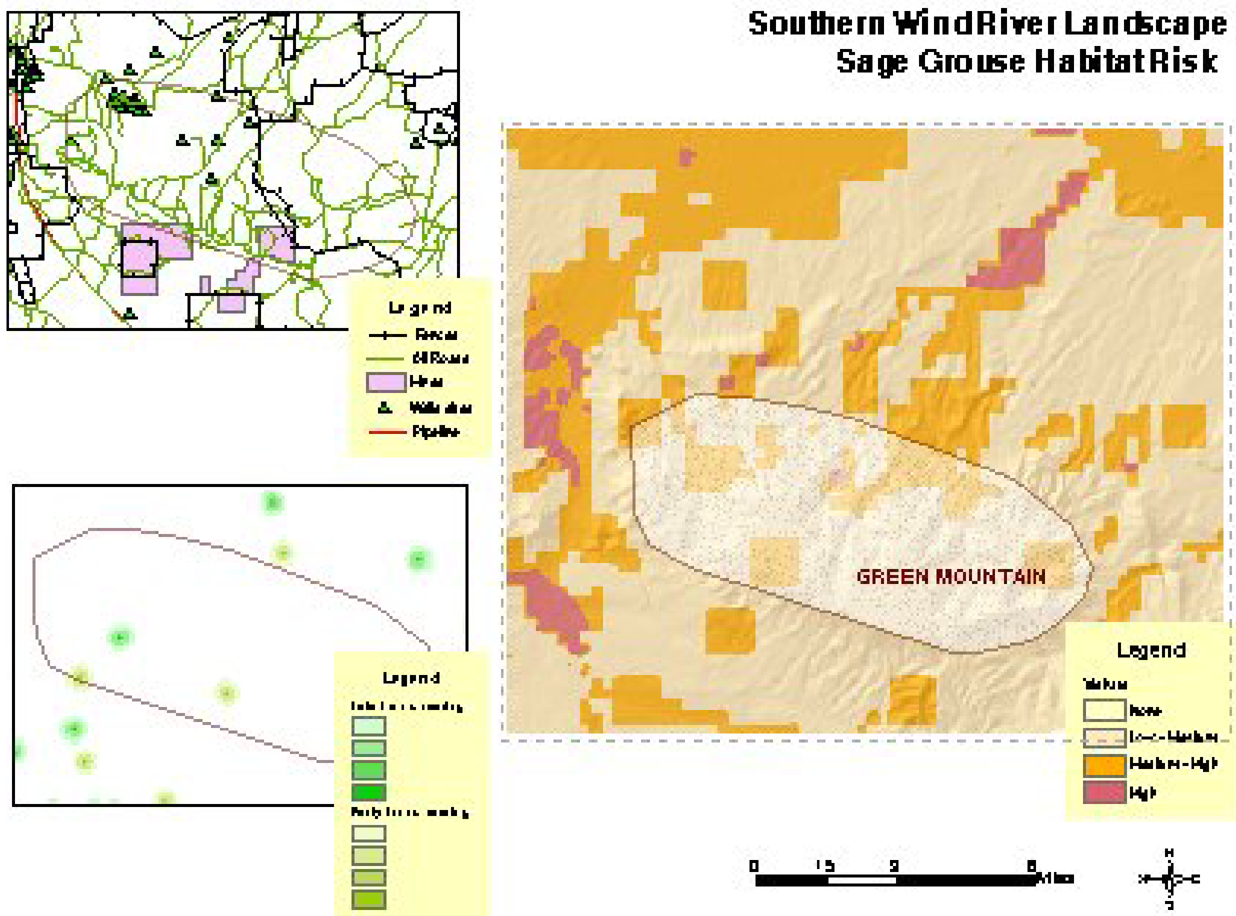
Map 9. Southern Wind River Landscape – Mule Deer Habitat



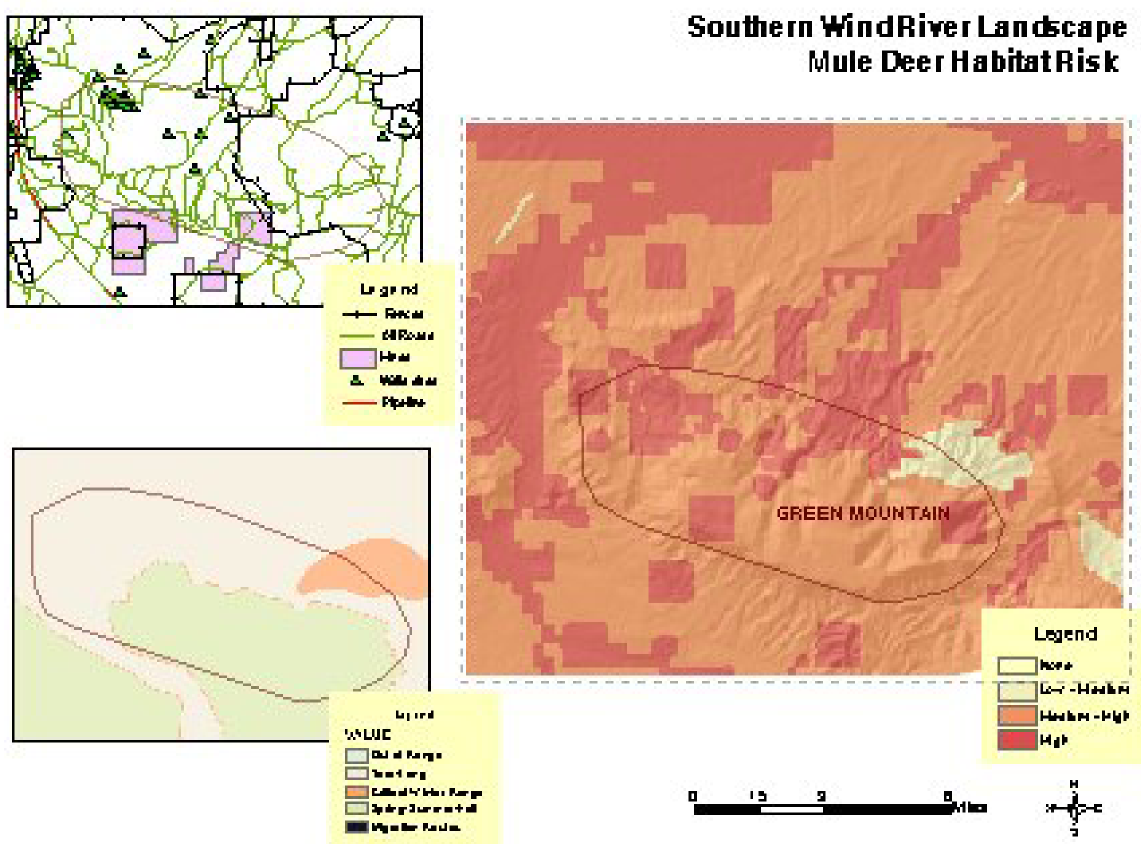
Map 10. Southern Wind River Landscape – Mink Habitat



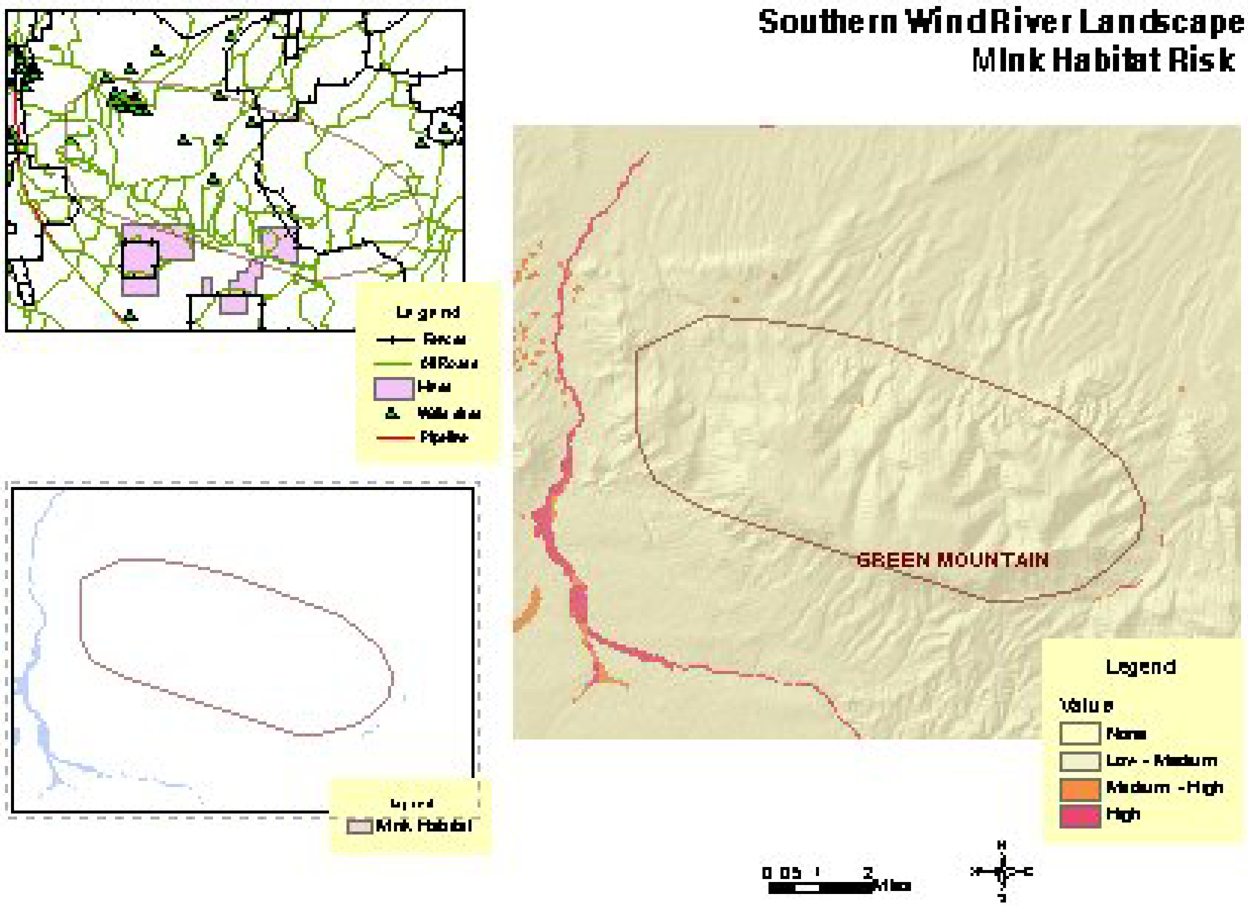
Map 11. Southern Wind River Landscape – Sage Grouse Point Data



Map 12. Green Mountain sage grouse risk map and associated surface features and habitat type layers.



Map 13. Green Mountain mule deer risk map and associated surface features and habitat type layers.



Map 14. Green Mountain mink risk map and associated surface features and habitat type layers.

Appendix B.

Interview Questionnaire and Results

Mule Deer Questionnaire Results

Agency Involvement:
USFS – Shoshone NF, Range
BLM - Range

Questions:

A. Topic: Establishing risk(s) to mule deer habitat:

1. Is there risk to mule deer habitat?

YES – Medium (32% - discrete probability value)
Low risk

2. What are the risks to habitat?

Anecdote: Habitat fragmentation of shrubland habitat and Wyoming big sagebrush – fragmentation from land uses, specifically along the "Lander slope" resulting from rural subdivisions.
In addition, there are no economic incentives to keep land- selling for second homes causes pressure on the habitat and the populations. Drought posses a risk but is natural. Irrigation and municipal uses hurt habitat. The quality of habitat is reduced due to these pressures and changes in landscape.
Prescribed fire and any risk will decrease with changes in grazing practices affecting critical winter range.

B. Topic: Human-related activities – Roads:

1. Do roads posse a risk to mule deer habitat?
YES – Medium risk
NO – low risk (32% - discrete probability value)

2. What are those risks?
Anecdote: Risks may be possed by hunter access and antler hunting

3. Does road type matter in terms of risk to mule deer habitat?
YES

4. If so, do primary roads posse a risk to mule deer habitat?

YES - LOW & HIGH (52% - discrete probability value)

5. Does density of primary roads posse a risk?
YES – MEDIUM & HIGH (66% - discrete probability value)

6. Rate the following primary road densities as posing risk?
   a. One mile/square mile
   LOW (both) (21% - discrete probability value)

   b. Two miles/square mile
   MEDIUM (49% - discrete probability value)

   c. 3 or more mi./square mile
   MEDIUM & HIGH (66% - discrete probability value)

7. Is there a risk to mule deer habitat from secondary/improved roads?

YES – MEDIUM (27% discrete probability value)
NO - LOW

8. Rate the following road densities on posing risk?

   a. One mile/square mile
   LOW (21% discrete probability value)

   b. Two miles/square mile
   MEDIUM (49% discrete probability value)

   c. 3 or more mi./square mile
   HIGH (83% discrete probability value)

9. Is there a risk to mule deer habitat from unimproved roads?

YES - MEDIUM (27% discrete probability value)
NO – LOW

10. Does density of unimproved roads posse risk to mule deer habitat?

YES – LOW (49% discrete probability value)

11. Rate the following unimproved road densities as posing risk.

a. One mile/square mile
LOW (21% discrete probability value)

b. Two miles/square mile
MEDIUM (49% discrete probability value)

c. 3 or more mi./square mile
HIGH (83% discrete probability value)

12. Do roads posse risk to seasonal mule deer habitat?

YES – MEDIUM (44% discrete probability value)
NOT SURE

13. Rate the risk to each seasonal habitat type from roads.

a. Winter Range
HIGH & LOW (52% discrete probability value)

b. Summer
MEDIUM & LOW (35% discrete probability value)

c. Migration
LOW & MEDIUM (35% discrete probability value)

d. Yearlong (21% discrete probability value)
LOW

C. Topic: Other Surface Features: Energy Development

1. Does energy development posse risk to mule deer habitat?

YES - LOW (16% discrete probability value)

Anecdote: site specific in winter range; higher risk in winter range

2. What are the risks posed by energy development to mule deer habitat?

Fences

3. Rate the risk to each seasonal habitat type from energy development.

   a. Winter
   MEDIUM (49% discrete probability value)

   b. Summer
   LOW (21% discrete probability value)

   c. Migration
   LOW & MEDIUM (35% discrete probability value)

   d. Yearlong
   LOW & MEDIUM (35% discrete probability value)

4. Do well pads posse a risk to mule deer habitat?

   YES

5. At what proximity to mule deer habitat do well pads posse a risk?

   a. 0 – 100m
   HIGH (83% discrete probability value)

   b. 100 – 300m
   LOW & MEDIUM (35% discrete probability value)

   c. 300 – 500m
   LOW (both) (21% discrete probability value)

6. Rate the risk to each seasonal habitat type from well pads.

   a. Winter Range
   HIGH & LOW (52% discrete probability value)

   b. Summer
   MEDIUM & LOW (35% discrete probability value)

   c. Migration
   HIGH & MEDIUM (66% discrete probability value)

   d. Yearlong
   LOW & MEDIUM (35% discrete probability value)

7. Do pipelines posse a risk to mule deer habitat?

YES – HIGH (83% discrete probability value)

Anecdote: dependent on time – within 3 – 5 years risks are higher and improves after 5 yrs.

8. At what proximity to mule deer habitat pipelines posse a risk?

a. 0 – 100m
LOW (21% discrete probability value)

b. 100 – 300m
LOW (21% discrete probability value)

c. 300 – 500m
LOW (21% discrete probability value)

9. Rate the risk to each seasonal habitat type from pipelines.

a. Winter Range
LOW (21% discrete probability value)

b. Summer
MEDIUM & LOW (35% discrete probability value)

c. Migration
LOW & MEDIUM (35% discrete probability value)

d. Yearlong
LOW & MEDIUM (35% discrete probability value)

D. Topic: Other Surface Features: Land Development

1. Fences posse a risk to mule deer habitat?

YES – MEDIUM (35% discrete probability value)
NO – LOW

2. Does land conversion posse a risk to mule deer habitat?

YES – HIGH (83% discrete probability value)

3. Do subdivisions posse a risk to mule deer habitat?

   YES - HIGH (83% discrete probability value)

4. Rate the risk to each seasonal habitat type from development.

   a. Winter Range
   HIGH & LOW (52% discrete probability value)

   b. Summer
   MEDIUM & LOW (35% discrete probability value)

   c. Migration
   LOW & MEDIUM (35% discrete probability value)

   d. Yearlong
   LOW & MEDIUM (35% discrete probability value)

5. What other risks does land conversion posse to mule deer habitat?

Anecdote: Dogs, pet-related problems associated with land conversion/subdivisions particularly in winter range; vehicles causing displacement and stressors on range as well as the structures associated with development such as fences that inhibit movement; and, trash.

6. At what proximity do houses posse risk to mule deer habitat?

   MEDIUM (49% discrete probability value)

E. Optimal numbers & carrying capacity of landscape for mule deer?

Anecdote: Unknown data but competition with sheep and cattle grazing regimes can posse risk. Duration and prescription of grazing regimes influence habitat.

F. Information Sources

Personal observation and experience

Working relationships with other professionals
Professional meetings and conferences
Scientific literature
Landowners and hunters

Mink Questionnaire Results

Agency Involvement:
USFS – Shoshone NF, Range
BLM - Range

Questions:

D. Topic: Establishing risk(s) to mink habitat:

1. Is there risk to mule deer habitat?
   YES – Medium (Both) (49% - discrete probability value)

2. What are the risks to habitat?

E. Topic: Human-related activities – Roads:

1. Do roads posse a risk to mink habitat?
   YES – medium risk (49% - discrete probability value)

2. Does road type matter in terms of risk to mink habitat?

   YES

3. If so, do primary roads posse a risk to mink habitat?

   YES - LOW & MEDIUM (35% - discrete probability value)

4. Does density of primary roads posse a risk?

   NO – LOW (16% - discrete probability value)

5. Rate the following primary road densities as posing risk?

   a. One mile/square mile
   LOW (both) (21% - discrete probability value)

b. Two miles/square mile
LOW (21% - discrete probability value)

c. 3 or more mi./square mile
LOW (21% - discrete probability value)

6. Is there a risk to mink habitat from secondary/improved roads?

YES – LOW (21% discrete probability value)

7. Rate the following road densities on posing risk?

a. One mile/square mile
LOW & NOT SURE (16% discrete probability value)

b. Two miles/square mile
NOT SURE & MEDIUM (44% discrete probability value)

c. 3 or more mi./square mile
MEDIUM & HIGH (49% discrete probability value)

8. Is there a risk to mink habitat from unimproved roads?

YES - LOW (21% discrete probability value)

9. Rate the following unimproved road densities as posing risk.

a. One mile/square mile
LOW (21% discrete probability value)

b. Two miles/square mile
MEDIUM & LOW (35% discrete probability value)

c. 3 or more mi./square mile
LOW & MEDIUM (35% discrete probability value)

10. Do roads posse risk to seasonal mink habitat?
NO
LOW (16% discrete probability value)

F. Topic: Other Surface Features: Energy Development

1. Does energy development posse risk to mink habitat?

   YES - LOW (21% discrete probability value)

Anecdote: water quality

2. What are the risks posed by energy development to mule deer habitat?

   NONE

3. Do well pads posse a risk to mink habitat?

   NO (.05% discrete probability value)

4. At what proximity to mink habitat do well pads posse a risk?

   a. 0 – 100m HIGH (83% discrete probability value)

   b. 100 – 300m LOW (21% discrete probability value)

   c. 300 – 500m LOW (21% discrete probability value)

5. Do pipelines posse a risk to mink habitat?

   YES – MEDIUM (44% discrete probability value)
   NOT SURE

6. At what proximity to mink habitat pipelines posse a risk?

   a. 0 – 100m
   HIGH (83% discrete probability value)

   b. 100 – 300m
   LOW (21% discrete probability value)

   c. 300 – 500m
   LOW (21% discrete probability value)

D. Topic: Land Development

1. Do fences posse a risk to mink habitat?

NO (.05 % discrete probability value)

2. Does land conversion posse a risk to mink habitat?

YES – MEDIUM (49% discrete probability value)

3. Do subdivisions posse a risk to mink habitat?

YES - MEDIUM (49% discrete probability value)

4. What other risks does land conversion posse to mink habitat?

Anecdote: Dogs, pet-related problems associated with land conversion or subdivisions particularly roads causing loss of habitat, spraying lands with pesticides.

5. At what proximity do houses posse risk to mink habitat?

Anecdote: The species is adaptive to human activities; but shy and will avoid audible and visual disturbances

E. Optimal numbers & carrying capacity of landscape for mink?

Unknown Data

F. Information Sources

Personal observation and experience
Working relationships with other professionals
Professional meetings and conferences
Scientific literature
Landowners and hunters

Sage Grouse Questionnaire Results

Agency Involvement:
BLM – Lander Region, Wildlife Biologist
Wyoming Game & Fish Dept., Wildlife Biologist

Questions:

A. Topic: Establishing risk(s) to sage grouse habitat:

1. Is there risk to sage grouse habitat?

YES – Medium (Both) (49% - discrete probability value)

2. What are the risks to habitat?

Anecdote: Grazing practices (seasonal conflicts, duration in each allotment), range development, drought, vegetation requirements are not met, fire suppression, fire rehabilitation, land- use planning inadequate and does not address species of concern, mineral development, land exchanges, waste and landfills, recreation management (OHV), development in riparian habitat, wild horses, conflicting wildlife management, excessive numbers of elk, grasses and forbes not available, landscape/habitat fragmentation, habitat changes too wide, development, fences, oil/gas development (coal-bed methane), subdivisions, climate, less insects & poor quality of habitat, susceptibility to predation, downward trend.

B. Topic: Human-related activities – Roads:

1. Do roads posse a risk to sage grouse habitat?

YES – low risk (21% - discrete probability value)

Anecdote: Site- specific

2. What are those risks?

Anecdote: Type of road matters, topography, slope, effects of roads that impact area such as nesting sites – the closer the road = increased success but they provide corridors for predators, type of road use matters as well.

3. Does road type matter in terms of risk to sage grouse? YES (both)

4. If so, do primary roads posse a risk to sage grouse habitat?

YES - LOW
NO – LOW (16% - discrete probability value)

5. Does density of primary roads posse a risk?

YES – LOW
NO – LOW (16% - discrete probability value)

6. Rate the following primary road densities as posing risk?

a. One mile/square mile
LOW (both) (21% - discrete probability value)

b. Two miles/square mile
MEDIUM & HIGH (66% - discrete probability value)

c. 3 or more mi./square mile
HIGH (both) (83% - discrete probability value)

7. Is there a risk to sage grouse habitat from secondary/improved roads?

YES (both)
MEDIUM (49% discrete probability value)

8. Rate the following road densities on posing risk?

a. One mile/square mile
LOW & MEDIUM (35% discrete probability value)

b. Two miles/square mile
MEDIUM & HIGH (66% discrete probability value)

c. 3 or more mi./square mile
HIGH (83% discrete probability value)

9. Is there a risk to sage grouse habitat from unimproved roads?

YES - MEDIUM & HIGH (66% discrete probability value)

10. Does density of unimproved roads posse risk to sage grouse habitat?

YES

11. Rate the following unimproved road densities as posing risk.

a. One mile/square mile
LOW & MEDIUM (35% discrete probability value)

b. Two miles/square mile
LOW & MEDIUM (35% discrete probability value)

c. 3 or more mi./square mile
HIGH (both) (83% discrete probability value)

12. Do roads posse risk to seasonal sage grouse habitat?

YES – LOW & NOT SURE (16% discrete probability value)

13. Rate the risk to each seasonal habitat type from roads.

a. Winter Range
HIGH & LOW (51% discrete probability value)

b.Reproduction/Lek
LOW (21% discrete probability value)

c. Early brood rearing
LOW & MEDIUM (49% discrete probability value)

d. late brood rearing
MEDIUM & HIGH (66% discrete probability value)

E. Topic: Other Surface Features: Energy Development

1.Does energy development posse risk to sage grouse habitat?

YES - LOW (21% discrete probability value)

Anecdote: Site- specific

2. What are the risks posed by energy development to sage grouse habitat?

Anecdote: Density of development.
Risk is attributed to fragmentation of habitat from roads, noise related to wells, compressor plants, road traffic = lek abandonment and other human uses such as overall disturbance, habitat loss from development construction and facilities.

4 wells/section and the number of roads = 2.5 mile/one square mile
MEDIUM RISK *(49% discrete probability value)*

16 wells/section and the number of roads = 2.5 mile/square mile of
HIGH RISK *(83% discrete probability value)*

4. Rate the risk to each seasonal habitat type from energy development.

a. Winter Range
YES-LOW (21% discrete probability value)

b. Reproduction
YES-MEDIUM (49% discrete probability value)

c. EBR
YES
MEDIUM (49% discrete probability value)

d. LBR
LOW (21% discrete probability value)

5. Do well pads posse a risk to sage grouse habitat?

YES - LOW (21% discrete probability value)

Anecdote: may improve habitat

6. At what proximity to sage grouse habitat do well pads posse a risk?

a. 0 – 100m
HIGH (83% discrete probability value)

b. 100 – 300m
LOW & MEDIUM (35% discrete probability value)

c. 300 – 500m
LOW (both) (21% discrete probability value)

7. Rate the risk to each seasonal habitat type from well pads.

a. Winter Range
YES
LOW (21% discrete probability value)

b. Reproduction
YES
HIGH (both) (83% discrete probability value)

c. EBR
YES
MEDIUM & HIGH (66% discrete probability value)

d. LBR (35% discrete probability value)
LOW & MEDIUM

8. Do pipelines posse a risk to sage grouse habitat?

YES – MEDIUM (49% discrete probability value)

Anecdote: risk from fragmentation, pipelines become predator travel corridors, roads associated with pipelines, and the physical reduction of high quality habitat = loss of habitat particularly in lower elevations.

9. At what proximity to sage grouse habitat pipelines posse a risk?

a. 0 – 100m
HIGH (83% discrete probability value)

b. 100 – 300m
MEDIUM & LOW (35% discrete probability value)

c. 300 – 500m
LOW (21% discrete probability value)

10. Rate the risk to each seasonal habitat type from pipelines.

a. Winter Range
NO & LOW (13% discrete probability value)

b. Reproduction
NO & MEDIUM (32% discrete probability value)

c. EBR
YES
MEDIUM & LOW (35% discrete probability value)

d. LBR
LOW (21% discrete probability value)

D. Topic: Land Development

1. Do fences posse a risk to sage grouse habitat?

YES – LOW (21% discrete probability value)

Anecdote: Risk attributed to ridge top collisions, predator perches & grazing associated with fenced areas. This risk is indirectly related as well to grazing regimes. High intensity grazing = high risk and season-long grazing = high risk. In addition, livestock travel along fence lines.

2. Does land conversion posse a risk to sage grouse habitat?

YES – HIGH (83% discrete probability value)

3. Do subdivisions posse a risk to sage grouse habitat?

YES - LOW
NO – LOW (16% discrete probability value)

4. Rate the risk to each seasonal habitat type from development.

a. Winter Range (35% discrete probability value)
YES – MEDIUM/LOW

b. Reproduction (83% discrete probability value)
YES - HIGH

c. EBR (66% discrete probability value)
YES – MEDIUM/HIGH

e. LBR (21% discrete probability value)
YES - LOW

5. At what proximity do houses posse risk to sage grouse habitat

HIGH – (both) (83% discrete probability value)

E. Optimal numbers & carrying capacity of landscape for sage grouse?
Unknown.

F. Information Sources

Personal observation and experience
Working relationships with other professionals
Professional meetings and conferences
Scientific literature
Landowners and hunters

Appendix C.

BBN Models

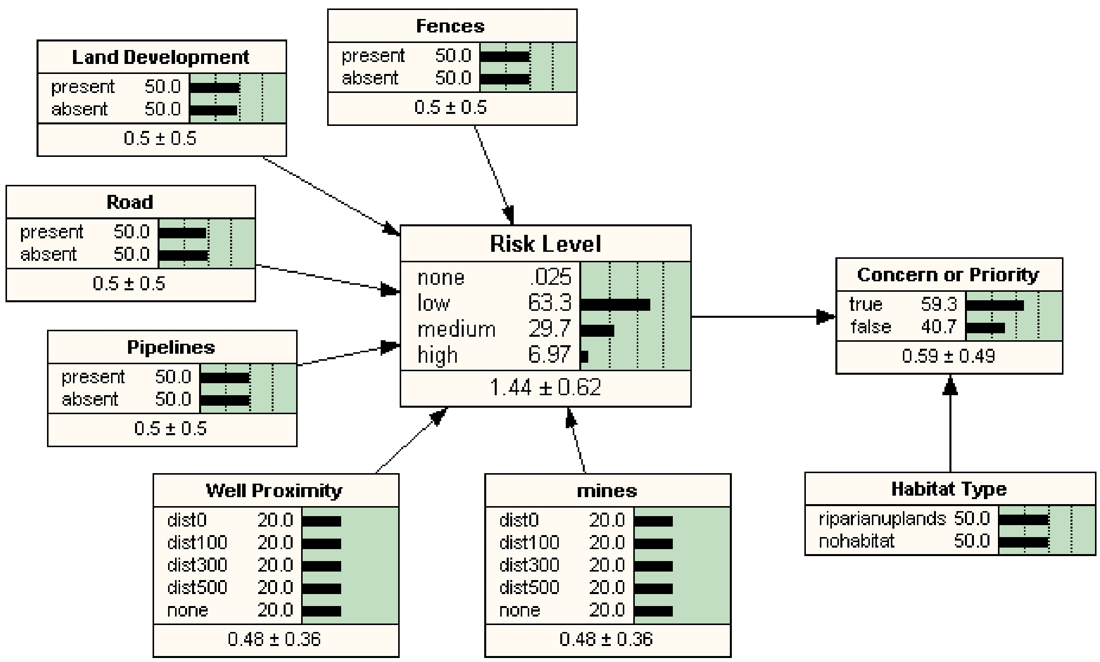


Figure 1. Bayesian Belief Network Mink Model using Netica 1.12 Software, Norsys, Inc.

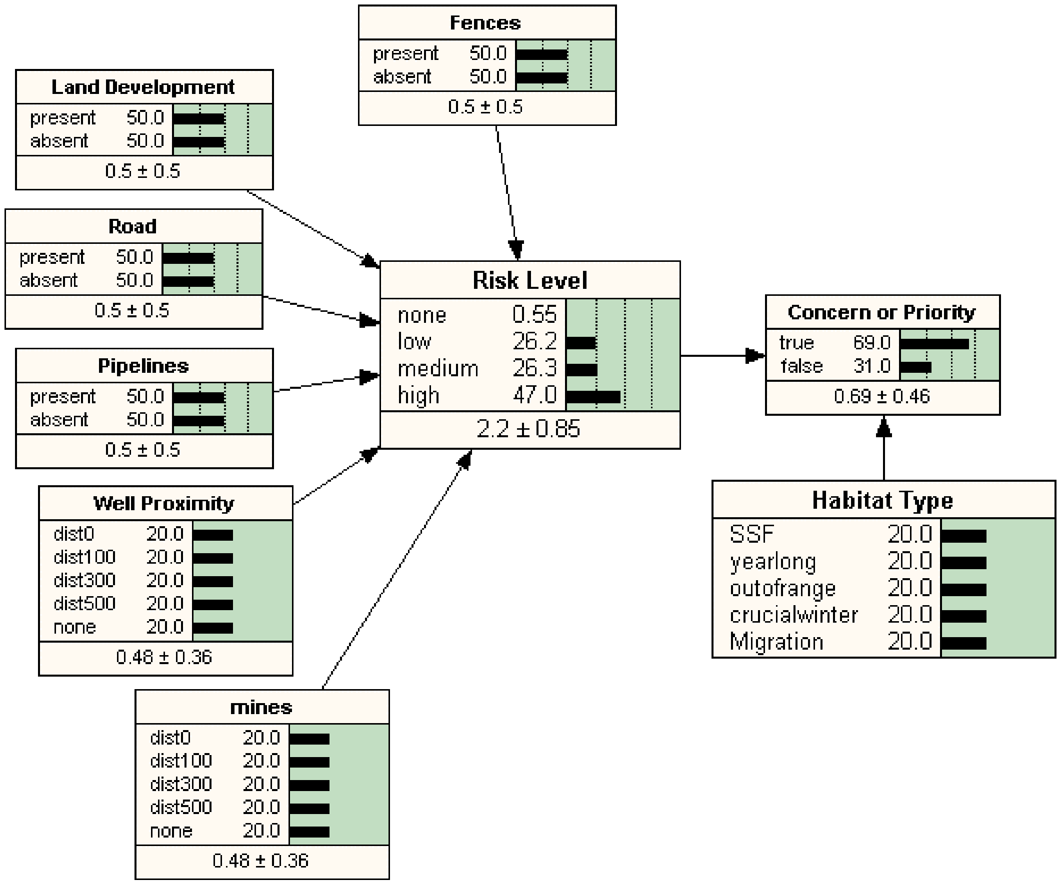


Figure 2. Bayesian Belief Network Mule Deer Model using Netica 1.12 Software, Norsys, Inc.

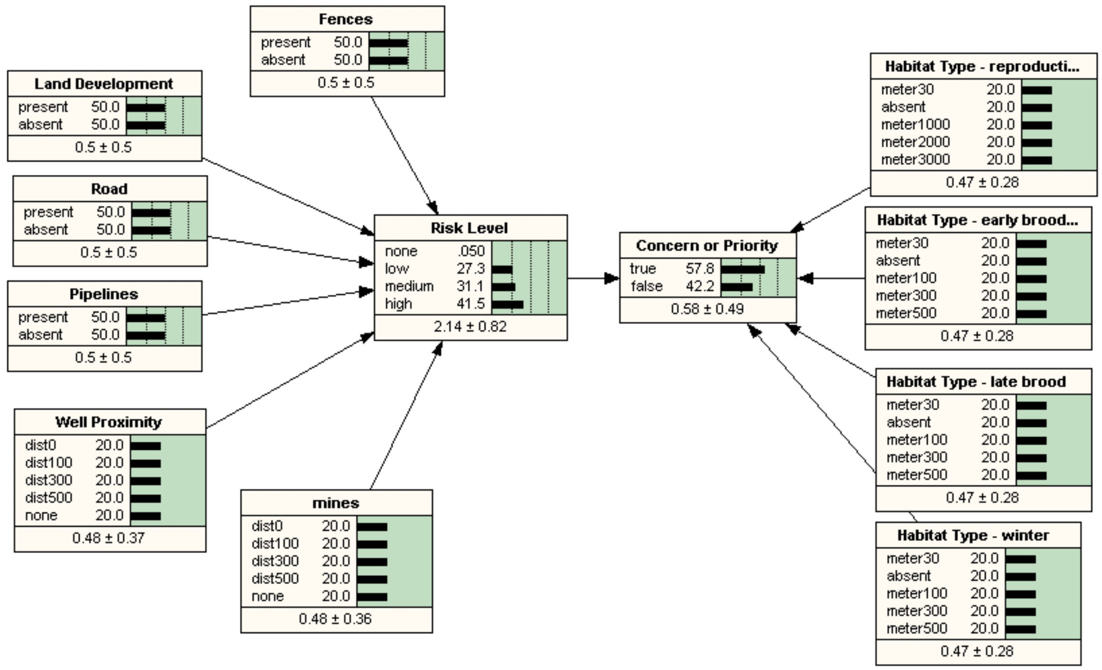


Figure 3. Bayesian Belief Network Sage Grouse Model using Netica 1.12 Software, Norsys, Inc.

Appendix D.

Conditional Probability Tables

Develop	Well_Prox	Road	PipeLine	fences	mines	none	low	medium	high
present	dist0	present	present	present	dist0	0.0500	30.950	28.000	41.000
present	dist0	present	present	present	dist100	0.0500	30.950	28.000	41.000
present	dist0	present	present	present	dist300	0.0500	30.950	28.000	41.000
present	dist0	present	present	present	dist500	0.0500	30.950	28.000	41.000
present	dist0	present	present	present	none	0.0500	30.950	28.000	41.000
present	dist0	present	present	absent	dist0	0.000	31.000	27.000	42.000
present	dist0	present	present	absent	dist100	0.000	31.000	27.000	42.000
present	dist0	present	present	absent	dist300	0.000	31.000	27.000	42.000
present	dist0	present	present	absent	dist500	0.000	31.000	27.000	42.000
present	dist0	present	present	absent	none	0.000	31.000	27.000	42.000
present	dist0	present	absent	present	dist0	0.0500	29.000	30.000	40.950
present	dist0	present	absent	present	dist100	0.0500	29.000	30.000	40.950
present	dist0	present	absent	present	dist300	0.0500	29.000	30.000	40.950
present	dist0	present	absent	present	dist500	0.0500	29.000	30.000	40.950
present	dist0	present	absent	present	none	0.0500	29.000	30.000	40.950
present	dist0	present	absent	absent	dist0	0.000	29.000	31.000	40.000
present	dist0	present	absent	absent	dist100	0.000	29.000	31.000	40.000
present	dist0	present	absent	absent	dist300	0.000	29.000	31.000	40.000
present	dist0	present	absent	absent	dist500	0.000	29.000	31.000	40.000
present	dist0	present	absent	absent	none	0.000	29.000	31.000	40.000

Figure 1. An example of the Mink BBN model Conditional Probability Table.

Develop	Well_Prox	Road	PipeLine	fences	mines	none	low	medium	high
present	dist0	present	present	present	dist0	0.0900	9.910	20.000	70.000
present	dist0	present	present	present	dist100	0.0900	9.910	20.000	70.000
present	dist0	present	present	present	dist300	0.0900	9.910	20.000	70.000
present	dist0	present	present	present	dist500	0.0900	9.910	20.000	70.000
present	dist0	present	present	present	none	0.0900	9.910	20.000	70.000
present	dist0	present	present	absent	dist0	0.810	11.190	18.000	70.000
present	dist0	present	present	absent	dist100	0.810	11.190	18.000	70.000
present	dist0	present	present	absent	dist300	0.810	11.190	18.000	70.000
present	dist0	present	present	absent	dist500	0.810	11.190	18.000	70.000
present	dist0	present	present	absent	none	0.810	11.190	18.000	70.000
present	dist0	present	absent	present	dist0	0.700	12.300	17.000	70.000
present	dist0	present	absent	present	dist100	0.700	12.300	17.000	70.000
present	dist0	present	absent	present	dist300	0.700	12.300	17.000	70.000
present	dist0	present	absent	present	dist500	0.700	12.300	17.000	70.000
present	dist0	present	absent	present	none	0.700	12.300	17.000	70.000
present	dist0	present	absent	absent	dist0	0.700	12.300	17.000	70.000
present	dist0	present	absent	absent	dist100	0.700	12.300	17.000	70.000
present	dist0	present	absent	absent	dist300	0.700	12.300	17.000	70.000
present	dist0	present	absent	absent	dist500	0.700	12.300	17.000	70.000

Figure 2. An example of the Mule Deer BBN model Conditional Probability Table.

Develop	Well_Prox	Road	PipeLine	fences	mines	none	low	medium	high
present	dist0	present	present	present	dist0	0.0500	5.000	20.000	74.950
present	dist0	present	present	present	dist100	0.0500	5.000	20.000	74.950
present	dist0	present	present	present	dist300	0.0500	5.000	20.000	74.950
present	dist0	present	present	present	dist500	0.0500	5.000	20.000	74.950
present	dist0	present	present	present	none	0.0500	5.000	20.000	74.950
present	dist0	present	present	absent	dist0	0.0500	5.000	20.000	74.950
present	dist0	present	present	absent	dist100	0.0500	5.000	20.000	74.950
present	dist0	present	present	absent	dist300	0.0500	5.000	20.000	74.950
present	dist0	present	present	absent	dist500	0.0500	5.000	20.000	74.950
present	dist0	present	present	absent	none	0.0500	5.000	20.000	74.950
present	dist0	present	absent	present	dist0	0.0500	14.000	24.000	61.950
present	dist0	present	absent	present	dist100	0.0500	14.000	24.000	61.950
present	dist0	present	absent	present	dist300	0.0500	14.000	24.000	61.950
present	dist0	present	absent	present	dist500	0.0500	14.000	24.000	61.950
present	dist0	present	absent	present	none	0.0500	14.000	24.000	61.950
present	dist0	present	absent	absent	dist0	0.0500	14.000	24.000	61.950
present	dist0	present	absent	absent	dist100	0.0500	14.000	24.000	61.950
present	dist0	present	absent	absent	dist300	0.0500	14.000	24.000	61.950
present	dist0	present	absent	absent	dist500	0.0500	14.000	24.000	61.950

Figure 3. An example of the Sage Grouse BBN model Conditional Probability Table.

Appendix E.

Sensitivity Analyses

MINK SENSITIVITY ANALYSIS RESULTS

Sensitivity of 'risk' due to a finding at another node:

Node	Variance Reduction	Mutual Info	Variance of Belief
risk	0.3859	1.20908	0.2927771
Develop	0.063	0.13866	0.0248282
Well_Prox	0.02419	0.09994	0.0038020
Concern	0.01197	0.02468	0.0062524
Road	0.0003713	0.00076	0.0001947
PipeLine	9.529e-005	0.00019	0.0000279
fences	1.284e-005	0.00030	0.0000031
HabitatType	0	0.00000	0.0000000
mines	0	0.00000	0.0000000

Sensitivity of 'Concern' due to a finding at another node:

Node	Variance Reduction	Mutual Info	Variance of Belief
Concern	0.2414	0.97501	0.2413886
risk	0.008059	0.02468	0.0080594
HabitatType	0.004801	0.01440	0.0048012
Develop	0.00124	0.00371	0.0012397
Well_Prox	0.0002709	0.00081	0.0002709
Road	8.465e-006	0.00003	0.0000084
PipeLine	1.594e-006	0.00000	0.0000016
fences	2.626e-007	0.00000	0.0000002
mines	0	0.00000	0.0000000

MULE DEER SENSITIVITY RESULTS

Sensitivity of 'risk' due to a finding at another node:

Node	Variance Reduction	Mutual Info	Variance of Belief
risk	0.7151	1.56649	0.4230569
Concern	0.03786	0.04170	0.0073483
Develop	0.01777	0.02119	0.0043224
Well_Prox	0.01618	0.01818	0.0034372
Road	0.001657	0.00172	0.0003311
PipeLine	0.0002387	0.00035	0.0000443
fences	8.333e-005	0.00009	0.0000149
mines	7.143e-006	0.00002	0.0000030
HabitatType1	0	0.00000	0.0000000

Sensitivity of 'concern' due to a finding at another node:

Node	Variance Reduction	Mutual Info	Variance of Belief
Concern	0.214	0.89346	0.2139949
risk	0.01228	0.04169	0.0122789
HabitatType1	0.00905	0.02888	0.0090504
Develop	0.0003398	0.00115	0.0003397
Well_Prox	0.0002962	0.00099	0.0002962
Road	2.886e-005	0.00010	0.0000289
PipeLine	3.684e-006	0.00001	0.0000037
fences	1.326e-006	0.00000	0.0000014
mines	1.528e-007	0.00000	0.0000001

SAGE GROUSE SENSITIVITY RESULTS

Sensitivity of 'risk' due to a finding at another node:

Node	Variance Reduction	Mutual Info	Variance of Belief
risk	0.6707	1.56748	0.4344514
Concern	0.09205	0.10863	0.0164005
Develop	0.03205	0.04388	0.0082038
Well_Prox	0.01105	0.01272	0.0024641
Road	0.0006311	0.00068	0.0001160
PipeLine	0.0002443	0.00027	0.0000424
fences	2.082e-005	0.00002	0.0000038
HabitatType4	0	0.00000	0.0000000
HabitatType3	0	0.00000	0.0000000
HabitatType2	0	0.00000	0.0000000
HabitatType1	0	0.00000	0.0000000
mines	0	0.00000	0.0000000

Sensitivity of 'Concern' due to a finding at another node:

Node	Variance Reduction	Mutual Info	Variance of Belief
Concern	0.2403	0.97177	0.2402810
risk	0.03589	0.10863	0.0358880
Develop	0.001142	0.00343	0.0011416
Well_Prox	0.0004673	0.00141	0.0004673
HabitatType1	0.0002093	0.00063	0.0002093
HabitatType4	5.744e-005	0.00017	0.0000575
HabitatType3	5.744e-005	0.00017	0.0000574
Road	3.001e-005	0.00009	0.0000300
HabitatType2	2.245e-005	0.00007	0.0000225
PipeLine	1.265e-005	0.00004	0.0000127
fences	9.794e-007	0.00000	0.0000010
mines	0	0.00000	0.0000000