2014

Proactive Management of Pneumonia Epizootics in Bighorn Sheep in Montana

Sarah N. Sells
University of Montana - Missoula

PROACTIVE MANAGEMENT OF PNEUMONIA EPIZOOTICS

IN BIGHORN SHEEP IN MONTANA

By

SARAH NELSON SELLS

B.S. in Fisheries and Wildlife Science, Oregon State University, Corvallis, Oregon, 2005

Thesis

presented in partial fulfillment of the requirements
for the degree of

Master of Science
in Wildlife Biology

The University of Montana
Missoula, MT

December 2014

Approved by:

Sandy Ross, Dean of The Graduate School
Graduate School

Mike Mitchell, Chair
Montana Cooperative Wildlife Research Unit

Paul Lukacs
Wildlife Biology

Paul R. Krausman
Wildlife Biology

Neil Anderson
Montana Fish, Wildlife and Parks

Sells, Sarah, M.S., December 2014 Wildlife Biology

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Chairperson: Mike Mitchell

Pneumonia epizootics are a major challenge for management of bighorn sheep (*Ovis canadensis*), often causing high mortality and subsequent long-term impacts that may continue for decades. There have been at least 22 epizootics in herds in Montana from 1979–2013, including 1 that led to a herd's extirpation, several that appear to be affecting herds up to 3 decades later, and 11 in the last 6 years. The disease is complex and associated risk factors are poorly understood. A lack of tools to help predict and proactively manage risk of pneumonia epizootics in attempt to prevent die-offs has led to reactive rather than proactive management. We developed risk and decision models to facilitate proactive management of pneumonia epizootics in bighorn sheep in Montana. Our risk model identifies risk factors and addresses biological questions about risk. We used Bayesian logistic regression with repeated measures to analyze 43 herds that experienced 22 epizootics out of 637 herd years from 1979–2013. Within an area of high risk for pathogen exposure (a herd's distribution plus a 14.5-km buffer), a herd's odds of a pneumonia epizootic increased >1.5 times per additional unit of private land, >3.3 times if domestic sheep or goats were used for weed control, and >10.2 times if the herd or its neighbors had a pneumonia epizootic since 1979. A herd at medium density compared to low had >5.2 times greater odds of a pneumonia epizootic, and at high density had nearly 15 times greater odds. Our decision model incorporates predictions from the risk model and uses a structured decision making approach to help make more proactive decisions about how to best manage herds, given herd-specific probabilities of pneumonia epizootics and management objectives. The model addresses uncertainty, risk tolerance, and the multi-objective nature of management of bighorn sheep while providing a consistent, transparent, and deliberative approach for making decisions. The risk and decision models are unique tools that will help wildlife agencies more proactively address pneumonia epizootics in bighorn sheep while providing a case study for developing similar tools for proactive management of other wildlife diseases.

ACKNOWLEDGMENTS

I cannot communicate the extent of my gratitude to the innumerable people who made this work possible and contributed to my professional and personal growth. I thank Montana Fish, Wildlife and Parks and the Montana Cooperative Wildlife Research Unit for funding this project. I am extremely grateful to my advisor, Mike Mitchell, for providing me the opportunity to work on this project with the Coop Unit and MFWP, and for endless support and mentoring. Mike taught me a great deal about scientific research and communication and was one of my greatest supporters through trying times. I feel very lucky to say that Mike has also been a friend, from whom I received a crash course in humor and taking some things in life a little less seriously. I am also grateful to my committee, Paul Lukacs, Paul R. Krausman, and Neil Anderson, for their invaluable support and guidance throughout this project.

My primary MFWP collaborators, Neil Anderson, Jennifer Ramsey, and Justin Gude, provided critical knowledge, assistance, and expert advice throughout this project. I thank biologists and employees of MFWP, the U.S. Fish and Wildlife Service, Bureau of Land Management, U.S. Forest Service, U.S. Geological Survey, National Park Service, Confederated Salish and Kootenai Tribes, Chippewa Cree Tribe, the Garrott Lab at Montana State University, Montana Conservation Science Institute, British Columbia Fish and Wildlife Branch, Idaho Fish and Game, and Wyoming Game and Fish; this project would not have been possible without the many dozens of people from these agencies and organizations who contributed data, assistance, and expertise. Matthew Nordhagen provided valuable assistance with data preparation. Paul Lukacs and Josh Nowak provided countless hours of support during the analysis phase of this project, for which I am extremely grateful and would have been lost without. My coauthors (my committee, primary MFWP collaborators, and Josh Nowak), Vickie Edwards, and 2 anonymous reviewers helped prepare and improve the risk model chapter for publication. Vickie Edwards and MFWP workshop participants Justin Gude, Neil Anderson, Jennifer Ramsey, Bruce Sterling, Mike Thompson, Julie Cunningham, Howard Burt, Brent Lonner, Shawn Stewart, and Scott Hemmer provided invaluable assistance and expertise with the decision model and analyses of representative herds. Tina Anderson, Vanetta Burton, and Jeanne Franz assisted with many administrative tasks. My lab mates, Charlie Henderson, Nate Borg, Dave Ausband, Sarah Bassing, Jeff Stetz, Mark Hurley, and Ben Jimenez, also taught me a great deal and were always there for me. I'm afraid to say the Mitchell Lab reprobates will always be friends who I can rely on for beer drinking, fascinating discussion topics, and great humor. Thank you for making this experience awesome.

Finally, I would like to thank my family. My parents are the reason I got into this field in the first place, by introducing me to the great outdoors, wild places, and wildlife. My sisters were my sidekicks in these adventures from the start. Most importantly, my partner provided more emotional support than I could ask for, helped keep me sane throughout, and made life fun, even during the toughest parts of this experience. We have been through more challenging times than we could ever have imagined this past year and a half, but your strength, courage, and will to fight have been incredible. Between the trials of grad school and (especially) everything else these days, I think we've proven that we can get through anything; we have so many future adventures ahead!

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CHAPTER 1:

INTRODUCTION TO PROACTIVE MANAGEMENT OF PNEUMONIA EPIZOOTICS IN BIGHORN SHEEP IN MONTANA

Pneumonia epizootics are a major challenge for successful management and conservation of bighorn sheep (*Ovis canadensis*; Gross et al. 2000, Cahn et al. 2011, Wehausen et al. 2011, Cassirer et al. 2013, Plowright et al. 2013). Such epizootics often include high mortality across all age classes, with implications for persistence of herds, satisfaction of stakeholders, and resource allocation by management agencies (Enk et al. 2001, Montana Fish, Wildlife and Parks [MFWP] 2010). Long-lasting effects include lamb die-offs and other sporadic pneumonia outbreaks that may continue for decades (Enk et al. 2001, Cassirer and Sinclair 2007, Cassirer et al. 2013, Plowright et al. 2013) and require extensive management such as culling (Edwards et al. 2010), augmentations (MFWP 2010), and reintroductions (Singer et al. 2000). In some cases, herds may never fully recover to pre-epizootic abundance and health (e.g., Enk et al. 2001, MFWP 2010, Cassirer et al. 2013, Plowright et al. 2013).

Due to a lack of tools to predict and proactively manage risk of pneumonia epizootics, a reactive “crisis management” response is typical following epizootic events (Woodroffe 1999, Mitchell et al. 2013). Despite many previous studies on pneumonia in bighorn sheep, risk factors that contribute to pneumonia epizootics remain unclear, as does an understanding of how available data are associated with potential risk factors and how these data could help predict epizootics. Importantly too, a means to estimate risk would not automatically imply appropriate proactive management to reduce that risk.

We developed risk and decision models to facilitate proactive management of pneumonia epizootics in bighorn sheep in Montana, based on prototypes from Mitchell et al. (2013). Our first objective was to develop an empirical risk model of pneumonia epizootics using available data that we hypothesized could contribute to epizootics in bighorn sheep. Our second objective was develop a decision model to evaluate consequences and trade-offs of potential alternative decisions given predictions of risk and the objectives and constraints of managers.

Our purpose in Chapter 2 was to develop a risk model to predict probability of pneumonia epizootics, identify risk factors, and answer biological questions about risk. We developed the model by analyzing histories of 43 herds in Montana that experienced 22 epizootics out of 637 herd years from 1979–2013. Within an area of high risk (herd distribution plus a 14.5-km buffer), odds of a pneumonia epizootic increased >1.5-fold per additional unit of private land, >3.3-fold when domestic sheep or goats were used for weed control in that area, and >10.2-fold if a herd or its neighbors within that area had a previous epizootic since 1979. Herds at medium density had >5.2-fold greater risk compared to when they were at low density and nearly 15-fold greater risk at high density. Through further analysis, we found that odds were 0.4-fold per additional unit of spring precipitation, as well. Our risk model provides 1-year predictions of probability of a pneumonia epizootic, from which long-term predictions can be calculated for use in the decision model.

Our purpose in Chapter 3 was to design and demonstrate a decision model to identify the best way to manage risk of pneumonia epizootics and clarify the decision based on structured decision making (Gregory et al. 2012, Conroy and Peterson 2013, Mitchell et al. 2013). Structured decision making (SDM) helps identify deliberative, transparent, and defensible management actions most likely to achieve desired outcomes while accounting for multiple competing objectives, uncertainty, and risk tolerance (Gregory et al. 2012, Conroy and Peterson 2013). Using the decision model, decision-makers can develop portfolios of potential management alternatives for their herds, predict risk, estimate consequences, identify risk attitude, determine weights for objectives, and calculate overall support and trade-offs for each portfolio to identify the recommended decision. In an analysis of representative herds, the model recommended various types of proactive decisions to reduce risk. These decisions were relatively insensitive to the model components we tested, meaning the recommended decisions were robust and would be the best means to manage herds based on herd-specific risk, objectives, and consequences.

The risk and decision models are unique tools that will help wildlife agencies more proactively manage risk of pneumonia epizootics in bighorn sheep. We designed the models with a simple user interface for independent use, without a need for statistical expertise, SDM expertise, or meetings and working groups typically relied upon for SDM-based decision-making. An adaptive management approach will continuously improve the models in the future and adapt them to local conditions as needed (Gregory et al. 2012, Conroy and Peterson 2013). Ultimately, too, the models are examples of the roles of risk and decision models for wildlife management. They provide a case study and foundation for future modeling efforts that will ultimately yield a more effective approach to address diverse management challenges, particularly wildlife disease issues.

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CHAPTER 2:

MODELING RISK OF PNEUMONIA EPIZOOTICS IN BIGHORN SHEEP

This is the accepted version of the following article: Sells, S. N., M. S. Mitchell, J. J. Nowak, P. M. Lukacs, N. J. Anderson, J. M. Ramsey, J. A. Gude, and P. R. Krausman. 2015. Modeling risk of pneumonia epizootics in bighorn sheep. Journal of Wildlife Management 79:2, which has been published in final form at http://onlinelibrary.wiley.com/journal/10.1002/(ISSN)1937-2817.

ABSTRACT Pneumonia epizootics are a major challenge for management of bighorn sheep (*Ovis canadensis*) affecting persistence of herds, satisfaction of stakeholders, and allocations of resources by management agencies. Risk factors associated with the disease are poorly understood, making pneumonia epizootics hard to predict; such epizootics are thus managed reactively rather than proactively. We developed a model for herds in Montana that identifies risk factors and addresses biological questions about risk. Using Bayesian logistic regression with repeated measures, we found that private land, weed control using domestic sheep or goats, pneumonia history, and herd density were positively associated with risk of pneumonia epizootics in 43 herds that experienced 22 epizootics out of 637 herd-years from 1979–2013. We defined an area of high risk for pathogen exposure as the area of each herd distribution plus a 14.5-km buffer from that boundary. Within this area, the odds of a pneumonia epizootic increased by >1.5 times per additional unit of private land (unit is the standardized % of private land where global $\bar{x}$ = 25.58% and SD = 14.53%). Odds were >3.3 times greater if domestic sheep or goats were used for weed control in a herd's area of high risk. If a herd or its neighbors within the area of high risk had a history of a pneumonia epizootic, odds of a subsequent pneumonia epizootic were >10 times greater. Risk greatly increased when herds were at high density, with nearly 15 times greater odds of a pneumonia epizootic compared to when herds were at low density. Odds of a pneumonia epizootic also appeared to decrease following increased spring precipitation (odds = 0.41 per unit increase, global $\bar{x}$

= 100.18% and SD = 26.97%). Risk was not associated with number of federal sheep and goat allotments, proximity to nearest herds of bighorn sheep, ratio of rams to ewes, percentage of average winter precipitation, or whether herds were of native versus mixed or reintroduced origin. We conclude that factors associated with risk of pneumonia epizootics are complex and may not always be from the most obvious sources. The ability to identify high-risk herds will help biologists and managers determine where to focus management efforts and the risk factors that most affect each herd, facilitating more effective, proactive management.

INTRODUCTION

Pneumonia epizootics present an important challenge for effective management of bighorn sheep (*Ovis canadensis*; Gross et al. 2000, Cahn et al. 2011, Wehausen et al. 2011, Cassirer et al. 2013, Plowright et al. 2013). Once pneumonia pathogens are introduced to a population of bighorn sheep, initial all-age mortality can exceed 80% (Enk et al. 2001, Montana Fish, Wildlife and Parks [MFWP] 2010). The pathogens also may become endemic, resulting in pneumonia outbreaks that can cycle for years to decades (Enk et al. 2001, Cassirer and Sinclair 2007, Cassirer et al. 2013, Plowright et al. 2013). Of critical concern, lamb recruitment often remains chronically low for many years following an epizootic, which further threatens a herd's long-term persistence, particularly if pre-epizootic abundance was low, mortality rates were high, or other stochastic events (e.g., environmental or demographic) occur that further suppress or push the herd to extinction (Woodroffe 1999, Singer et al. 2000*c*, Cassirer and Sinclair 2007, Cassirer et al. 2013, Plowright et al. 2013). Herds may require extensive management to recover, including removal of diseased individuals (Edwards et al. 2010), augmentation from other herds (MFWP 2010), or reintroductions (Singer et al. 2000*b*). Despite great outlays of time and expense in attempt to restore herds after a pneumonia epizootic, they may never fully recover to pre-epizootic abundance and health (e.g., Enk et al. 2001, MFWP 2010, Cassirer et al. 2013, Plowright et al. 2013).

Identifying causes and influences of pneumonia epizootics has been the goal of extensive study; the etiology remains poorly understood, however, and the need for further research is commonly cited (Monello et al. 2001; Cassaigne et al. 2010; Miller et al. 2011, 2012). Presence of certain pathogens such as *Mycoplasma ovipneumoniae* and *Mannheimia haemolytica* are likely indicative of risk (Miller et al. 2011; Besser et al. 2012*a*, *b*, 2013; Shanthalingam et al. 2014). After decades of research, however, relationships between the various known and hypothesized risk factors affecting transmission, spread, and susceptibility of the pathogens that lead to pneumonia remain unclear. A single risk factor associated with all pneumonia epizootics has yet to be found, if it exists (Miller et al. 2012). Elucidation of risk factors and novel management tools for this complicated, much-debated management challenge and serious threat to persistence of herds of bighorn sheep are much needed.

The central role of domestic sheep and goats in exposure to pathogens is well documented; pathogen transmission from domestic to bighorn sheep is the only supported hypothesis in experimental trials (Wehausen et al. 2011). Healthy captive bighorn sheep sicken and die when penned with domestic sheep (Foreyt and Jessup 1982, Onderka and Wishart 1988, Foreyt 1989, Lawrence et al. 2010) or after accidental contact with domestic sheep (Foreyt and Jessup 1982). Analysis of pathogens in epizootics of free-ranging bighorn sheep also supports the hypothesis that pathogens are transmitted between Old World Caprinae species and immunologically naïve bighorn sheep (Besser et al. 2012*b*, 2013). Proximity of bighorn sheep to grazing allotments with domestic sheep is associated with increased susceptibility to pneumonia (Monello et al. 2001) and decreased persistence of the herd over time (Singer et al. 2000*b*, 2001; Epps et al. 2004; Clifford et al. 2009; Carpenter et al. 2014). Contact with feral goats also appears to result in exposure to pathogens (Rudolph et al. 2003). Contact with sheep or goats on commercial and hobby farms or when sheep or goats are used for weed control (i.e., targeted grazing to manage noxious weeds) may result in exposure to pathogens (Miller et al. 2011, 2012; Wild Sheep Working Group 2012). Evidence also suggests herds of bighorn sheep are likely more interconnected than previously thought (Singer et al. 2000*a*, DeCesare and Pletscher 2006), and that proximity among herds may increase risk of exposure to pneumonia pathogens through such connectivity (Onderka and Wishart 1984, George et al. 2008, Edwards et al. 2010, Besser et al. 2013).

Conditions other than comingling between bighorn sheep and domestic sheep or goats may be associated with spread of and susceptibility to pneumonia pathogens, because comingling does not always quickly lead to pneumonia epizootics and some epizootics occur without known or confirmed contact (e.g., Onderka and Wishart 1984, George et al. 2008, Edwards et al. 2010). Rams have a greater tendency than ewes to make long movements (Singer et al. 2000*b*, DeCesare and Pletscher 2006, O'Brien et al. 2014), probably more so at relatively high densities (Singer et al. 2000*a*, Monello et al. 2001). Such movements increase their risk of contacting domestic sheep or other infected herds and spreading pathogens upon return to their own herds (Onderka and Wishart 1984, George et al. 2008, Besser et al. 2013). High densities of bighorn sheep may also result in high rates of contact between individuals, increasing the rate of spread of pathogens (Monello et al. 2001, Lafferty and Gerber 2002, Clifford et al. 2009). Disease processes can also be influenced by complex environmental interactions, including those that may place stress on the health and immune response of animals (Scott 1988, Wobeser 2006). Harsh winters have been associated with disease events (Monello et al. 2001, MFWP 2010), and pneumonia incidence increases in the fall and winter (Cassirer and Sinclair 2007). Harsher winter conditions may stress animals by affecting energy budgets or reducing access to adequate forage (Goodson et al. 1991, Butler et al. 2013). Low precipitation has been linked to lower lamb survival (Portier et al. 1998) and to herd extinctions (Epps et al. 2004), perhaps because dry growing seasons might increase susceptibility to disease through decreased forage quality (Enk et al. 2001, Monello et al. 2001). Herds that are augmented or reintroduced appear to be at higher risk of pneumonia than native herds, perhaps because of factors associated with reintroduction, the source herd, or the possibility that sites where herds were previously extirpated are more risky for pneumonia than where herds have not died out (Monello et al. 2001, Rudolph et al. 2007, Plowright et al. 2013).

Several models have been developed to simulate impacts of pneumonia from exposure to allotments, distance to domestic sheep, or contact with nearby infected herds of bighorn sheep and to predict population size, mortality rates, or herd persistence in relation to pneumonia (Gross et al. 2000, Clifford et al. 2009, Cassaigne et al. 2010, Cahn et al. 2011, Carpenter et al. 2014). Recent models also estimate the overall probability of transitioning between healthy and all-age, lamb-only, or adult-only pneumonia (Cassirer et al. 2013) and immune response by modeling how pneumonia exposure affects an individual's risk of dying from pneumonia (Plowright et al. 2013). Another recent model estimates probability of contact between individual bighorn sheep and allotments with domestic sheep and goats (O'Brien et al. 2014). Several models simulate the effect of management actions, primarily focused on changing management of grazing allotments (Clifford et al. 2009, Cahn et al. 2011, Carpenter et al. 2014) as well as modifying habitat, colonization of new patches, or impacts of stochastic events (Gross et al. 2000). These models predict the consequences of epizootics, but none predict risk of epizootics for individual herds (but see Clifford et al. [2009] and Carpenter et al. [2014]).

Despite the breadth of previous studies on pneumonia in bighorn sheep, state wildlife agencies generally do not have a clear understanding of risk factors contributing to epizootics in herds they manage, how data available to them might be associated with such risk factors, or how these data might be used to predict epizootics. Agencies need risk assessment models to help prioritize herds and allocate limited resources to proactively manage risk of disease (Mitchell et al. 2013). Such a model should capture variability across the range of environmental conditions in which managed herds exist; models developed under more limited spatial or temporal extents may have little predictive power. Without such models, management of pneumonia epizootics in bighorn sheep has historically been reactive, resulting in crisis management rather than proactive prevention (Woodroffe 1999).

To begin addressing this issue, Mitchell et al. (2013) developed a preliminary pneumonia risk model and proactive decision model for bighorn sheep in Montana. The goal of the risk model was to predict the likelihood of pneumonia epizootics for herds managed by Montana Fish, Wildlife and Parks (MFWP). The predictions were then used to inform the decision model designed to facilitate proactive management decisions given the objectives and constraints of managers. Their risk model was based only on expert opinion of biologists and managers and did not attempt to empirically quantify risk factors associated with pneumonia epizootics. Our objective, therefore, was to develop an empirical risk model of pneumonia epizootics using readily available data that we hypothesized could contribute to epizootics in bighorn sheep, based on previous work. Our model was designed to facilitate making herd-specific predictions and decisions regarding epizootic risk as part of comprehensive statewide management of bighorn sheep herds in Montana (Fig. 2.1). We used decision curve analysis (Vickers and Elkin 2006, Steyerberg et al. 2010) to evaluate the capacity of our model to inform such decisions. This analysis allowed us to assess our model's relative capacity for separating high-risk herds from low-risk herds and the relative merits of using reactive or proactive management of all herds in the absence of a predictive model.

STUDY AREA

Populations of bighorn sheep are found in western Montana and in portions of the Missouri Breaks in central Montana (Fig. 2.1). Habitat characteristics vary widely across these regions. Elevations range from 600 m to 4,000 m (MFWP 2010). Northwestern Montana is characterized by dense forests and generally rugged and mountainous terrain with a climate typical of the Pacific Northwest. Southwestern Montana is characterized by rolling foothills and rugged mountains, with heavier snow cover on western aspects, rain shadows on eastern aspects, and shrubs and bunchgrasses leading to conifers and alpine vegetation at increasing elevations. West-central Montana is characterized by low rolling hills and rugged mountain canyons, with a transitional mix of climate characteristics typical of southwestern and eastern Montana. South-central Montana includes sheer mountain canyons and rolling hills with shrub desert, montane forest, intermountain grasslands, alpine plateaus, and widely varying climates. The Missouri Breaks is semiarid with flat or rolling benchlands, rugged badlands, riparian areas, and ponderosa pine (*Pinus ponderosa*) savannahs. Federal sheep and goat grazing allotments have been distributed throughout Montana for the past 3 decades except in the northwestern region. Weed control with domestic sheep and goats has occurred throughout the state, as have commercial and hobby farms on private lands that can include domestic sheep and goats.

METHODS

Survey Data for Bighorn Sheep

We developed a disease risk model using survey and management data for 43 of 52 bighorn sheep herds in Montana from 1979 to 2013 (9 herds were not consistently monitored). We selected 1979 as the preliminary year because data from monitoring surveys and pneumonia epizootics were rare prior to that time. We defined a herd as a group of bighorn sheep that generally form a spatially and demographically distinct group (Wells and Richmond 1995). Not all 43 herds were extant in all years; 9 were established after 1979, 1 of which was extirpated after a pneumonia epizootic. Survey data included air and ground observations of bighorn sheep counts, age classifications, and sex classifications collected at intervals that varied from intermittent to annual, depending on the herd. These observations were primarily collected by MFWP (>90% of all years surveyed). Additional observations were collected jointly between MFWP and the Confederated Salish and Kootenai Tribes (CSKT; <3%), by the CSKT (<2%), or in association with the United States Fish and Wildlife Service (<4%), Bureau of Land Management (BLM; <1%), or the University of Montana (<1%; Fralick 1984).

We defined herd-year as 1 July to 30 June following MFWP's definition for a management year, which encompasses a complete reproductive cycle from breeding through lambing. We defined a pneumonia epizootic as a die-off with ≥25% mortality (Young 1994) caused by pneumonia (n = 22; Fig. 2.1) based on data and expertise from herd biologists and disease specialists at the MFWP Wildlife Laboratory. We included mortalities due to culling of symptomatic bighorn sheep during verified pneumonia events (Edwards et al. 2010). Pneumonia was generally confirmed by necropsy and histological examination of lung tissue, culture, and/or pathology reports (n = 18). One die-off was attributed to pneumonia based on biologist knowledge and information presented in Enk et al. (2001). When carcasses or biological samples were unavailable from an epizootic event (n = 3), pneumonia was determined based on other evidence (drops of ≥25% in survey numbers, numerous reports of symptomatic individuals, reports of carcasses, and detection of *Mycoplasma ovipneumoniae* in survivors the year following the die-offs; Brent Lonner, MFWP, unpublished data). For each herd experiencing a pneumonia epizootic (n = 18), we excluded the 3 following herd-years from analysis because most herds continued to experience noticeable mortality rates in the few years immediately following the preliminary epizootic year (MFWP 2010). We also excluded all herd-years following a pneumonia epizootic if a herd was augmented with animals from other herds because the need for augmentation meant that the herd was not recovering well, and the addition of animals confounded mortality rates and signs of recovery from the epizootic (n = 5 herds). We excluded herd-years where die-offs were caused by winter storms (n = 1) or unknown factors (n = 2). As with the 3 herd-years after pneumonia epizootics, we excluded the 3 herd-years following die-offs caused by unknown factors because they may have been pneumonia epizootic events.

Conceivably, pneumonia epizootics could have gone undetected between 1979 and 2013. To address this possibility and separate years with pneumonia epizootics from those without, we calculated percentage change in survey counts between consecutive herd-years for each herd. We classified herd-years as free of pneumonia epizootics by the following criteria: 1) for herds surveyed annually, the herd had grown, declined <25%, or declined ≥25% followed by ≥200% growth the next year; 2) when surveys occurred every 2 years, the herd grew between surveys; and 3) when surveys occurred every 3 years, the herd grew by ≥200% between surveys. When calculating percentage change, we excluded harvested animals, documented vehicle mortalities, and additions and removals due to transplantation to analyze unexplained change only. Out of 1,333 herd-years available, we used 637 ($\bar{x}$ = 14.8 herd-yr per herd, SD = 8.65, range = 1–34) for analysis including the 22 herd-years with pneumonia epizootics. Largely because of a lack of survey data, we excluded remaining herd-years from analysis because of uncertainty of whether herd-years could safely be classified as free of epizootics.

Risk Factor Covariates

We selected 10 covariates we hypothesized were predictive of pneumonia epizootics in Montana and for which sufficient data were available. Many covariates were spatial, based on herd distributions, so we obtained agency records and elicited expert opinion of agency biologists to delineate approximate boundaries of distributions of herds in each herd-year (Conroy and Peterson 2013). We categorized each covariate as a potential risk factor we hypothesized could primarily contribute to 1) risk of exposure to pathogens, 2) risk of spread of pathogens, or 3) susceptibility to pneumonia epizootics (Mitchell et al. 2013).

Risk of exposure to pathogens.—We hypothesized 5 covariates were positively related to risk of pathogen transmission: proximity to number of domestic sheep and goat allotments (Singer et al. 2000*b*, 2001; Monello et al. 2001; Epps et al. 2004; Clifford et al. 2009), amount of private land (Miller et al. 2011, 2012; Wild Sheep Working Group 2012), use of domestic sheep and goats for weed control (Miller et al. 2012, Wild Sheep Working Group 2012), a history of a pneumonia epizootic in the herd or its neighbors (Onderka and Wishart 1984, George et al. 2008, Edwards et al. 2010, Besser et al. 2013), and close proximity to other herds (Onderka and Wishart 1984, Singer et al. 2000*a*, George et al. 2008, Edwards et al. 2010, Besser et al. 2013). We hypothesized that amount of private land would be representative of risk from hobby or commercial farms with domestic sheep or goats, for which data were not available. For each herd, we estimated an area of high risk for pathogen exposure (distribution of the herd plus a 14.5-km buffer from that perimeter; Wild Sheep Working Group 2012) using a geographical information system (GIS; ArcMap 10.1, Environmental Systems Research Institute, Inc., Redlands, CA). For the first 4 covariates, we modeled risk of pathogen exposure within each area of high risk using 1) number of federally managed sheep and goat allotments, 2) percentage of private land, 3) knowledge of the wildlife biologist responsible for the herd regarding the use of domestic sheep or goats for weed control, and 4) history of a pneumonia epizootic in the herd in a previous herd-year, or a current or previous pneumonia epizootic in a neighboring herd within the area of high risk. We calculated average proximity to the 3 closest herds for the covariate of herd proximity.

We interviewed personnel and consulted records of federal and state agencies to gather data on allotments, private land, weed control, neighbor risk, and herd proximity (Table 2.1). For data on allotments, we interviewed agency personnel and obtained BLM allotment bills from 1988 onward from the Rangeland Administration System (RAS). We obtained associated geospatial data on allotments from each agency and determined the number of allotment boundaries intersected by each area of high risk using a GIS ($\bar{x}$ = 0.54, SD = 1.32 for 565 herd-yr with allotment data). For private land, we obtained land ownership data and calculated the amount of private land within each area of high risk using a GIS ($\bar{x}$ = 25.58, SD = 14.53%). We obtained weed control data through elicitation of expert opinion of agency biologists (13.97% of herd-yr had known weed control; Conroy and Peterson 2013). We obtained neighbor risk and herd proximity data through agency records and elicitation of expert opinion of agency biologists. For neighbor risk, when a herd experienced a pneumonia epizootic we assumed neighboring herds were at risk for that and subsequent herd-years. We also assumed a recurring risk to the initial herd in all subsequent herd-years (19.31% of herd-yr had neighbor risk). For herd proximity, we calculated the shortest distance to the perimeters of the distributions of the nearest 3 bighorn sheep herds using a GIS and then calculated the average of those distances (global $\bar{x}$ = 22.65 km, SD = 24.27 km). We considered distributions from all herds (including the 9 in Montana excluded from our primary analysis and several herds in British Columbia, Idaho, and Wyoming) for our covariates of neighbor risk if they were within the area of high risk and herd proximity if they were 1 of the 3 closest herds to any of our 43 primary herds.

Risk of spread of pathogens.—We hypothesized high ram:ewe ratios represented increased risk of rams wandering, encountering, and spreading pathogens (Onderka and Wishart 1984, Singer et al. 2000*a*, Monello et al. 2001, George et al. 2008, Besser et al. 2013), and that higher relative density increased risk through greater rates of spread of pathogens (Monello et al. 2001, Lafferty and Gerber 2002, Clifford et al. 2009). We obtained herd survey data from the Montana Bighorn Sheep Conservation Strategy (MFWP 2010) and directly from biologists (Table 2.1). For ram:ewe ratios ($\bar{x}$ = 0.65, SD = 0.39), we excluded ratios from analysis where <80% of observed animals were classified by sex, recorded ratios did not match adults counted, or <1 ram or ewe was counted (n = 50 excluded ratios associated with included herd-yr). To estimate herd density in each year, we divided the total number of animals counted by the area of the herd's distribution. We then calculated average density, yearly percentage of average density, and the range in percentage of average density for each herd. We assigned each herd's density estimate into 3 equally sized bins of low, medium, and high based on the percentage of average density relative to their 1979–2013 range. Thus, each set of cut-offs were herd-specific, based on historical densities of each herd ($\bar{x}$ cut-off for low density ≤ 92.15% of average, SD = 13.15; $\bar{x}$ cut-off for medium density ≤ 151.11% of average, SD = 31.02; 43.80% herd-yr had low density, 36.42% medium, and 19.78% high). When density estimates were not available for years without pneumonia epizootics, we excluded those herd-years from analysis (n = 65 of excluded herd-yr). When density estimates were unavailable for years with pneumonia epizootics (n = 3), we used the most recent density estimate prior to the epizootic (n = 2), or estimated density based on reports of percent declines (n = 1). We used a 1-year lag for both covariates because surveys were usually done in spring and thus represented the minimum number of animals likely to be present at the start of the following herd-year.

Susceptibility to pneumonia epizootics.—We hypothesized that relatively harsh winters contributed to susceptibility to pneumonia epizootics by draining energy budgets (Goodson et al. 1991, Monello et al. 2001, Butler et al. 2013). We used percentage of 30-year normal precipitation to represent winter severity. We hypothesized that relatively dry springs contributed to susceptibility to pneumonia epizootics by decreasing forage quality (Portier et al. 1998, Enk et al. 2001, Monello et al. 2001, Epps et al. 2004) and used percentage of 30-year normal precipitation to represent dry spring conditions. Lastly, we hypothesized that mixed (i.e., native herds augmented with animals from other populations) or non-native (reintroduced) herds had increased susceptibility to pneumonia epizootics because these sites might be more risky if conditions that contributed to a previous herd reduction or extirpation persisted in the area (Monello et al. 2001). For winter and spring precipitation, we calculated percentage of normal precipitation using a GIS to determine monthly PRISM precipitation values and 1980–2010 Normals (PRISM Climate Group, Corvallis, Oregon) in each delineated herd distribution (winter $\bar{x}$ = 98.68%, SD = 30.16%; spring $\bar{x}$ = 100.18%, SD = 26.97%). Similar to Butler et al. (2013) but because spring lambing season began in April in some herds, we considered winter to be 1 November–31 March, and spring 1 April–30 June. We used a 1-year lag for both effects to capture the influence of the most recent winter and spring on the next herd-year (Portier et al. 1998, Butler et al. 2013). For herd origin, we obtained agency transplant records (Table 2.1) to determine in each herd-year if herds were native (21.82% of herd-yr), mixed (20.25%), or reintroduced (57.93%).

Development of Risk Model

Analysis of competing models.—We developed 30 a priori models to test how our hypothesized risk factors predicted pneumonia epizootics (Appendix). We analyzed the models in a Bayesian framework to allow for modeling of missing values and associated uncertainty and to simplify the use of herd-level random effects due to repeated measurements (Kéry 2010). We centered and scaled covariate data and tested for correlations between continuous covariates; we did not include covariates with >40% correlation in the same model (Dormann et al. 2013). We used JAGS (Version 3.3.0, http://mcmc-jags.sourceforge.net, accessed 14 Mar 2013) called through R (Version 2.13.1, www.r-project.org, accessed 10 Sep 2011) using the package R2jags (Version 0.02–17, http://CRAN.R-project.org/package=R2jags, accessed 14 Mar 2013) to run the logistic regression models (Hosmer and Lemeshow 2000) from these data, with repeated measures and a random effect for herd (Gelman and Hill 2007, Royle and Dorazio 2008, Kéry 2010). We used vague, uniform priors for all parameters (Link et al. 2002). We modeled missing values for ram:ewe ratios (n = 84) and number of domestic sheep and goat allotments (n = 72) by setting priors equal to the herd mean where available or the global mean otherwise. We ran 100,000 Markov chain Monte Carlo (MCMC) iterations with 3 chains, discarding the first 25,000 iterations as burn-in (Link et al. 2002). We evaluated convergence of the MCMC simulation with the Gelman and Rubin convergence diagnostic ($\widehat{R}$; Brooks and Gelman 1998) and visual inspection of the posteriors and chains for mixing (Link and Barker 2010) to ensure convergence for accurate estimates of parameters.

We identified top models based on Deviance Information Criterion (DIC; Spiegelhalter et al. 2002). We excluded models >10 ΔDIC from further consideration. We considered covariates within each model to be fully supported if the 95% credibility interval posterior densities (CRIs; Kéry 2010) did not include 0. Where 95% CRIs included 0, we identified the broadest CRI that would exclude 0 to investigate uncertainty of the covariate.

We used a spreadsheet to calculate probability of a pneumonia epizootic for each herd using the parameter estimates from the top models and covariate data from each herd. The risk model provided probability of a pneumonia epizootic in any given year. We calculated probability of ≥1 epizootic occurring in the next 10 years as $\{1 - [1 - \Pr(\text{Epizootic}_{1\text{-yr}})]^{10}\}$ (Mood et al. 1974).

Assessment of model fit and usefulness.—We used decision curve analysis (DCA; Vickers and Elkin 2006, Steyerberg et al. 2010) to compare net benefits of the top models (<10 ΔDIC) to estimate fit of each model to the data and usefulness of the model. This method allowed assessment of whether the top models were useful compared to totally reactive (i.e., treat all herds as low risk) or totally proactive (i.e., treat all herds as high risk) management of all herds, and the relative consequences of wrong predictions, which is important because a false negative prediction is arguably more harmful for conservation and public enjoyment of bighorn sheep than a false positive prediction. For each model, risk of a pneumonia epizootic could be classified as high if it exceeded a pre-defined threshold probability (p_t). We evaluated a range of p_t (0 to the value of the max.

predicted probability of pneumonia epizootic for the 637 herd-yr from each model) for which we calculated sensitivity, specificity, and net benefits,

$$\text{net benefit}_{\text{model}} = \frac{\text{true positive count}}{n} - \frac{\text{false positive count}}{n} \times \left(\frac{\mathrm{p_t}}{1 - \mathrm{p_t}}\right)$$

to estimate and summarize performance and advantages of the model, where $n = 637$. Weighting by the ratio $\mathrm{p_t}/(1 - \mathrm{p_t})$ accounts for the harm of false positive predictions to harm of false negative predictions at each $\mathrm{p_t}$. For each model, we plotted decision curves of the net benefits across values of $\mathrm{p_t}$ to identify the best model that tended to have higher net benefits than the others.

Finally, we determined if the best model was more useful than abandoning the model and instead managing all herds as low risk, which is a management option in absence of a predictive model. We calculated the model advantage across the range of $\mathrm{p_t}$ over the option of assuming all herds are low risk as:

$$\text{net increase in true positives} = \text{net benefit}_{\text{model}} \times 100$$

This measure of the model's usefulness calculates the increase in true positives with no increase in false positive per 100 estimates compared to treating all herds as low risk. Similarly, the model advantage across the range of $\mathrm{p_t}$ over the option of assuming all herds are high risk is:

$$\text{net reduction in false positives} = \frac{\left(\text{net benefit}_{\text{model}} - \text{net benefit}_{\text{all high}}\right) \times 100}{\mathrm{p_t}/(1 - \mathrm{p_t})}$$

The net reduction in false positives is the reduction of false positives per 100 estimates provided by the risk model without increasing the number of false negatives compared to abandoning the model and treating all herds as high risk. Here, net $\text{benefit}_{\text{all high}}$ is calculated with the net $benefit_{model}$ formula except true positive count is the total number of pneumonia epizootic cases (22) and false positive count the total non-pneumonia epizootic cases (615).

Second generation model.—We developed an a posteriori, second generation model by calculating the inclusion probability of each covariate. Inclusion probabilities resulted from introducing a Bernoulli distributed indicator variable with probability equal to 0.5 (Ntzoufras 2009). We ran 3 chains for 500,000 iterations, discarding the first 125,000 iterations as burn-in (Link et al. 2002). We calculated the proportion of times each indicator variable assumed a value of 1 and identified covariates with inclusion probabilities >0.15 (similar to Ntzoufras 2009). We then evaluated a new second generation model with these covariates using the techniques described above for analysis of competing models.

RESULTS

Development of Risk Model

The top-ranked model included private land, weed control, neighbor risk, and density (Table 2.2). The posterior density CRIs excluded 0 except for private land (95% CRI, $-0.03 \leq x \leq 0.91$), but a 93% CRI for private land excluded 0 ($0.01 \leq x \leq 0.87$). The second best model included neighbor risk and density (ΔDIC = 6.9). Smooth unimodal posteriors, history plots (Link and Barker 2010), and $\widehat{R}$ values of <1.1 indicated convergence (Brooks and Gelman 1998). All other models had ΔDIC > 10, so we excluded them from further consideration.

The top-ranked model was superior to the second-ranked model based on sensitivity, specificity, and net benefits. Sensitivity and specificity were simultaneously maximized for the top model at a p_t of 0.0312, achieving 81.8% sensitivity, 80.2% specificity, and a correct overall classification rate of 80.2% (Fig. 2.2). Sensitivity and specificity for the second best model were simultaneously maximized at a p_t of 0.0288 with 81.8% sensitivity, 75.3% specificity, and 75.5% correct overall classification rate. We selected the top model as the final risk model because it had a higher overall net benefit than the second model across most p_t's (Fig. 2.3).

Based on DCA, over a wide range of p_t the final risk model was superior to the 2 alternative options of treating all herds reactively or proactively in absence of a predictive model. The risk model's decision curve had higher net benefits than the decision curve for the alternative of treating all herds as high risk at a p_t of approximately ≥ 0.001 (Fig. 2.3). The risk model's decision curve was also higher than the decision curve for treating all as low risk at a p_t of approximately ≤ 0.389. Between 0.001–0.389, the risk model would therefore provide both a net reduction in false positive estimates over assuming all herds are high risk and a net increase in true positives over assuming all herds are low risk. Using the risk model with any p_t between these levels would be better than fully reactive management or the alternative of total proactive management of all herds, considering limited resources. It is therefore useful as a model for predicting risk of pneumonia epizootics at any p_t within this range. The model would yield fewer false negative predictions at low values of p_t and fewer false positive predictions at high values of p_t (Table 2.3).

Effect Sizes for Top Model

Parameters in the risk model provide estimated effects of each risk factor on probability of a pneumonia epizootic. Holding other parameters constant, the odds of a pneumonia epizootic increased 1.54 (95% CRI, $0.97 \leq x \leq 2.48$) times per additional unit of private land within the area of high risk (global $\bar{x} = 25.58\%$, SD = 14.53%). Herds where domestic sheep or goats were known to be used to control weeds within the area of high risk that year had 3.35 (95% CRI, $1.12 \leq x \leq 9.59$) times greater odds of a pneumonia epizootic than those without. Odds of a pneumonia epizootic were 10.29 (95% CRI, $3.79 \leq x \leq 29.73$) times greater for herds if they or their neighbors in the area of high risk previously experienced a pneumonia epizootic. Herds at medium or high density had odds of a pneumonia epizootic 5.26 (95% CRI, $1.36 \leq x \leq 24.05$) and 14.86 (95% CRI, $3.79 \leq x \leq 70.74$) times greater, respectively, than when they were at low density. Altogether, a herd with no private land, weed control, or neighbor risk and with low density was estimated to have 0.0009 (95% CRI, $0.0001 \leq x \leq 0.0045$) probability of a pneumonia epizootic during any year and represents the least risky extreme. On the most risky extreme, a herd in an area of high risk with 100% private land, weed control, neighbor risk, and high density was estimated to have 0.8992 (95% CRI, $0.4256 \leq x \leq 0.9910$) annual probability of a pneumonia epizootic.

Second Generation Model

Inclusion probabilities were >0.15 for private land, weed control, neighbor risk, and density, which aligns with the top model we developed a priori. A fifth and final covariate with >0.15 inclusion probability was spring precipitation. An a posteriori model with these 5 covariates had a DIC of 4 lower than that of our original best model, indicating greater support for the new model. Parameter estimates of the original 4 risk factors were very similar (Tables 2.2 and 2.4).

Spring precipitation was negatively correlated with probability of a pneumonia epizootic the next herd-year (starting 1 Jul). Holding other parameters constant, odds of a pneumonia epizootic were 0.41 (95% CRI, $0.20 \leq x \leq 0.78$) times that of years of average spring precipitation per standardized unit increase ($\bar{x}$ = 100.18%, SD = 26.97%). Thus, each increase of 27% from average precipitation was associated with less than half the odds of a pneumonia epizootic compared to years with average spring precipitation. Conversely, for each unit decrease in spring rainfall, risk of a pneumonia epizootic more than doubled.

DISCUSSION

Historically, state wildlife agencies have managed pneumonia epizootics in bighorn sheep largely reactively because they have not had the ability to predict epizootics. Existing models related to pneumonia in bighorn sheep focus largely on predicting consequences of epizootics (e.g., mortality rates and population persistence). Our model was designed to predict the risk of pneumonia epizootics before they happen, which no other model has directly done before (although see Clifford et al. [2009] and Carpenter et al. [2014] for models of disease transmission from allotments). If probability of epizootics cannot be predicted, herds cannot be separated by high and low risk to proactively prevent pneumonia epizootics. Proactively treating all herds as high risk would likely be prohibitively expensive, resulting in the general reactive management status quo.

A more proactive approach integrating wildlife health with wildlife conservation would lead to more effective conservation and management of wildlife populations (Deem et al. 2001). For more proactive management of pneumonia epizootics in bighorn sheep, agencies need risk assessment tools to better understand risk factors that contribute to pneumonia epizootics. They also need to know how to use available data to predict pneumonia epizootics. Models based on more limited temporal and spatial extents may make more precise estimates on such scales, but lose generality across larger ones. A general model that combines information from herds across a state would aid in prediction of risk at the necessary scale for state wildlife agencies to make decisions on how to allocate resources for proactive management. Accordingly, we analyzed epizootic histories and potential risk factors for 43 herds across Montana from 1979–2013 to create a statewide risk model for pneumonia.

Risk Factors

Risk of pneumonia epizootics was positively associated with greater amount of private land, weed control with domestic sheep and goats, history of a pneumonia epizootic in a herd or a nearby herd, and higher density. Based on our second generation model, risk also appeared to be associated with spring precipitation. Risk was not associated with number of allotments, herd proximity, ram:ewe ratios, winter precipitation, or herd origin, nor did a single risk factor affect all pneumonia epizootics based on our multivariate model. Although the existence of a single risk factor that we did not evaluate cannot be ruled out, our results agree with the findings of Miller et al. (2012) in their review of hypothesized risk factors of die-offs in bighorn sheep. They failed to find evidence of a single etiological agent and concluded that predictive models of epizootics are needed based on the likely complexity of the etiology of such outbreaks.

Risk of exposure to pathogens.—As we hypothesized, greater percentage of private land in and near areas used by herds of bighorn sheep was associated with increased risk of pneumonia epizootics by >1.5-fold per additional unit of private land. Risk associated with contact with domestic livestock on private land has not previously been quantified and tends to be neglected (Miller et al. 2011, 2012), perhaps because data on locations of hobby and commercial farms are generally unavailable and would be highly fluid through time. Exposure to sheep or goats may occur on farms on private lands, whereas exposure on public lands likely occurs primarily on allotments, for which data exist and which agencies can more directly manage. Although risk due to private land was slightly uncertain (the 95% CRI contained 0, however the 93% CRI did not), these results provide the first empirical support for the suggestions of Miller et al. (2011, 2012) and the Wild Sheep Working Group (2012) that risk of exposure to pathogens on private land should receive more focus and concern. The uncertainty of this parameter at the 95% CRI is likely due to the probably low correlation between private land and farms with domestic sheep and goats, because not every parcel of private land contains domestic Caprinae species. Were data available, the effect of commercial and hobby farms could likely be estimated more precisely, yet the readily available percentage of private land was still predictive of risk. Examples of management actions to reduce risk associated with private land might include public education on separation of bighorn sheep and domestic sheep and goats, removal of wandering bighorn sheep in proximity to farms with domestic sheep or goats (Mitchell et al. 2013), or purchasing conservation easements (Sells 2014). We note that the association between private land and pneumonia epizootics could also be related to high human densities or human disturbance (e.g., development) on some areas of private land. Such disturbances could increase stress and potentially predispose herds to pneumonia epizootics.

Our hypothesis that risk of pneumonia epizootics increases when domestic sheep and goats are used for weed control in or near areas occupied by herds of bighorn sheep was supported, with a >3.3-fold increase in risk compared to areas or years without known weed control using domestic Caprinae species. To our knowledge, our results are the first to support the suggestion by Miller et al. (2012) and the Wild Sheep Working Group (2012) that such operations increase risk of pathogen exposure. Potential management actions to mitigate this risk include public education about separation between bighorn sheep and domestic sheep and goats (Mitchell et al. 2013), managing timing of grazing to avoid temporal overlap with bighorn sheep, or using other methods to control weeds that do not involve domestic sheep or goats (Sells 2014).

As we hypothesized, risk of pneumonia epizootics increased for a herd when that herd or a nearby herd within 14.5 km had a history of a pneumonia epizootic. Increased risk for a herd after an epizootic is intuitive. Evidence suggests that pathogens become endemic and may cycle for years to decades within herds (Enk et al. 2001, Cassirer and Sinclair 2007, Cassirer et al. 2013). Further evidence suggests that whereas ewes may develop temporary protective immunity, this may wane after exposure to pathogens and does not effectively transfer to lambs, leading to ongoing outbreaks of pneumonia (Plowright et al. 2013). Additionally, Plowright et al. (2013) found that translocated, naïve adults appear to be at particularly high risk of dying from pneumonia. We hypothesized that other naïve individuals in nearby herds may be at a similar risk of contracting pneumonia. Whereas the exposure and spread of pathogens to nearby herds has been hypothesized to contribute to epizootics (Onderka and Wishart 1984, George et al. 2008, Edwards et al. 2010), this risk has not been quantified or received as much focus as other hypothesized risk factors. We found that a pneumonia epizootic was associated with >10-fold risk of pneumonia epizootics for all herds within 14.5 km. Cassirer et al. (2013) reported a slight but uncertain increase in probability of pneumonia for neighboring populations located <20 km apart if a neighbor had any pneumonia mortalities that or the previous year. The reason for this difference may be attributable to an inclusion of short timeframes with all cases of pneumonia as opposed to our use of longer timeframes with high-mortality epizootics. We included histories of epizootics from 1979 to the end of the study given the evidence that pathogens can cycle for decades (Enk et al. 2001, Cassirer et al. 2013). We included only high-mortality epizootics because we hypothesized that pneumonia widely spread in a herd would be linked to more potential exposure between herds (Onderka and Wishart 1984, George et al. 2008, Edwards et al. 2010, Besser et al. 2013), compared to limited cases of pneumonia that may result in less exposure between herds. Thus, across broad temporal and spatial scales, we conclude that pneumonia epizootics have long-term consequences for herds experiencing epizootics and for neighboring herds as well. Potential actions that may reduce this risk could include creating lethal removal zones between infected and naïve herds, culling symptomatic individuals, and avoiding establishing new herds close to those with epizootic histories (Sells 2014). Additionally, we note that past epizootics in or near a herd could be predictive of future epizootics because of shared or recurring conditions in an area besides pathogens (e.g., environmental factors) that could make herds more susceptible to pneumonia epizootics.

Our other hypothesis that proximity to other herds, measured by Euclidean distance, increased risk of pathogen exposure was not supported. The global mean for average proximity to the 3 closest herds (22.65 km, SD = 24.27 km) was >1.56 times farther and highly variable compared to the maximum distance for those herds we considered neighbors (within 14.5 km). Although bighorn sheep are known to move distances comparable to our mean herd proximity (e.g., O'Brien et al. [2014] reported that >10% of rams forayed ≥21.7 km from core herd home ranges each summer), this does not mean they will necessarily come in contact with other herds. By not accounting for barriers to movement, Euclidean distance may misrepresent distances that bighorn sheep would actually travel between herds, particularly at greater distances. Additionally, average distance to the 3 closest herds did not account for epizootic histories, whereas our identified risk factor of neighboring herds with epizootic histories did. The hypothesis Cassirer et al. (2013) tested for distance to nearest herd with recent cases of pneumonia also allowed for herds at much greater distances (≤70 km) and did not have support. Risk therefore appears to be associated with relatively close neighboring herds with histories of pneumonia epizootics, not to Euclidean distance to herds in general.

Proximity to greater number of allotments was not predictive of pneumonia epizootics, contrary to results reported by other researchers. Monello et al. (2001) reported that herds with pneumonia were closer to domestic sheep allotments than were herds without pneumonia. In their analysis, they included allotments at much greater distances compared to our area of high risk. Clifford et al. (2009) estimated risk of pathogen transmission was higher where strong overlap existed between allotments and known bighorn sheep movements. Our result is counter-intuitive because pneumonia in bighorn sheep is strongly associated with exposure to domestic sheep and goats (Wehausen et al. 2011), which is presumably more likely on allotments. In Montana, however, mean number of allotments within 14.5 km of herds was only 0.54 per herd-year (SD = 1.32). Of herd-years with ≥1 allotment (*n* = 134), mean number was 2.29 allotments (SD = 1.83, max. = 14). Only 14 of the 43 herds were within 14.5 km of allotments with sheep or goats for at least 1 year between 1979 and 2013; of these herds, only 4 had pneumonia epizootics. Simple presence or absence of allotments within 14.5 km was not predictive of epizootics upon further investigation, either. For herds that are close to allotments, exposure may further depend on numerous factors unique to each allotment, including how they are managed (e.g., timing of grazing, management of strays). It may also depend on the degree of actual overlap between species as suggested by Clifford et al. (2009), for which we had no data commensurate with the large spatial and temporal scales at which we worked. We suggest further, more detailed evaluation of how allotments might contribute to risk of pneumonia epizootics is needed before discarding allotments as a potentially predictive risk factor for future models.

Risk of spread of pathogens.—Our hypothesis that relative density within a herd is associated with increased risk of a pneumonia epizootic was supported, lending empirical support to the hypotheses of other researchers (Miller et al. 1991, Monello et al. 2001, Clifford et al. 2009). Risk of a pneumonia epizootic increased >5-fold when herds were at medium density and nearly 15-fold when herds were at high density compared to when they were at low density. Substantial herd variation (e.g., habitat quality and estimated area used by each herd) yielded incomparable absolute densities between herds, so we defined density as relatively low, medium, or high. More analysis on density would be useful in the future, including what absolute values might lead to higher risk of pneumonia epizootics, or if group aggregation size is predictive. Density is a component of risk that has previously received little attention because the positive association between risk of pneumonia and higher densities had not been quantified. The association between higher herd density and risk may appear to contradict the idea that herds of larger population size should be less threatened by extirpation than smaller herds (Woodroffe 1999, Singer et al. 2001, Cassaigne et al. 2010). Rather than reducing herd size only, expanding the distribution of an existing herd (e.g., through habitat improvements that attract animals to new areas or, potentially, short-distance transplant operations to unoccupied areas nearby) would also reduce density by increasing the total area that a herd occupies (Sells 2014).

Ram:ewe ratios were not associated with increased risk. We chose these ratios to represent the likelihood that rams would wander in search of breeding opportunities, thus potentially encountering and spreading pathogens. Our results suggest that rams may not be as important vectors of pathogens in their herds as we hypothesized. Rams are known to make long movements (Singer et al. 2000*b*, DeCesare and Pletscher 2006, O'Brien et al. 2014), probably even more so at relatively high densities (Singer et al. 2000*a*, Monello et al. 2001). To increase risk of pneumonia for its herd, however, a wandering ram would have to become infected, survive long enough to come in contact with other herd members, and successfully transmit pathogens. These odds may be independent of ram:ewe ratios alone. Historically, MFWP often removed wandering rams when discovered comingling with domestic sheep or goats, and this management effort may have further reduced risk from wandering rams in specific cases. Additionally, not all age classes of rams may be at greater risk of wandering. The ratio of young rams in a herd may be more predictive of this potential source of risk of spread of pathogens, but these data were only occasionally collected over the years we analyzed.

Susceptibility to pneumonia epizootics.—We used percentage of normal spring (Apr–Jun) precipitation to represent the hypothesized impact of decreased forage quality on susceptibility to pneumonia epizootics but found no relationship during analysis of our a priori models. This suggested that forage quality might not affect risk of pneumonia epizootics, or that percentage of normal spring precipitation may not be a suitable index to forage quality because it does not account for other environmental factors that also affect forage quality (e.g., timing of precipitation and temperature). We think it more likely, however, that this covariate did not have support because no a priori model included it alongside the other identified risk factors. Based on our a posteriori, second generation model, spring precipitation appeared predictive of pneumonia epizootics. Odds of a pneumonia epizootic were reduced by a factor of 0.41 times per unit of spring precipitation beyond average in the previous spring ($\bar{x}$ = 100.18%, SD = 26.97%). Monello et al. (2001) also noted qualitative evidence for a relationship between summer and fall pneumonia outbreaks and lower than average precipitation. The second generation model could be used to predict risk of pneumonia epizootics instead of our a priori risk model; the effect sizes of the other 4 risk factors were comparable, with a largest difference in any parameter estimate of <0.4 (Tables 2.2 and 2.4).

We selected percentage of normal winter precipitation to represent the hypothesized impact of harsh winters on susceptibility to pneumonia epizootics because of increased energy expenditures but found no relationship. This result suggests that harsh winters do not increase risk of pneumonia epizootics, consistent with similar results of Monello et al. (2001). Alternatively, percentage of normal winter precipitation may not have been a suitable index for the effects of harsh winters on energy budgets of bighorn sheep because it did not account for patterns and timing of winter precipitation. These factors could be important components of winter severity but related data were unavailable at the scale of our analysis.

Herds in Montana of mixed or reintroduced origin did not have higher risk of pneumonia epizootics than native herds. This finding contrasts with those of Monello et al. (2001) who evaluated a subset of herds throughout North America and hypothesized that sites of previous herd extirpations could continue to be risky for pneumonia based on characteristics of the site itself. If this were the case, reintroduced herds at sites of historical herd extirpations in Montana could have comparable risk to native herds. This could be true because MFWP has tried to avoid reintroducing herds near areas with domestic sheep. Alternatively, whereas we defined epizootics as events with ≥25% mortality, Monello et al. (2001) defined all detected pneumonia events as epizootics including those with <10% mortality. A difference in risk for native versus reintroduced herds may have been more pronounced if reintroduced herds were more likely to experience low-mortality pneumonia events. Reintroduced herds might also have been monitored more closely, providing the ability to better detect low-mortality events.

Overall Model

Availability of certain data limited our ability to analyze additional hypothesized risk factors. Most important was the paucity of pathogen data. Presence of *Mycoplasma ovipneumoniae* or *Mannheimia haemolytica* may be important in predicting risk if sufficient data, understanding, and tests for disease agents were available. Although Montana had over 60 herd-years of *Mycoplasma ovipneumoniae* data and nearly 100 herd-years of *Mannheimia haemolytica* data, more intensive, consistent efforts with larger sample sizes would have been needed for our analysis because so many herd-years were still lacking in data. Also, traditional culture-based methods for *Mycoplasma ovipneumoniae* (Besser et al. 2008) and *Mannheimia haemolytica* (Shanthalingam et al. 2014) appear to miss many positive results compared to new culture-independent methods that detect genetic signatures of the pathogen. This suggests that analysis of these data for our study could lead to misleading and erroneous predictions; therefore, we excluded them from analysis. In addition to pathogen data, body condition data such as body fat levels, parasite loads, mineral levels, or blood parameters may also be of potential value in a future risk model (Mitchell et al. 2013).

Evaluating our model's capacity to predict future epizootics in Montana, or those occurring in other states, offers an opportunity to evaluate and improve the model. It would also constitute a test of the hypothesized relationships posed by our model and its covariates, providing an opportunity to learn more about risk factors for pneumonia epizootics. Our evaluation of 10 hypothesized risk factors clarified the importance of poorly understood risk factors in Montana to better predict risk. These risk factors could differ in their relative importance for herds in places unlike Montana. To maximize usefulness of the model, we recommend that potential variation in risk factors should be tested and calibrated to local conditions as part of an adaptive approach to disease management. Alternative risk factors may also be important in other areas and a subject for future research toward development of predictive models elsewhere. The evidence, based on our second generation model, that spring precipitation is predictive of pneumonia epizootics deserves further attention in future work.

The scope and scale of our study required data collected from numerous biologists, literature sources, and other agency personnel. Because misclassification of pneumonia epizootics could reduce precision, we excluded herd-years for which we were not reasonably certain were free of pneumonia epizootics. Accuracy and precision of spatially related covariates would be compromised if biologists were unable to delineate approximate distributions of herds, so we excluded herds without sufficient spatial data due to limited herd histories or biologist knowledge.

The statistically rare nature of pneumonia epizootic events makes their prediction challenging. Pneumonia epizootics occurred in 22 out of 637 (3.45%) of the herd-years we analyzed. A statistical model based on such data has the potential to incorrectly predict epizootics (i.e., false positives) more often than correctly. Our use of decision curve analysis helped evaluate the extent to which managers can rely on our risk model to make accurate predictions, given the number of pneumonia epizootic events we observed. This relatively new analysis determines the net benefits of using a predictive model for making decisions (i.e., its usefulness; Vickers and Elkin 2006, Steyerberg et al. 2010). This assessment first allowed us to conclude that our top model was more useful than our second model. It also allowed us to evaluate whether using our model to make a decision was more useful than using no model at all. If no model such as ours existed, the status quo decision would generally be reactive management (i.e., treat all herds as low risk) because herds cannot be distinguished by risk level and proactive management of all herds would almost certainly be too costly. To be useful, our predictive model should provide more correct classifications than either alternative in absence of the model.

Decision curve analysis showed that our model is expected to be more useful than the status quo. For example, at a threshold probability of 0.028, our model is expected to provide a net increase in true positive detections of 2.390 per 100 herd-years compared to total reactive management. It would also provide a net reduction in false positive detections of 59.632 per 100 herd-years compared to total proactive management, meaning our model would reduce false positive predictions by 60% over completely proactive management. Thus, many more correct classifications will be provided by our model compared to fully reactive management or fully proactive management of all herds. This ability to reliably differentiate herds by risk level will assist managers in making decisions on where to direct appropriate, potentially costly proactive actions.

An important advantage of DCA is that tolerance for false positive versus false negative predictions can be accounted for by selecting different threshold probabilities. Individual managers will have different risk tolerances when making decisions. Some managers will be more risk averse given the severe implications of pneumonia epizootics. More risk-averse managers could select a lower threshold probability to separate high from low risk herds. Other managers may be more risk tolerant if management actions would be too costly, in which case they could then select a higher threshold probability.

MANAGEMENT IMPLICATIONS

Our model can be used to estimate risk (Table 2.5), compare and prioritize herds for proactive management, and simulate how potential alternative actions may reduce risk. The model is not only useful for predicting risk for existing herds, but for estimating future risk for new transplant herds as well. Our approach and results are unique because of the extensive spatial and temporal scales used to develop the risk model and make it valuable for herd-specific decisions as part of regional or statewide management of bighorn sheep in Montana. Used to inform decisions in a structured decision making framework (Mitchell et al. 2013), the model can be used to estimate herd-specific recommendations that best meet agency objectives given each herd's predicted risk. Importantly, sophisticated software is not required; a simple spreadsheet can be used to calculate risk using the parameter estimates from the risk model (Table 2.2). A spreadsheet for a decision model similar to that shown in Mitchell et al. (2013) would help managers use the risk model to inform decisions. Use of both models will lead to a unified, transparent, and consistent approach to making proactive management decisions given the regional or statewide scale, while simultaneously remaining highly specific to each herd's estimated risk and each manager's goals.

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Figure Captions

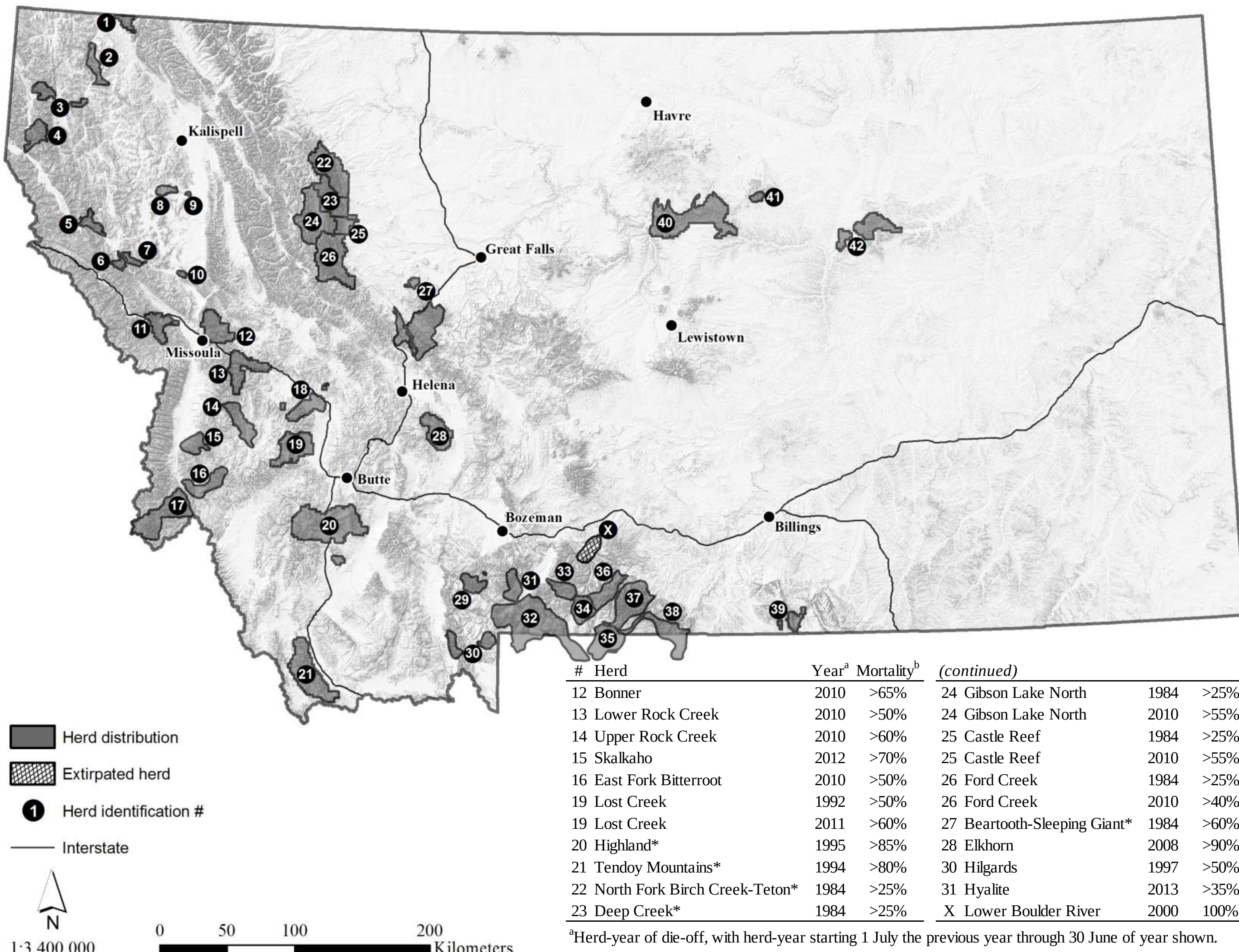
Figure 2.1. Locations of 43 herds of bighorn sheep with 22 pneumonia epizootic events with ≥25% mortality between 1979 and 2013, which we used to develop a pneumonia risk model for Montana. We excluded several additional epizootics from our analysis. Numbers correspond to risk estimates in Table 2.5 and to the table for epizootics within the map, where a * after the herd name indicates that we excluded post-epizootic herd-years from analysis because the herd received transplants, confounding signs of recovery.

Figure 2.2. Sensitivity (dashed lines) and specificity (solid lines) at various threshold probabilities (p_t's) for 2 pneumonia risk models developed using data from 1979–2013 for bighorn sheep in Montana. The top-ranked model (black lines) had a higher sensitivity and specificity than the second-ranked model (gray lines): at $p_t = 0.0312$ sensitivity and specificity were simultaneously maximized with 81.8% sensitivity and 80.2% specificity compared to the second-ranked model which had the same sensitivity and 75.3% specificity at $p_t = 0.0288$.

Figure 2.3. Decision curves for 2 final a priori models considered for selection as a pneumonia risk model for bighorn sheep in Montana. The most supported model (black line) outperformed the second-best model (gray line) over much of the threshold probability range based on the higher net benefit overall. We selected the most supported model for the risk model. Using the risk model would be superior to treating all herds as high risk (dotted line; i.e., indiscriminate proactive management of all herds) at any threshold probability (p_t) of approximately ≥0.001, and better than treating no herds as

high risk (dashed line at net benefit = 0; i.e., reactive management of all herds) at any p_t approximately ≤ 0.389.

Figure 2.1.

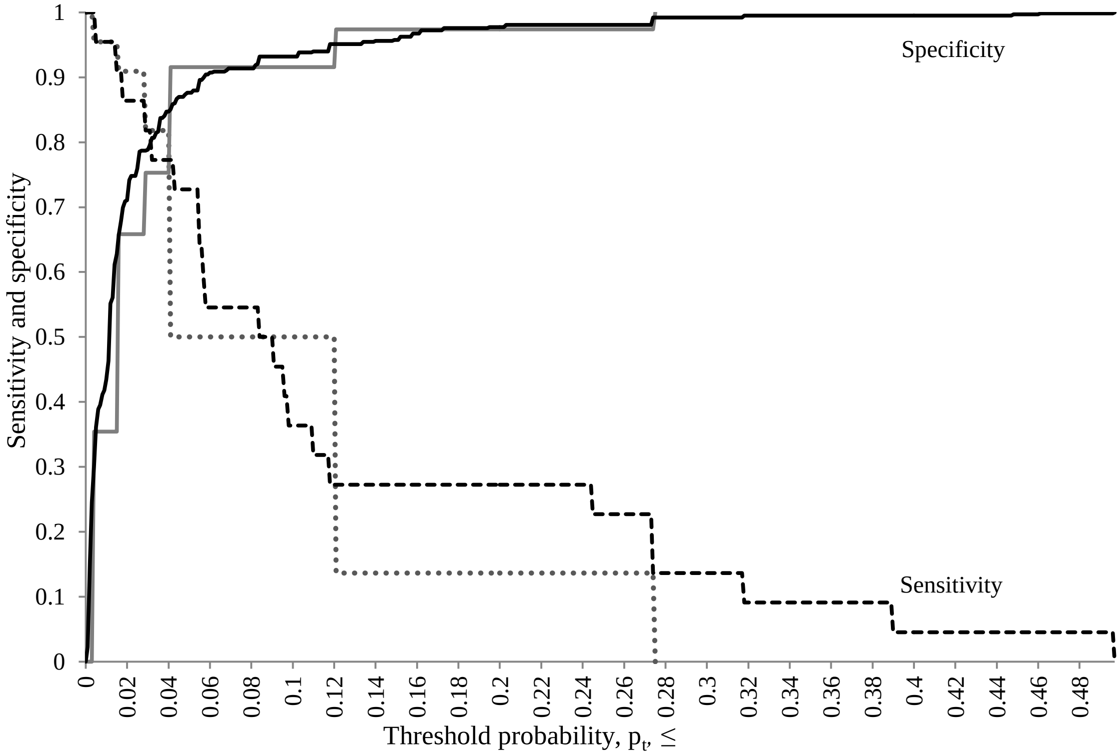


#	Herd	Year[a]	Mortality[b]
12	Bonner	2010	>65%
13	Lower Rock Creek	2010	>50%
14	Upper Rock Creek	2010	>60%
15	Skalkaho	2012	>70%
16	East Fork Bitterroot	2010	>50%
19	Lost Creek	1992	>50%
19	Lost Creek	2011	>60%
20	Highland*	1995	>85%
21	Tendoy Mountains*	1994	>80%
22	North Fork Birch Creek-Teton*	1984	>25%
23	Deep Creek*	1984	>25%
(continued)			
24	Gibson Lake North	1984	>25%
24	Gibson Lake North	2010	>55%
25	Castle Reef	1984	>25%
25	Castle Reef	2010	>55%
26	Ford Creek	1984	>25%
26	Ford Creek	2010	>40%
27	Beartooth-Sleeping Giant*	1984	>60%
28	Elkhorn	2008	>90%
30	Hilgards	1997	>50%
31	Hyalite	2013	>35%
X	Lower Boulder River	2000	100%

[a]Herd-year of die-off, with herd-year starting 1 July the previous year through 30 June of year shown.

[b]Approximate total mortality from pneumonia epizootic event.

Figure 2.2.



Specificity
Sensitivity
Sensitivity and specificity
Threshold probability, p_t, ≤
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
0
0.02
0.04
0.06
0.08
0.1
0.12
0.14
0.16
0.18
0.2
0.22
0.24
0.26
0.28
0.3
0.32
0.34
0.36
0.38
0.4
0.42
0.44
0.46
0.48

Figure 2.3.


0.035
0.030
0.025
0.020
0.015
0.010
0.005
0.000
Net benefit
0
0.02
0.04
0.06
0.08
0.1
0.12
0.14
0.16
0.18
0.2
0.22
0.24
0.26
0.28
0.3
0.32
0.34
0.36
0.38
0.4
Threshold probability, p_t

Table 2.1. Data types and associated agencies we collected covariate data from to model risk of pneumonia epizootics for 43 herds of bighorn sheep in Montana from 1979–2013. Numbers represent the approximate percentage of data associated with each agency out of all herd-years with data for that covariate, unless otherwise indicated. Where applicable, we included additional herds beyond our 43 primary herds if they were within 14.5 km of our primary herds or were 1 of the 3 closest herds. Agencies were Montana Fish, Wildlife and Parks (MFWP), United States Fish and Wildlife Service (USFWS), Bureau of Land Management (BLM), United States Forest Service (USFS), National Park Service (NPS), Confederated Salish and Kootenai Tribes (CSKT), Chippewa Cree Tribe (CCT), British Columbia Fish and Wildlife Branch (BCFW), Idaho Fish and Game (IDFG), and Wyoming Game and Fish (WGFD). Blank cells indicate data were not associated with these agencies.

Data	MFWP	USFWS	BLM	USFS	NPS	CSKT	CCT	BCFW	IDFG	WGFD
Allotments[a]		0[b]	68	32						
Private land			100							
Weed control	94	5				1				
Neighbor risk[c]	75	2			5	4		4	5	5
Herd proximity[d]	72	2			5	3	2	5	7	5
Ram:ewe ratios	93	6				1				
Density	94	5				1				
Herd origin	94	5				1				

[a] Of unique allotments ≤14.5 km of herd distributions (n = 47), % associated with each agency.

(continued)

(continued)

[b] No allotments on USFWS land were ≤14.5 km of herd distributions.

[c] Of all herds ≤14.5 km from 43 primary herds (n = 56, including 13 non-primary herds), % associated with each agency.

[d] Of all herds that were 1 of 3 closest to 43 primary herds (n = 61, including 18 non-primary herds), % associated with each agency. Sum >100 is due to rounding.

Table 2.2. Parameter estimates of supported a priori models of risk of pneumonia epizootics for 43 herds of bighorn sheep in Montana from 1979–2013. We do not present models with change in Deviance Information Criterion (ΔDIC) >10. Within the distribution of each herd plus a 14.5-km buffer from that perimeter, private land = percentage of private land, weed control = whether the herd biologist knew of the use of domestic sheep or goats for weed control, and neighbor risk = whether the herd or a neighboring herd had a pneumonia epizootic previously. Density = the number of individuals counted divided by the area of each herd's distribution, assigned into 1 of 3 equally sized bins of low, medium (md), and high (hi) density relative to the herd's 1979–2013 percentage of average. Herd effect is the among-herd variation for the herd-level random effect.

	Mean	SD	Credibility interval	
			0.025	0.975
Best model				
β_0 Intercept	−6.269	0.761	−7.931	−4.911
β_1 Private land	0.433	0.239	−0.028	0.910
β_2 Weed control	1.210	0.547	0.115	2.261
β_3 Neighbor risk	2.331	0.524	1.332	3.392
β_4 Density(md)	1.660	0.728	0.309	3.180
β_5 Density(hi)	2.699	0.742	1.332	4.259
Herd effect	0.242	0.131	0.143	0.609
Deviance	153.624	4.125	146.679	162.973

(continued)

(continued)

	Mean	SD	Credibility interval	
			0.025	0.975
Second model (ΔDIC = 6.9)				
β_0 Intercept	−5.705	0.709	−7.246	−4.445
β_1 Neighbor risk	2.184	0.488	1.244	3.164
β_2 Density(md)	1.535	0.731	0.200	3.085
β_3 Density(hi)	2.548	0.731	1.206	4.090
Herd effect	0.249	0.147	0.143	0.666
Deviance	161.519	3.874	154.019	169.736

Table 2.3. Comparison of net benefits and advantages for our pneumonia risk model for 43 herds of bighorn sheep in Montana from 1979–2013. Risk of a pneumonia epizootic is classified as high if it exceeds a pre-defined threshold probability (p_t), and low otherwise. The net benefit at each threshold estimates the advantage of the model and can aid selection in p_t for more conservative or liberal estimation based on tolerance of false positives versus false negatives.

			Net benefit		Advantage of model	
p_t, ≤	Sensitivity	Specificity	Risk model	Treat all[a]	Increase in TP[b]	Decrease in FP[c]
0.000	1.000	0.000	0.035	0.035	3.454	0.000
0.004	1.000	0.302	0.032	0.031	3.183	29.199
0.008	0.955	0.411	0.028	0.027	2.838	20.251
0.012	0.955	0.551	0.028	0.023	2.770	40.293
0.016	0.909	0.657	0.026	0.019	2.601	44.113
0.020	0.864	0.711	0.024	0.015	2.412	45.526
0.024	0.864	0.748	0.024	0.011	2.384	53.061
0.028	0.864	0.787	0.024	0.007	2.390	59.632
0.032	0.773	0.807	0.021	0.003	2.051	54.121
0.036	0.773	0.837	0.021	−0.002	2.083	59.829
0.040	0.773	0.847	0.021	−0.006	2.054	62.951
0.050	0.727	0.876	0.019	−0.016	1.884	66.719
0.060	0.545	0.907	0.013	−0.027	1.313	63.004

(continued)

(continued)

p_t, ≤	Sensitivity	Specificity	Net benefit		Advantage of model	
			Risk model	Treat all[a]	Increase in TP[b]	Decrease in FP[c]
0.070	0.545	0.914	0.013	−0.038	1.258	67.369
0.080	0.545	0.914	0.012	−0.049	1.160	70.173
0.090	0.500	0.932	0.011	−0.061	1.075	72.493
0.100	0.364	0.932	0.005	−0.073	0.523	70.173
0.200	0.273	0.977	0.004	−0.207	0.392	84.301
0.300	0.136	0.992	0.001	−0.379	0.135	88.802

[a] Net benefits for treat all herds as high risk, a management alternative in absence of using our risk model to predict and separate high from low risk herds.

[b] Increase in true positives per 100 estimates without increase in false positives compared to treating all herds as low risk.

[c] Reduction in false positives per 100 estimates without increase in false negatives compared to treating all herds as high risk.

Table 2.4. Parameter estimates of the second generation model for risk of pneumonia epizootics for 43 herds of bighorn sheep in Montana from 1979–2013. The Deviance Information Criterion (DIC) of our second generation model was 4 lower than that of our top-ranked a priori model. Within the distribution of each herd plus a 14.5-km buffer from that perimeter, private land = percentage of private land, weed control = whether the herd biologist knew of the use of domestic sheep or goats for weed control, and neighbor risk = whether the herd or a neighboring herd had a pneumonia epizootic previously. Density = the number of individuals counted divided by the area of each herd's distribution, assigned into 1 of 3 equally sized bins of low, medium (md), and high (hi) density relative to the herd's 1979–2013 percentage of average. Spring = the percentage of average 1 April–30 June precipitation in the herd distribution compared to the average from 1980–2010. Herd effect is the among-herd variation for the herd-level random effect.

	Mean	SD	Credibility interval	
			0.025	0.975
Second generation model				
β_0 Intercept	−6.856	0.935	−8.925	−5.288
β_1 Private land	0.487	0.256	−0.002	1.005
β_2 Weed control	1.300	0.577	0.144	2.409
β_3 Neighbor risk	2.474	0.549	1.426	3.583
β_4 Density(md)	1.876	0.809	0.447	3.633
β_5 Density(hi)	3.066	0.843	1.577	4.884

(continued)

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	Mean	SD	Credibility interval	
			0.025	0.975
β_6 Spring	−0.882	0.342	−1.587	−0.244
Herd effect	0.250	0.149	0.143	0.676
Deviance	147.583	4.593	139.739	157.825

Table 2.5. Estimates for risk of pneumonia epizootics as of 2012 for 42 herds of bighorn sheep in Montana, calculated with the pneumonia risk model we developed. The 10-year risk is the probability of ≥1 pneumonia epizootic occurring in 10 years if levels of risk factors remain unchanged. Map ID # corresponds to Figure 2.1. Within the distribution of each herd plus a 14.5-km buffer from that perimeter, private land = percentage of private land, weed control = whether the herd biologist knew of the use of domestic sheep or goats for weed control, and neighbor risk = whether the herd or a neighboring herd had a pneumonia epizootic previously. Density = the number of individuals counted divided by the area of each herd's distribution, assigned into 1 of 3 equally sized bins of low, medium, and high density relative to the herd's 1979–2013 percentage of average. Where density estimates were unavailable for 2012, we used the most recent density before that year.

		Risk factors:				Pr(Epizootic):	
Map ID #	Herd name	Private land (%)	Weed control	Neig-hbor risk	Density	1 yr (2012)	10 yr (beginning 2012)
1	Ten Lakes	21.25	No	Yes	High	0.203	0.897
2	Koocanusa	6.08	No	No	Low	0.001	0.011
3	Kootenai Falls	25.75	No	No	Low	0.002	0.019
4	Berray Mountain	15.06	No	No	Low	0.001	0.014
5	Thompson Falls	34.96	No	No	Low	0.002	0.025
6	Cut-off	30.04	No	No	High	0.031	0.271

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Map ID #	Herd name	Risk factors: Private land (%)	Weed control	Neig-hbor risk	Density	Pr(Epizootic): 1 yr (2012)	10 yr (beginning 2012)
7	Perma-Paradise	32.20	No	No	Medium	0.012	0.114
8	Hog Heaven	57.43	No	No	Low	0.005	0.048
9	Wildhorse Island	39.32	No	No	High	0.041	0.340
10	Bison Range	47.81	No	No	High	0.052	0.412
11	Petty Creek	36.79	No	No	High	0.038	0.320
12	Bonner	46.27	Yes	Yes	Low	0.108	0.681
13	Lower Rock Creek	39.75	Yes	Yes	Low	0.091	0.613
14	Upper Rock Creek	29.33	No	Yes	Low	0.021	0.194
15	Skalkaho[a]	34.29	Yes	No	High	0.109	0.685
16	East Fork Bitterroot	10.60	Yes	Yes	Low	0.040	0.336
17	Painted Rocks	6.03	Yes	Yes	Medium	0.161	0.827
18	Garrison	54.37	Yes	Yes	Low	0.134	0.761
19	Lost Creek	35.73	Yes	Yes	Low	0.081	0.571
20	Highland	35.14	No	Yes	Low	0.025	0.226
21	Tendoy Mountains	26.14	No	Yes	Low	0.019	0.178
22	North Fork Birch Creek-Teton	27.24	No	Yes	Low	0.020	0.183
23	Deep Creek	26.66	No	Yes	Low	0.020	0.181
24	Gibson Lake North	6.04	No	Yes	Low	0.011	0.103
25	Castle Reef	34.46	No	Yes	Medium	0.118	0.714

(continued)

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Map ID #	Herd name	Risk factors: Private land (%)	Weed control	Neig-hbor risk	Density	Pr(Epizootic): 1 yr (2012)	10 yr (beginning 2012)
26	Ford Creek	21.81	No	Yes	Medium	0.084	0.584
27	Beartooth-Sleeping Giant	74.67	Yes	Yes	Low	0.220	0.917
28	Elkhorn	51.41	No	Yes	Low	0.040	0.338
29	Spanish Peaks	28.83	No	No	Medium	0.011	0.103
30	Hilgards	14.58	No	Yes	High	0.173	0.850
31	Hyalite[b]	26.86	No	No	Low	0.002	0.019
32	Upper Yellowstone	9.26	No	Yes	High	0.151	0.806
33	Mill Creek	17.63	Yes	No	Medium	0.026	0.229
34	Monument Peak	0.31	No	No	High	0.013	0.123
35	East Yellowstone	0.75	No	No	High	0.013	0.125
36	Stillwater	8.53	No	No	High	0.017	0.155
37	West Rosebud	16.28	No	No	High	0.021	0.190
38	Hellroaring	9.27	Yes	No	Low	0.004	0.038
39	Pryor Mountains	14.26	Yes	No	Low	0.005	0.044
40	Missouri River Breaks	44.91	Yes	No	High	0.144	0.788
41	Little Rockies	31.18	No	No	Low	0.002	0.022
42	Middle Missouri Breaks	24.57	No	No	Low	0.002	0.018

[a] Had epizootic in 2012 and is now positive for neighbor risk, increasing Pr(Epizootic$_{10\text{-yr}}$) after 2012.

[b] Had epizootic in 2013 and is now positive for neighbor risk, increasing Pr(Epizootic$_{10\text{-yr}}$) after 2013.

CHAPTER 3:

MODELING PROACTIVE DECISIONS TO MANAGE PNEUMONIA EPIZOOTICS IN BIGHORN SHEEP

ABSTRACT Pneumonia epizootics in bighorn sheep (*Ovis canadensis*) are a major challenge for wildlife agencies due to the complexity of the disease, long-term impacts, and lack of tools to manage risk. We developed a decision model to facilitate proactive management of pneumonia epizootics in bighorn sheep in Montana. Our decision model integrates a risk model to predict probability of pneumonia epizootics based on identified risk factors. It uses a structured decision making (SDM) approach to analyze potential decisions based on predictions from the risk model, herd-specific management objectives, and predicted consequences and trade-offs. We demonstrated our model's use with an analysis of representative herds and analyzed the recommended decisions to understand them clearly. We learned that proactive management for each herd was expected to outperform in meeting multiple, competing management objectives compared to ongoing status quo management. Based on sensitivity analyses, we also learned that the recommended decisions were relatively robust with limited sensitivity to variations in model inputs and uncertainties; we expect this to be the case in future analyses as well. Our decision model addressed the challenges of uncertainty, risk tolerance, and the multi-objective nature of management of bighorn sheep while providing a consistent, transparent, and deliberative approach for making decisions for each herd. It is a unique tool for managing pneumonia epizootics using an accessible framework for biologists and managers. Our work also provides a case study for developing similar SDM-based

decision models, particularly for other wildlife diseases, to address challenges of making complex decisions.

INTRODUCTION

Pneumonia epizootics pose a critical challenge for management of bighorn sheep (*Ovis canadensis*; Gross et al. 2000, Cahn et al. 2011, Wehausen et al. 2011, Cassirer et al. 2013, Plowright et al. 2013). All-age epizootic events result in high initial mortality that can exceed 80% (Enk et al. 2001, Montana Fish, Wildlife and Parks [MFWP] 2010, Sells et al. 2015). Subsequent pneumonia outbreaks may continue for decades, often resulting in chronically low lamb recruitment which may ultimately lead to the herd's extirpation (Enk et al. 2001, Cassirer and Sinclair 2007, Cassirer et al. 2013, Plowright et al. 2013, Sells et al. 2015). This is a particular threat for herds with low pre-epizootic abundance, high mortality rates during the epizootic, or that experience other random events that further threaten the herd with extirpation (Woodroffe 1999, Singer et al. 2000, Cassirer and Sinclair 2007, Cassirer et al. 2013, Plowright et al. 2013). In Montana there have been at least 22 epizootics of ≥25% mortality from 1979–2013, 15 of which resulted in >50% mortality (MFWP 2010, Sells et al. 2015); 11 epizootics have occurred since 2008 alone. Impacts of epizootics have included total extirpation of 1 herd and poor recovery in at least 3 others, despite up to 30 years of recovery efforts by Montana Fish, Wildlife and Parks (MFWP).

A lack of tools to predict and proactively manage risk of pneumonia epizootics often leads to reactive "crisis management" following epizootic events (Woodroffe 1999, Mitchell et al. 2013, Sells et al. 2015). Intensive, costly management may be required to help herds recover, including culling (Edwards et al. 2010), augmentation (MFWP 2010), and reintroductions (Singer et al. 2000), although herds may never entirely recover to their former abundance and state of health (e.g., Enk et al. 2001, MFWP 2010, Cassirer et al. 2013, Plowright et al. 2013, Sells et al. 2015).

Proactive management to prevent pneumonia epizootics requires tools to predict risk and to develop and evaluate potential proactive decisions to reduce that risk. Sells et al. (2015) developed an empirical model for predicting risk of pneumonia epizootics in Montana. The model is expected to reduce false positive and negative binary predictions of risk and therefore be reliable and useful for making decisions (Sells et al. 2015). Estimating risk accurately does not, however, automatically imply appropriate proactive management. Given multiple approaches and objectives for proactively managing pneumonia epizootics, a decision model is needed to evaluate the consequences and trade-offs of alternative approaches. Incorporating uncertainty in such a model is critical to making good decisions, particularly for relatively rare, hard-to-predict epizootic events. We used structured decision making (Gregory et al. 2012, Conroy and Peterson 2013, Mitchell et al. 2013) to develop such a decision model for proactive management of pneumonia epizootics in bighorn sheep in Montana, based on a prototype developed by Mitchell et al. (2013). Structured decision making (SDM) is a deliberative, transparent, and defensible method for identifying a management action most likely to achieve desired outcomes. It provides a consistent approach for making decisions, allows inclusion of multiple competing objectives, accounts for uncertainty, and can account for risk tolerance (Gregory et al. 2012, Conroy and Peterson 2013). In this paper, we describe each general step of the SDM-based components of our decision model. We apply our model to hypothetical management of representative herds of bighorn sheep in Montana, and analyze sensitivity of the recommended decision to potential influences that could affect the outcome of the analysis.

COMPONENTS OF THE DECISION MODEL

An SDM-based decision model breaks a decision down into its logical components: 1) problem statement, 2) fundamental objectives, 3) alternatives, and 4) decision analysis (Gregory et al. 2012, Conroy and Peterson 2013). The problem statement defines the decision context, fundamental objectives are the goals, and alternatives are the various management approaches. Decision analysis involves evaluating risk, consequences, and trade-offs for alternatives. Mitchell et al. (2013) presented these steps for proactively managing epizootics from a workshop held with MFWP managers and biologists. In 2014 we met with a working group consisting of different MFWP biologists and managers to revisit the Mitchell et al. (2013) work and complete the decision model for pneumonia epizootics in bighorn sheep. We then designed the decision model in spreadsheet format to allow easy use by any decision-maker. Generally, the appropriate decision-maker is the biologist or manager responsible for each herd. Decisions therefore remain local and community-based within MFWP because the appropriate decision-makers can easily use the model to evaluate potential decisions specific to their herds, without the SDM expertise, working groups, or meetings typically relied upon for SDM-based decision analyses.

Problem Statement

We refined the problem statement from Mitchell et al. (2013) to describe the issue of pneumonia epizootics in bighorn sheep as follows:

MFWP has direct experience with bighorn sheep pneumonia epizootic events that have affected conservation and public enjoyment of bighorn sheep. MFWP currently has no tools for evaluating whether taking actions to proactively prevent similar events will produce more desirable results. MFWP wildlife managers and biologists need risk assessment and decision analysis tools to help prioritize and allocate resources to identify and manage the risk of major disease events. These tools need flexibility in their implementation so that decisions about bighorn sheep management and conservation remain local and community-based. Management actions and tools should be implemented with a monitoring program in a way that will reduce uncertainty and risk in the future.

Fundamental Objectives

In SDM, fundamental objectives define what a fully successful solution to the problem would accomplish (Gregory et al. 2012, Conroy and Peterson 2013) and are used to evaluate potential decisions. Each fundamental objective has an associated measurable attribute used to quantify the extent to which a fundamental objective is achieved by a solution to the problem. We refined the fundamental objectives and associated measurable attributes for pneumonia epizootics presented by Mitchell et al. (2013) as:

1. Maximize the probability of herd persistence (measured as utility in terms of the probability of avoiding an epizootic).
2. Minimize costs in terms of:
    a. operational costs; i.e., cost of day-to-day activities associated with management of bighorn sheep (measured in dollars),

b. personnel costs; i.e., cost of day-to-day activities associated with management activities (measured in days), and
c. crisis response costs, i.e., operating costs and costs of personnel time for responding to an epizootic (measured in dollars).

3. Maximize public satisfaction in terms of:
   a. viewing opportunity (measured as relatively low, medium, or high for the herd), and
   b. hunting opportunity (measured in the predicted number of licenses issued).

Alternatives

Alternatives are the potential management approaches a decision maker could use to solve the problem (Gregory et al. 2012, Conroy and Peterson 2013). For managing pneumonia epizootics in bighorn sheep, we developed alternatives related to risk factors identified in the Sells et al. (2015) risk model. Through analysis of histories of 43 herds in Montana from 1979–2013, Sells et al. (2015) identified 4 risk factors positively associated with probability of pneumonia epizootics within herds (Table 3.1). These were:

1. greater amounts of private land in a herd's area of high risk (herd distribution plus a 14.5-km buffer), expected to represent risk from hobby or commercial farms with domestic sheep or goats ("private land"),
2. when domestic sheep or goats were known to be used to control weeds in the herd's area of high risk ("weed control"),
3. when the herd or a neighboring herd in the herd's area of high risk had a pneumonia epizootic since 1979 ("neighbor risk"), and

4. when the within-herd density was medium or high rather than low, based on the herd-specific variation in density from 1979–2013 (“density”).

We developed the alternatives based on management techniques biologists and managers thought would successfully reduce risk from these factors, and organized the alternatives in a matrix based on each risk factor and from generally least to most aggressive alternatives (Fig. 3.1). Decision-makers can combine these and other alternatives they create to evaluate unique portfolios of management actions for their specific herds in the decision model. Each portfolio is an alternative management approach the decision-maker wants to analyze for their herd. Current management actions are detailed in a “status quo” portfolio for comparison. During the decision analysis, the status quo and each new portfolio are analyzed to identify which has most support for implementation.

Representative Herds for Analysis.—We selected 3 herds representative of challenges of pneumonia epizootics in bighorn sheep for which decision-makers (the MFWP biologist responsible for each herd) designed portfolios and tested with our decision model (Fig. 3.2). The Petty Creek herd was a moderate-risk herd of >125 individuals as of 2014. Given recent epizootics nearby, the decision-maker for Petty Creek was very risk averse towards pneumonia epizootics for this herd.

In contrast, the nearby high-risk Bonner herd experienced one such epizootic in 2010. The decision-maker for Bonner was very risk tolerant toward pneumonia epizootics given the recent epizootic, counts of only 11 animals in 2014, and a situation that seemed unlikely to improve in the near future without extensive, costly management.

The low-risk Perma-Paradise herd was managed by the Confederated Salish and Kootenai Tribes on the Perma side of the herd distribution and by MFWP on the Paradise side. The herd was popular with the hunting public, with the third highest number of applicants for licenses within a single MFWP hunting district in Montana. Due to a robust size of >250 individuals and the herd's popularity, the decision-maker for the Paradise portion of the herd was very risk averse toward pneumonia epizootics in this herd.

Portfolios for Representative Herds.—Decision-makers described the status quo portfolio for their herds and then developed unique portfolios for comparison. Portfolios were herd-specific, based on the risk factors affecting the herd and what actions the decision-maker thought would reduce that risk. Portfolios for Petty Creek included the:

1. Status Quo Portfolio (including public education about risk from domestic sheep and goats, surveys and inventories, harvest management, and responding to wandering domestic sheep and goats),
2. Transplant Removal Portfolio (focused on removing bighorn sheep through a transplant operation, plus public education about risk from domestic sheep and goats on private land, surveys and inventories, harvest management, and both removal and hazing of wandering domestic and bighorn sheep),
3. Lethal Removal Portfolio (focused on lethal removal zones around the herd, plus public education about risk from domestic sheep and goats on private land, surveys and inventories, harvest management, and removal of wandering domestic and bighorn sheep), and
4. Easement Portfolio (focused on conservation easements and fee title purchases to reduce risk from farms with domestic sheep and goats, plus improvement of range

health, public education about risk from domestic sheep and goats on private land, surveys and inventories, and harvest management).

The decision-maker for Bonner designed portfolios to build off the status quo and one-another. Portfolios included the:

1. Status Quo Portfolio (including surveys and inventories, post-epizootic monitoring, necropsies, public education about risk from domestic sheep and goats, removal of wandering domestic or bighorn sheep if found comingling, and using fencing and herders for weed control operations),
2. Outreach Phase 1 Portfolio (all status quo actions plus increased outreach, with focus on more public education and working with the city of Missoula to end weed control with domestic sheep),
3. Outreach Phase 1+2 Portfolio (including all Outreach Phase 1 actions plus additional public education and outreach to amend the herd's management plan regarding contact between domestic and bighorn sheep), and
4. Ideal Portfolio (including all Outreach Phase 1 + 2 actions plus an augmentation to increase herd size).

Risk factors for Perma-Paradise were related to private land and density, so the decision-maker focused on alternatives addressing these risk factors and designed portfolios based on the relative level of aggression of alternatives (Fig. 3.1). Portfolios included the:

1. Status Quo Portfolio (including surveys and inventories and harvest management),
2. Least Aggressive Portfolio (including the least aggressive actions such as increased public education about risk from domestic sheep and goats on private land),

3. Moderately Aggressive Portfolio (including least and moderately aggressive actions such as conservation easements and fee title purchases, removal of wandering bighorn sheep, and increased harvest), and
4. Most Aggressive Portfolio (including least, moderate, and most aggressive actions designed to reduce risk from private land and density).

Decision Analysis

Decision analysis in SDM includes predicting risk, estimating consequences, and evaluating trade-offs for each portfolio (von Winterfeldt and Edwards 1986, Edwards and Barron 1994, Gregory et al. 2012, Mitchell et al. 2013). These steps comprise the analysis of the potential decisions by incorporating uncertainty, expected consequences of epizootics, and relative importance of fundamental objectives to quantify support for each portfolio.

Predicting Risk.—The first step of a decision analysis is for the decision-maker to predict, for each portfolio, the probability of potential outcomes that may occur once a decision is made. For pneumonia epizootics, the 2 potential outcomes are that an epizootic either does or does not occur. Predictions can be made using expert opinion (e.g., Mitchell et al. 2013) or an empirical risk model (e.g., Sells et al. 2015). These predictions incorporate uncertainty into the decision analysis, for the timing and location of a pneumonia epizootic can never be known with certainty in advance (Gregory et al. 2012, Mitchell et al. 2013).

Our decision model used the risk model of Sells et al. (2015) to help decision-makers predict risk for each portfolio in a risk prediction table (Table 3.2). The risk model yielded 1-year probability of a pneumonia epizootic, from which long-term risk could be calculated for use in the decision analysis (Sells et al. 2015). To begin, the decision-maker entered data associated with each risk factor, *R*, for the status quo, then estimated hypothetical risk for each portfolio by predicting how the portfolio would affect *R*. Whereas Sells et al. (2015) designed most risk factors as categorical, we treated all *R* as continuous with a 0–1 range because we expected few actions could realistically eliminate a risk factor entirely, i.e., completely reduce a categorical *R* from "1" (full effect) to "0" (no effect). Instead, the decision-maker estimated relative reductions in risk, e.g., if they thought public education about weed control with domestic sheep and goats would reduce that risk by 30%, they entered "0.7" for that *R*.

Once the decision-maker entered data for all *R*, logit risk was calculated with the parameter values (β) from the Sells et al. (2015) risk model:

$$\text{Logit risk} = \beta_{\text{intercept}} + \beta_{\text{private land}} \times R_{\text{private land}} + \beta_{\text{weed control}} \times R_{\text{weed control}} + \beta_{\text{neighbor risk}} \times R_{\text{neighbor risk}} + \beta_{\text{density(md)}} \times R_{\text{density(md)}} + \beta_{\text{density(hi)}} \times R_{\text{density(hi)}}$$

and transformed to the probability of pneumonia epizootic (i.e., risk) in any 1 year by:

$$\Pr(\text{Epizootic}_{\text{1-yr}}) = \left(e^{\text{Logit risk}}\right) / \left(1 + e^{\text{Logit risk}}\right)$$

(Ramsey and Schafer 1997). Long-term risk of ≥1 epizootic occurring in the next *y* years was:

$$\Pr(\text{Epizootic}_{\text{long-term}}) = 1 - [1 - \Pr(\text{Epizootic}_{\text{1-yr}})]^{y}$$

(Mood et al. 1974). Finally, probability of no epizootic in that long-term timeframe was:

$$\Pr(\text{No epizootic}_{\text{long-term}}) = 1 - \Pr(\text{Epizootic}_{\text{long-term}})$$

(De Veaux et al. 2012). These long-term predictions were used in the remaining decision analysis steps. Long-term predictions assumed *R* inputs remain unchanged for *y* years;

decision-makers could analyze shorter timeframes for *y* depending on how long they expected *R* would remain unchanged.

Estimating Consequences.—The second step of a decision analysis is predicting how each potential outcome (e.g., epizootic and no epizootic) will affect the fundamental objectives. (E.g., if an epizootic occurred, what would be the predicted costs of crisis response?) Decision-makers predicted consequences of an epizootic and no epizootic for each fundamental objective and each portfolio in a consequence table (Table 3.3). Consequence tables were structured by objectives and portfolios to enable organization, comparison, and analysis of the predicted consequences (Gregory et al. 2012, Mitchell et al. 2013).

Once the decision-maker entered each predicted consequence, the consequence table translated them into expected values for the decision analysis. The expected value (EV) of a consequence was the sum of consequences for the potential outcomes weighted by their probabilities:

$$\text{EV} = \text{Consequence}_{\text{Epizootic}} \times \Pr(\text{Epizootic}_{\text{long-term}}) + \text{Consequence}_{\text{No epizootic}} \times \Pr(\text{No epizootic}_{\text{long-term}})$$

(Gregory et al. 2012). The EV was thus the combined expected consequences, accounting for uncertainty. An exception to this calculation for EV is if risk attitude is important to an analysis of consequences. In our decision analysis, risk attitude toward herd persistence was important because different decision-makers had various degrees of risk tolerance or aversion toward probability of an epizootic. To factor risk attitude into the EV for persistence, decision-makers selected a risk attitude curve (Fig. 3.3; Conroy and Peterson 2013). We designed the curves as:

$$\text{Utility[Pr(No epizootic}_{\text{long-term}})] = 1 - \text{Pr(Epizootic}_{\text{long-term}})^{r}$$

where r was the risk tolerance factor (0.25, 0.5, 1, 2, or 4, corresponding to very risk averse, risk averse, risk neutral, risk tolerant, or very risk tolerant, accordingly). The EV for persistence for each portfolio, Utility[Pr(No epizootic$_{\text{long-term}}$)], accounted for the decision-maker's attitude toward Pr(Epizootic$_{\text{long-term}}$) of each portfolio.

Next, the consequence table translated EV to normalized values, *X'*. Normalizing put EV of each objective on a 0–1 scale to make EV of all objectives directly comparable. If the goal of an objective was to maximize it,

$$X' = (x - x_{min})/(x_{max} - x_{min}),$$

and if to minimize,

$$X' = (x - x_{max})/(x_{min} - x_{max}),$$

where x were the original EV within an objective (Gregory et al. 2012).

Evaluating Trade-offs.—Evaluation of trade-offs is the final step of a decision analysis. One type of trade-off is the relative importance of each objective, since rarely can any single portfolio perform best on all objectives. Swing weights, w_i, were the importance the decision-maker placed on each objective, calculated through swing weighting (Table 3.3; von Winterfeldt and Edwards 1986, Edwards and Barron 1994, Gregory et al. 2012). Swing weighting accounted for the predicted difference in EV from worst- to best-case scenario for each objective. This swing was important because if there was little difference from worst- to best-case predictions for an objective (i.e., all predictions for an objective were about equal), it need not have influenced the decision. Resulting w_i summed to 1.0.

Support for each portfolio was determined through weighted scores and overall scores. Weighted scores described each portfolio's performance within single objectives, whereas overall scores described each portfolio's performance over all objectives. Weighted scores were based on the normalized values and corresponding weight for that objective, calculated as $X' \times w_i$ (Table 3.3; von Winterfeldt and Edwards 1986, Edwards and Barron 1994, Gregory et al. 2012, Mitchell et al. 2013). Portfolios with higher weighted scores were predicted to perform better for that objective compared to portfolios with lower weighted scores. The sum of weighted scores of a portfolio was its overall score for all objectives. Portfolios with higher overall scores had more decision support based on the predicted risk, predicted consequences, and weighted importance of each objective.

To make a decision, the decision-maker compared overall scores and considered trade-offs between weighted scores. Trade-offs occur in SDM when no single portfolio has the highest weighted scores on all fundamental objectives. In some cases, a portfolio was the clear choice if no other portfolios scored closely and a lower-scored portfolio's benefits did not outweigh its negative trade-offs. When ≥2 portfolios performed similarly well in overall scores, trade-offs were an important consideration before identifying a final portfolio for implementation (Gregory et al. 2012). Portfolios with slightly lower overall scores could have provided a better compromise in meeting multiple objectives reasonably well, particularly if the highest-scored portfolio did poorly on certain objectives.

RESULTS OF THE DECISION ANALYSES

Using our decision model, decision-makers completed analyses for Petty Creek, Bonner, and Perma-Paradise. We analyzed whether our model was able to help identify decisions for each representative herd. We then analyzed sensitivity of these decisions to various model components.

Model Ability to Identify Decisions

For Petty Creek, the decision-maker chose to analyze a timeframe of 5 years; 5-year Pr(Epizootic$_{\text{long-term}}$) ranged from a low of 0.038 for the Transplant Removal Portfolio to 0.264 for the Status Quo (Table 3.2). The decision analysis resulted in high overall scores for 2 portfolios; either would be a good decision with slight trade-offs between each. The Transplant Removal Portfolio had greatest support with 0.74 overall score (Table 3.3; Fig. 3.4). It had the highest weighted scores for persistence, crisis response costs, and viewing opportunity, with trade-off of worst hunting opportunity and second-worst personnel costs. The Lethal Removal Portfolio scored nearly as highly at 0.71 overall score. Its trade-offs included lower weighted scores for objectives scoring highest in the Transplant Removal Portfolio, but slightly better weighted scores for personnel costs and hunting opportunity.

For Bonner and Perma-Paradise, decision-makers chose 10-year timeframes to implement a portfolio longer before re-analyzing each herd. Results supported 1 clear decision for each herd. For Bonner, 10-year Pr(Epizootic$_{\text{long-term}}$) ranged from 0.173 for the Ideal Portfolio to 0.719 for the Status Quo. The Ideal Portfolio had most support (0.61 overall score; Fig. 3.4), with highest weighted scores on all objectives except operating and personnel costs. Low overall scores of 0.39–0.44 for remaining portfolios were not comparable. For Perma-Paradise, 10-year Pr(Epizootic$_{\text{long-term}}$) ranged from 0.058 for the Most Aggressive Portfolio to 0.114 for the Status Quo. The Most Aggressive Portfolio had the highest overall score (0.80), with highest weighted scores for persistence, viewing opportunity, and hunting opportunity. Remaining portfolios with scores of 0.15–0.60 were not comparable.

Sensitivity Analyses

We evaluated performance of our model and analyzed sensitivity of results to uncertainty in risk predictions, risk attitude, and weights (von Winterfeldt and Edwards 1986, Conroy and Peterson 2013).

Sensitivity to Uncertainty.—The credibility intervals (CRIs; Kéry 2010) quantified uncertainty of Pr(Epizootic$_{\text{long-term}}$) in the risk prediction table (Table 3.2). We replaced Pr(Epizootic$_{\text{long-term}}$) in the consequence table (Table 3.3) with lower (10%) or upper (90%) CRIs in turn to test sensitivity of overall scores to this source of uncertainty.

The analyses for our representative herds were not sensitive to the uncertainty of Pr(Epizootic$_{\text{long-term}}$) from the risk model. For Petty Creek, overall scores did not change using lower CRIs. Overall scores for the Lethal Removal Portfolio and Status Quo decreased slightly using upper CRIs. For Bonner, the Ideal Portfolio remained highest scored; support for other portfolios barely changed. The same was true for Perma-Paradise, with the Most Aggressive Portfolio remaining highest scored. Despite potentially extensive uncertainty in Pr(Epizootic$_{\text{long-term}}$), it appears unlikely to affect the results of the decision analysis.

Sensitivity to Risk Attitude.—We compared overall scores at each different risk attitude (Fig. 3.3) to test the sensitivity of the recommended decisions for each herd to this subjective model component. Although overall scores between the highest-scored portfolios for Petty Creek slightly fluctuated at different risk attitudes, they remained almost identical. The original highest-scored portfolios retained the highest score at any risk attitude for both Bonner and Perma-Paradise; other portfolios were never comparable. The recommended decisions for the representative herds thus had minimal sensitivity to risk attitude.

Sensitivity to Weights.—We also tested sensitivity of the recommended decisions for each herd to weights on objectives (w_i). To do so, we varied w_i from 0–1 for an objective while holding remaining w_i at their original values to identify values for "switchover," the w_i at which the recommended portfolio changed (von Winterfeldt and Edwards 1986).

For Petty Creek, the Transplant Removal and Lethal Removal portfolios nearly always retained the highest overall scores regardless of w_i (Fig. 3.5). Switchover to the Lethal Removal Portfolio occurred for $w_{\text{persistence}} \leq 0.10$ or $w_{\text{personnel costs}} \geq 0.34$. Switchover to this portfolio also occurred at $w_{\text{hunting opportunity}} \geq 0.34$ and to the Easement Portfolio at ≥ 0.53. Results were not sensitive to remaining w_i. Altogether, overall scores between these portfolios remained close, meaning changes in w_i would not result in a clearly superior decision.

Bonner and Perma-Paradise were insensitive to w_i. For Bonner, switchover from Ideal to Status Quo occurred in the unlikely scenarios of $w_{\text{persistence}} \leq 0.07$, $w_{\text{operating costs}}$ ≥ 0.41, or $w_{\text{personnel costs}} \geq 0.43$. For Perma-Paradise, switchover to Moderately Aggressive occurred in the unlikely scenario of $w_{\text{personnel cost}} \geq 0.55$, and to Least Aggressive if $w_{\text{operating cost}} \geq 0.58$ or $w_{\text{personnel cost}} \geq 0.72$. The recommended decisions for the representative herds therefore had minimal sensitivity to w_i.

DISCUSSION

We created a decision model to facilitate proactive decisions for managing risk of pneumonia epizootics in bighorn sheep. We found that proactive decisions were recommended over the status quo management for each representative herd we analyzed. The portfolios that scored highest for each herd were predicted to meet fundamental objectives better than any other portfolios decision-makers developed and analyzed for their herds. We were not surprised that the generally more aggressive types of portfolios performed well for Petty Creek and Perma-Paradise given the decision-makers' risk aversion towards pneumonia epizootics. We were uncertain what to expect from the analysis for Bonner due to the herd's recent epizootic event and the decision-maker's higher risk tolerance towards pneumonia epizootics as a result, yet the more aggressive portfolio was also recommended. If this portfolio were excluded from the analysis, (e.g., if it was deemed too expensive), however, remaining portfolios would have approximately equal support. The decision may then be the Status Quo; we expected this would be true in a herd with few ways to improve consequences for most objectives after a recent epizootic.

One of the greatest challenges for good decision-making is addressing uncertainty. For pneumonia epizootics, there is extensive uncertainty about timing and location of relatively rare epizootic events. We factored this uncertainty into the decision model with the Sells et al. (2015) risk model so that probability of pneumonia epizootic was used throughout the decision analysis. Sells et al. (2015) used decision curve analysis to analyze the reliability of their model for making decisions by exploring the balance between false positives and negatives at various thresholds for binary risk level (Vickers and Elkin 2006, Steyerberg et al. 2010, Sells et al. 2015). They found that the risk model is expected to be reliable for making decisions, leading us to be confident in its use in our decision model. The decision analysis may still be sensitive to a decision-maker's estimates for effects of portfolios on risk (e.g., *R* inputs in Table 3.2), yet changes to these estimates are unlikely to influence the analysis unless overall rank or magnitude of estimated risk across portfolios change (von Winterfeldt and Edwards 1986).

Our sensitivity analyses of results for the representative herds revealed that the recommended decisions were not sensitive to uncertainty for risk predictions, risk attitude, and weights. The final decision is important rather than the exact values within a decision model, and changes to inputs often have limited effect on the decision unless changes are large (von Winterfeldt and Edwards 1986). Based on results from our representative herds, we expect the decision analyses from our model to generally be insensitive to any of these components, with only slight variations in overall scores when an analysis has >1 highly scored portfolio. When this is the case, trade-offs between multiple highly scored portfolios are the important consideration rather than the overall scores alone.

Our decision model is a unique tool that accounts for the important, inherent uncertainty surrounding timing and location of pneumonia epizootic events while simultaneously making explicit the many considerations needed to make good proactive decisions. It also exemplifies the role of SDM-based decision models for managing wildlife, particularly for managing disease. An adaptive management approach will improve the model through learning from implementation of each decision (Gregory et al. 2012, Conroy and Peterson 2013). A monitoring program on the efficacy of proactive actions and occurrence of future epizootics would provide data to continuously refine the model and future decisions, yielding increasingly effective proactive management of pneumonia epizootics in bighorn sheep.

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Figure Captions

Figure 3.1. Example management alternatives to address risk factors for pneumonia epizootics in bighorn sheep. Actions range from least to most aggressive and correspond to risk factors identified by Sells et al. (2015).

Figure 3.2. Location of several herds of bighorn sheep in western Montana. Decision-makers evaluated potential proactive management actions for pneumonia epizootics for Petty Creek, Bonner, and Perma-Paradise with our decision model.

Figure 3.3. Risk attitude curves for probability of pneumonia epizootics in bighorn sheep for the decision model we developed. After a decision-maker selected a curve for their tolerance toward risk of pneumonia epizootics, the decision model calculated corresponding utilities for each portfolio for the fundamental objective of maximizing persistence in the consequence table (Table 3.3).

Figure 3.4. Overall scores for portfolios (i.e., potential decisions) decision-makers evaluated to proactively manage risk of pneumonia epizootics in 3 herds of bighorn sheep in Montana. Scores were calculated using the decision model we developed; higher overall scores indicated greater support.

Figure 3.5. Sensitivity of decisions recommended by our decision model to weight on objectives, w_i, for managing risk of pneumonia epizootics in the Petty Creek herd of bighorn sheep in Montana. We varied a w_i from 0–1 while holding other w_i at original

values. Lines correspond to the various portfolios we evaluated, with higher overall scores indicating greater support. Where lines cross, the recommended decision changed, though similar overall scores indicated similar support for either portfolio. Our results had limited sensitivity to w_i.

Figure 3.1.

	Alternatives to address risk factors			
	Private land	**Weed control**	**Neighbor risk**	**Density**
Least aggressive actions	Do nothing	Do nothing	Do nothing	Do nothing
	Public education/Grazing systems/Livestock replacement	Public education	Manage for young ram season	Harvest - ewe, young ram, OTC/unlimited
	Conservation easement/Fee title purchase	Remove wandering bighorn	Create lethal removal zones around herd	Address range health - expand/improve habitat
	Covenants/Zoning	Create standards for fencing & herders	Cull herd	Trap/transplant/ relocate away from herd
	Remove wandering bighorn/Hazing/ Herding etc.	Change timing of grazing using sheep and goats		Trap/transplant/ relocate within herd to expand range
Most aggressive actions	Remove wandering domestics	Replace sheep and goats with bugs/herbicides		

Figure 3.2.

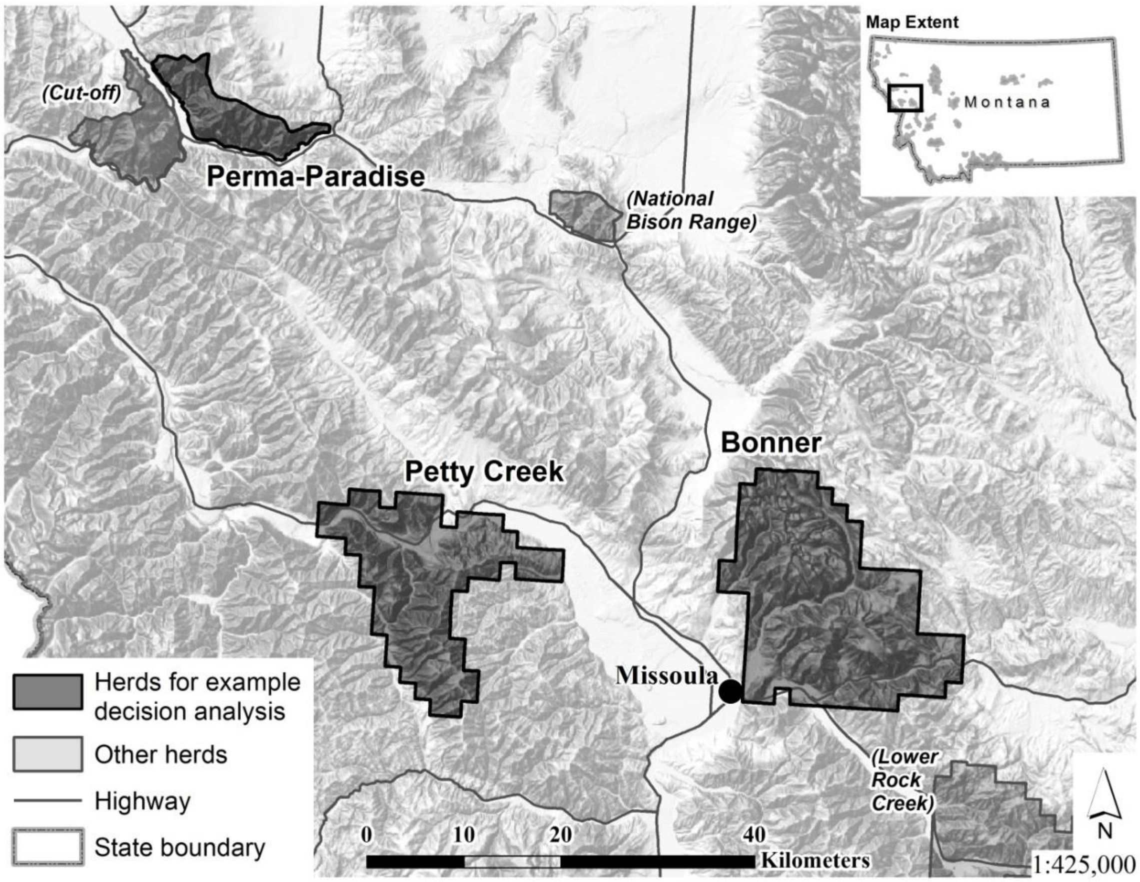

Map Extent
Montana
(Cut-off)
Perma-Paradise
(National
Bison Range)
Bonner
Petty Creek
Missoula
(Lower
Rock
Creek)
Herds for example
decision analysis
Other herds
Highway
State boundary
0
10
20
40
Kilometers
N
1:425,000

Figure 3.3.

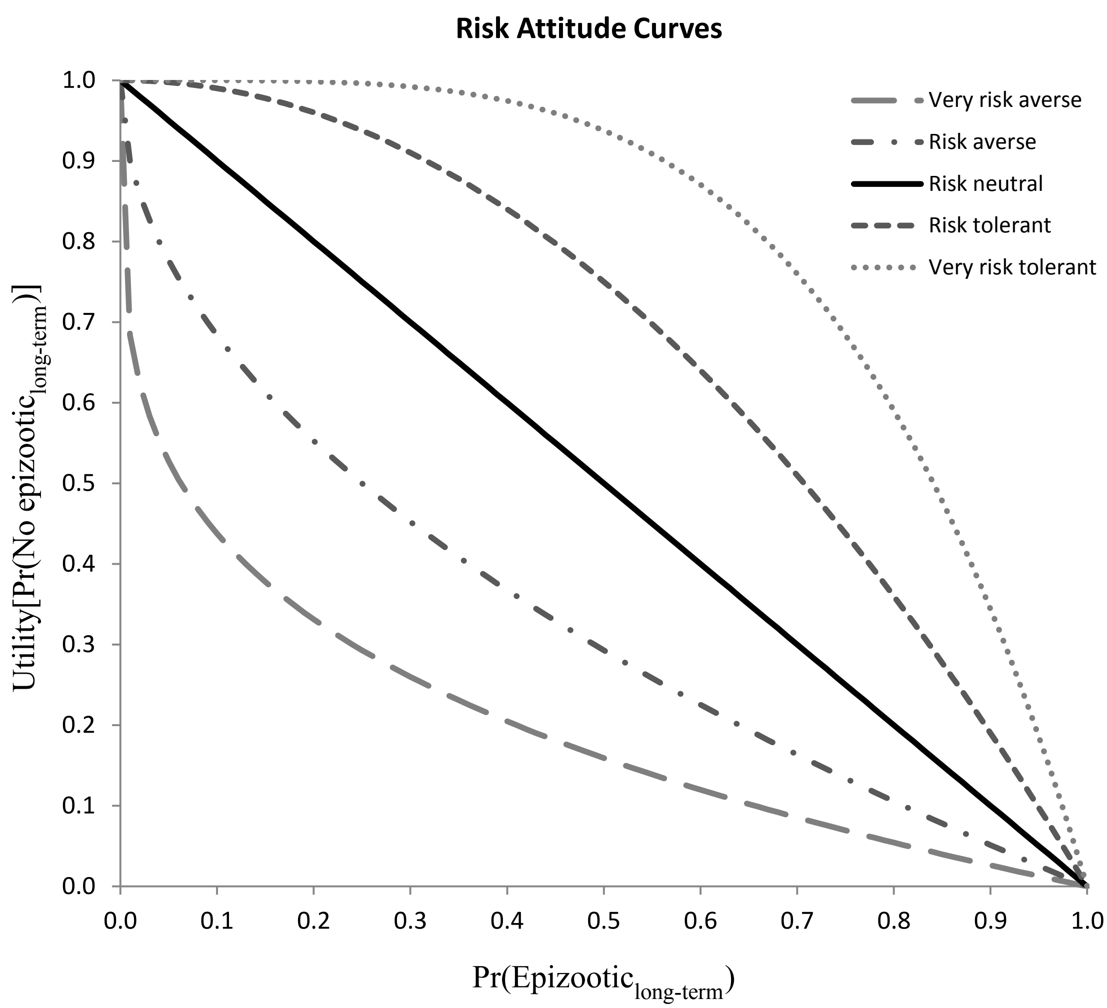

Risk Attitude Curves
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1.0
Very risk averse
Risk averse
Risk neutral
Risk tolerant
Very risk tolerant
Utility[Pr(No epizootic$_{\text{long-term}}$)]
Pr(Epizootic$_{\text{long-term}}$)

Figure 3.4.

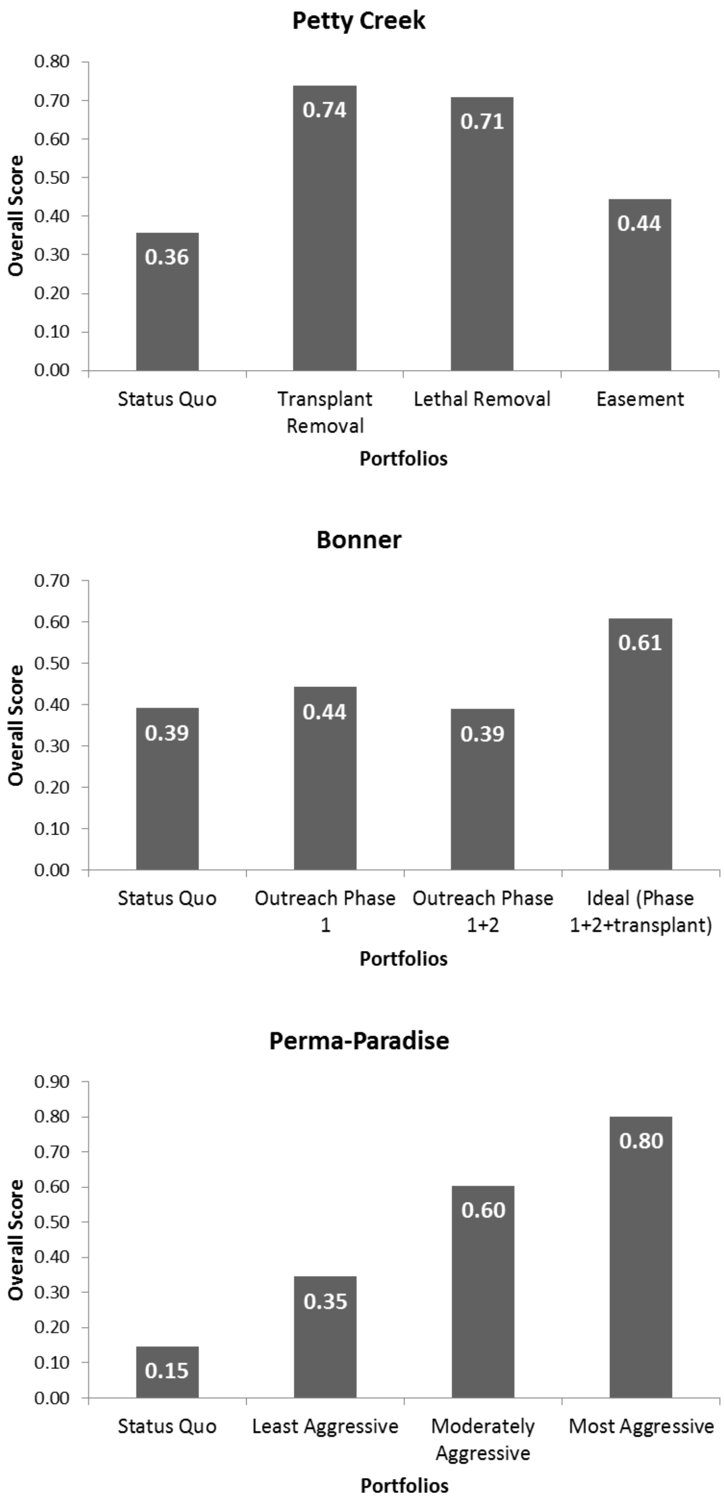
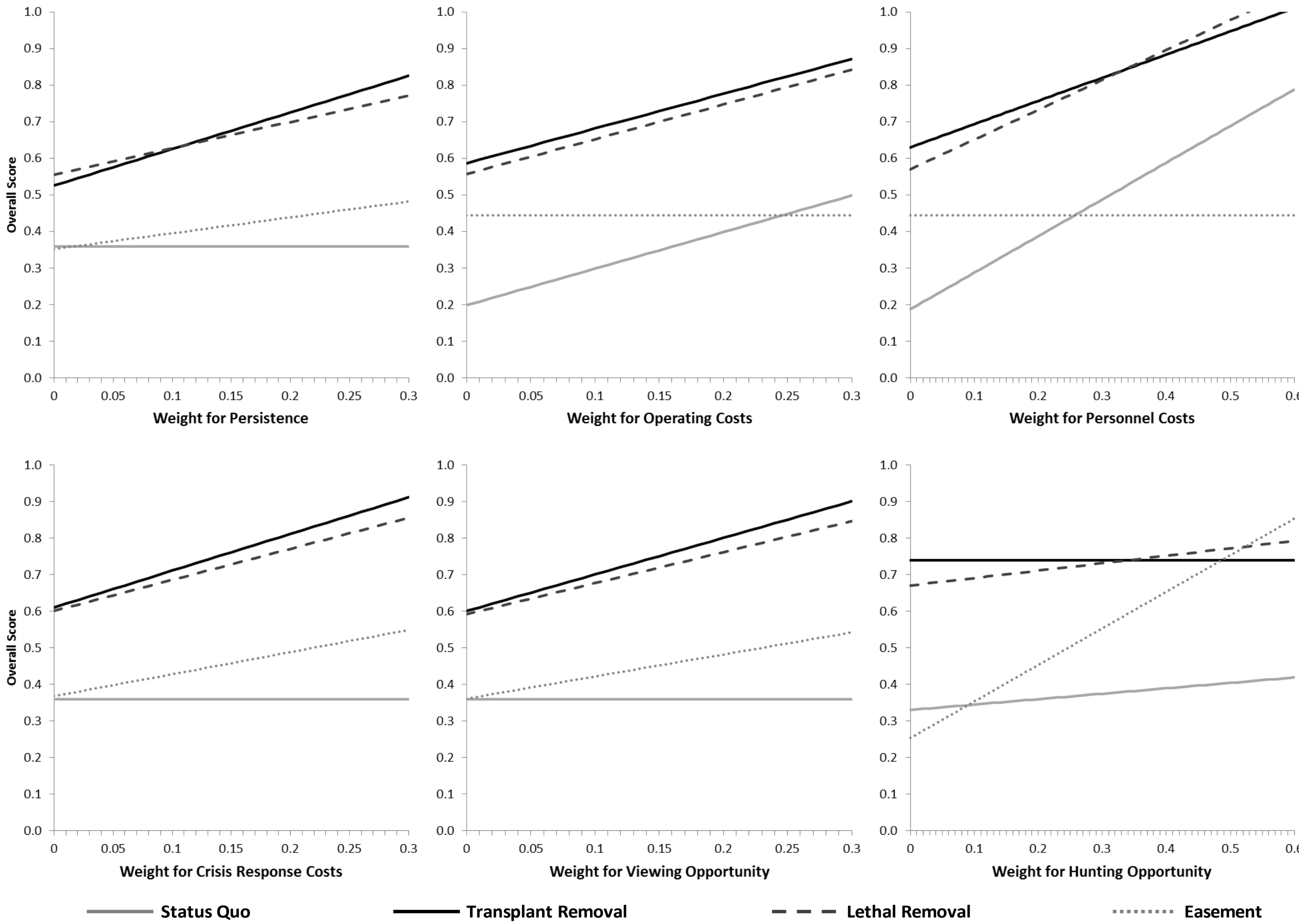

Petty Creek
Overall Score
0.80
0.70
0.60
0.50
0.40
0.30
0.20
0.10
0.00
0.36
0.74
0.71
0.44
Status Quo
Transplant Removal
Lethal Removal
Easement
Portfolios
Bonner
Overall Score
0.70
0.60
0.50
0.40
0.30
0.20
0.10
0.00
0.39
0.44
0.39
0.61
Status Quo
Outreach Phase 1
Outreach Phase 1+2
Ideal (Phase 1+2+transplant)
Portfolios
Perma-Paradise
Overall Score
0.90
0.80
0.70
0.60
0.50
0.40
0.30
0.20
0.10
0.00
0.15
0.35
0.60
0.80
Status Quo
Least Aggressive
Moderately Aggressive
Most Aggressive
Portfolios

Figure 3.5.



Overall Score
Weight for Persistence
Weight for Operating Costs
Weight for Personnel Costs
Weight for Crisis Response Costs
Weight for Viewing Opportunity
Weight for Hunting Opportunity
Status Quo
Transplant Removal
Lethal Removal
Easement

Table 3.1. Parameter estimates of the risk model (Sells et al. 2015) for pneumonia epizootics for bighorn sheep. Within the herd distribution plus a 14.5-km buffer from that perimeter, $\beta_{private\ land}$ is percentage of private land, $\beta_{weed\ control}$ is known use of domestic sheep or goats for weed control, and $\beta_{neighbor\ risk}$ is whether the herd or a neighboring herd had a pneumonia epizootic previously. $\beta_{density(md)}$ and $\beta_{density(hi)}$ are herd-specific at low, medium (md), and high (hi) density relative to the herd's 1979–2013 percentage of average.

Parameters	Mean	SD	Credibility interval	
			0.025	0.975
$\beta_{intercept}$	-6.269	0.761	-7.931	-4.911
$\beta_{private\ land}$	0.433	0.239	-0.028	0.910
$\beta_{weed\ control}$	1.210	0.547	0.115	2.261
$\beta_{neighbor\ risk}$	2.331	0.524	1.332	3.392
$\beta_{density(md)}$	1.660	0.728	0.309	3.180
$\beta_{density(hi)}$	2.699	0.742	1.332	4.259

Table 3.2. Risk prediction table from our decision model showing estimated probability of pneumonia epizootics, Pr(Epizootic), for portfolios evaluated for the Petty Creek herd of bighorn sheep. Decision-makers predicted how portfolios (i.e., potential decisions) would affect the risk factors identified by the Sells et al. (2015) risk model. The table provided corresponding Pr(Epizootic) for 1-yr and long-term timeframes (5 years for Petty Creek).

	R Inputs (Predicted Impact on Risk Factors):				Pr(Epizootic)		Pr($\text{Epizootic}_{\text{long-term}}$) CRI[a]:	
Portfolio	Private Land:	Weed Control (0-1):	Neighbor Risk (0-1):	Density (Lo, Md, or Hi, 0-1)[b]:	1-year[c]	Long-term[d]	10% CRI	90% CRI
Status Quo	50%	(N/A, 0)	15% impact (0.15)	Hi, 90% impact (0.90)	0.059	0.264	0.149	0.430
Transplant Removal	36%	(N/A, 0)	5% impact (0.05)	Md, 60% impact (0.60)	0.008	0.038	0.020	0.071
Lethal Removal	43%	(N/A, 0)	10% impact (0.10)	Md, 80% impact (0.80)	0.015	0.072	0.038	0.132
Easement	45%	(N/A, 0)	15% impact (0.15)	Hi, 65% impact (0.65)	0.027	0.128	0.071	0.217

[a] 80% credibility intervals quantify uncertainty for Pr($\text{Epizootic}_{\text{long-term}}$).

[b] Lo = low, md = medium, hi = high, based on herd-specific range in density from 1979–2013.

[c] $\Pr(\text{Epizootic}_{\text{1-yr}}) = \left(e^{\text{Logit risk}}\right)/\left(1 + e^{\text{Logit risk}}\right)$, where $\text{Logit risk} = \sum \beta_i \times R_i$, based on *R* inputs and β from the risk model (Table 3.1).

[d] $\Pr(\text{Epizootic}_{\text{long-term}}) = 1 - [1 - \Pr(\text{Epizootic}_{\text{1-yr}})]^y$ for *y* years.

Table 3.3. Consequence table showing the decision analysis for managing risk of pneumonia epizootics for the Petty Creek herd of bighorn sheep. The decision-maker predicted consequences for 2 potential outcomes (epizootic and no epizootic). The Transplant Removal and Lethal Removal portfolios scored highly. Trade-offs, based on weighted scores, are an important consideration in a decision analysis before selecting a final portfolio to implement.

Fundamental Objective:	Persistence	Operating Costs	Personnel Costs	Crisis Response	Viewing Opportunity	Hunting Opportunity	
Goal:	Maximize	Minimize	Minimize	Minimize	Maximize	Maximize	
Measurable Attribute & Scale:	Utility [Pr(No epiz.$_{\text{long-term}}$)][a]	Cost, $K, long-term	Person-days, long-term	Cost, $K, long-term	1=lo, 2=md, 3=hi[b]	Licenses, #, long-term	
Portfolio:			Consequences, Epizootic:				Pr(Epizootic$_{\text{long-term}}$)[c]:
Status Quo	0.00	37.50	70.00	45.00	2.00	20.00	0.26
Transplant Removal	0.00	75.00	180.00	45.00	2.00	12.50	0.04
Lethal Removal	0.00	75.00	125.00	45.00	2.00	20.00	0.07
Easement	0.00	787.50	370.00	45.00	2.00	50.00	0.13

(continued)

(continued)

Fundamental Objective:	Persistence	Operating Costs	Personnel Costs	Crisis Response	Viewing Opportunity	Hunting Opportunity	
Portfolio:			Consequences, No Epizootic:				Pr(No epiz.$_{\text{long-term}}$)[d]:
Status Quo	0.28	37.50	70.00	0.00	3.00	40.00	0.74
Transplant Removal	0.56	75.00	180.00	0.00	3.00	25.00	0.96
Lethal Removal	0.48	75.00	125.00	0.00	3.00	40.00	0.93
Easement	0.40	787.50	370.00	0.00	3.00	100.00	0.87
Portfolio:			Expected Values (EV)[e]:				
Status Quo	0.28	37.50	70.00	11.87	2.74	34.73	
Transplant Removal	0.56	75.00	180.00	1.73	2.96	24.52	
Lethal Removal	0.48	75.00	125.00	3.26	2.93	38.55	
Easement	0.40	787.50	370.00	5.75	2.87	93.61	

(continued)

(continued)

Fundamental Objective:	Persistence	Operating Costs	Personnel Costs	Crisis Response	Viewing Opportunity	Hunting Opportunity	
Portfolio:			Normalized Values (X')[f]:				
Status Quo	0.00	1.00	1.00	0.00	0.00	0.15	
Transplant Removal	1.00	0.95	0.63	1.00	1.00	0.00	
Lethal Removal	0.72	0.95	0.82	0.85	0.85	0.20	
Easement	0.43	0.00	0.00	0.60	0.60	1.00	
			Weighted Scores[g]:				
Portfolio: Weights (w_i)[h]:	0.21	0.16	0.17	0.13	0.14	0.19	Overall Score[i]:
Status Quo	0.00	0.16	0.17	0.00	0.00	0.03	0.36
Transplant Removal	0.21	0.15	0.11	0.13	0.14	0.00	0.74
Lethal Removal	0.15	0.15	0.14	0.11	0.12	0.04	0.71
Easement	0.09	0.00	0.00	0.08	0.08	0.19	0.44

(continued)

(continued)

[a] Consequences for persistence are based on the decision-maker's risk attitude toward Pr(Epizootic$_{\text{long-term}}$) (Fig. 3.3).

[b] Low (lo), medium (md) or high (hi) density.

[c] Pr(Epizootic$_{\text{long-term}}$) is calculated with the Sells et al. (2015) risk model (Tables 3.1 and 3.2).

[d] Pr(No epizootic$_{\text{long-term}}$) = 1 – Pr(Epizootic$_{\text{long-term}}$).

[e] Expected values, EV = Consequence$_{\text{Epizootic}}$ × Pr(Epizootic$_{\text{long-term}}$) + Consequence$_{\text{No epizootic}}$ × Pr(No epizootic$_{\text{long-term}}$).

[f] Normalized values, $X' = (x - x_{min})/(x_{max} - x_{min})$ if the goal is to maximize, $(x - x_{max})/(x_{min} - x_{max})$ if minimize.

[g] Weighted scores = $X' \times w_i$ and are the final scores for the consequences for each objective, for each portfolio.

[h] Weights, w_i, are based on swing weighting.

[i] Overall scores are summed across each row; higher scores have more support.

APPENDIX

Table A.1. List of 30 a priori models of risk of pneumonia epizootics for 43 herds of bighorn sheep in Montana from 1979–2013. Model number, effective number of parameters (pD), and Deviance Information Criterion (DIC) are provided, with models sorted by ΔDIC compared to the top-ranked model. Within the distribution of each herd plus a 14.5-km buffer from that perimeter, allotments = # federally managed sheep and goat allotments, private land = percentage of private land, weed control = whether the herd biologist knew of the use of domestic sheep or goats for weed control, and neighbor risk = whether the herd or a neighboring herd had a pneumonia epizootic previously. Herd proximity = the average distance to the 3 closest herds. Ram:ewe ratios = ratio of rams to ewes counted during surveys. Density = the number of individuals counted divided by the area of each herd's distribution, assigned into 1 of 3 equally sized bins of low, medium (md), and high (hi) density relative to the herd's 1979–2013 percentage of average. Winter = percentage of normal November−March precipitation in the herd distribution. Spring = percentage of normal April−June precipitation in the herd distribution. Herd origin = whether the herd was native, mixed, or reintroduced.

#	Model	pD	DIC	ΔDIC
19	Private land + Weed control + Neighbor risk + Density	8.5	162.1	0.0
14	Neighbor risk + Density	7.5	169.0	6.9
21	Private land + Neighbor risk + Herd origin	7.9	178.8	16.7
3	Neighbor risk	4.5	179.3	17.2

(continued)

(continued)

#	Model	pD	DIC	ΔDIC
13	Neighbor risk + Winter	5.6	181.4	19.3
15	Weed control + Density	11.8	183.7	21.6
22	Weed control + Proximity + Density + Herd origin	15.0	183.9	21.8
18	Private land + Proximity + Density	12.5	184.6	22.5
20	Private land + Weed control + Proximity	8.1	186.9	24.8
12	Private land + Proximity	8.0	192.1	30.0
4	Weed control	8.2	192.5	30.4
7	Density	14.1	193.6	31.5
16	Weed control + Spring	14.1	194.4	32.3
2	Private land	8.7	197.2	35.1
23	Weed control + Proximity + Winter + Spring	17.1	197.7	35.6
25	Proximity + Density + Spring	26.5	197.8	35.7
5	Proximity	8.5	198.1	36.0
9	Spring	12.3	198.6	36.5
8	Winter	7.9	199.1	37.0
10	Herd origin	10.9	202.5	40.4
27	Allotments + Neighbor risk + Density	54.5	1055.3	893.2
26	Allotments + Private land + Proximity + Spring	58.4	1070.8	908.7
11	Allotments + Private land	56.2	1081.2	919.1
1	Allotments	57.2	1084.6	922.5
29	Allotments + Proximity + Winter + Herd origin	67.7	1096.0	933.9
24	Neighbor risk + Rams + Spring	59.1	1637.4	1475.3

(continued)

(continued)

#	Model	pD	DIC	ΔDIC
17	Private land + Rams + Density + Winter	70.3	1659.1	1497.0
6	Rams	61.7	1661.4	1499.3
30	Global (all 10 covariates)	116.3	2507.9	2345.8
28	Allotments + Weed control + Rams	108.3	2540.0	2377.9