A STRUCTURED APPROACH TO INTERAGENCY AND CROSS-JURISDICTIONAL MONITORING AND MANAGEMENT OF SEA OTTERS (*Enhydra lutris kenyoni*) AND BROWN BEARS (*Ursus arctos*) IN ALASKA

by

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Under the Direction of Michael J. Conroy

ABSTRACT

Natural resource management over broad, heterogeneous landscapes is complicated by the inherent uncertainty in ecosystem processes and the ability of managers to predict the response of systems to management actions. Management decision-making is further complicated when multiple user-groups and management agencies with overlapping jurisdictions have fundamentally different objectives and policies. In these instances, formal decision making frameworks, such as structured decision making (SDM), can provide a means to evaluate management decisions in an integrated framework that can be used to address conflicting perceptions of system dynamics. In Alaska, brown bears (*Ursus arctos horribilis)* occur in large numbers on lands managed by the National Park Service (NPS) and other federal agencies and also are managed by the Alaska Department of Fish and Game and regulated as a game species by the Alaska Board of Game. Meanwhile, sea otter monitoring efforts in southwest Alaska are largely implemented by the National Park Service while the US Fish and Wildlife Service is the agency tasked with making decisions regarding sea otter management. Using SDM, we developed integrated modeling and decision support systems to explicitly link management, research, and monitoring of brown bears and sea otters in Alaska. The brown bear decision models tracked the state of bears through time in Katmai National Park and Preserve and Noatak National Preserve and estimated the effects of management actions on bear populations, harvest success, human-bear incidents, and park visitation. Sensitivity analysis identified key uncertainties that included factors that affected bear populations and human-bear incidents. In addition to eliciting values from decision-makers, benefit transfer was used as an alternate means of estimating values associated with fundamental objectives. This approach suggested that decision-makers' values reflected the public's non-consumptive use and harvest values but that the value they placed on the bear population objective may have been too high. The model estimates also were sensitive to the relative value of harvest, bear population, and non-consumptive use objectives. Limiting the scope of the problem to NPS jurisdictional boundaries allowed for transparent decision making but may slow learning in an adaptive management framework.

INDEX WORDS: Structured decision making, adaptive management, sea otters, brown bears, decision models, natural resource management, monitoring, National Parks

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A Dissertation Submitted to the Graduate Faculty of The University of Georgia in Partial Fulfillment of the Requirements for the Degree

DOCTOR OF PHILOSOPHY

ATHENS, GEORGIA

2014

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May 2014

ACKNOWLEDGEMENTS

My deepest appreciation goes to my fiancé, Fazal Khan. He provided the environment that allowed me to focus on successfully finishing my doctoral studies. Especially during the last year of my work, he held our home together and gave me the space and time I needed to focus on writing. He read, and provided review, of chapters, listened to countless success stories and frustrations, and offered unyielding support and positive feedback. He also made sure that Skyler, Ichabod, and I were well-cared for when I didn't have the time or energy to think about anything beyond this work. To that end, he gave without expecting in return, and I look forward to the days ahead when we can forge forward as partners, with both of us giving to each other the unconditional love and support that he has so graciously offered to me.

Special thanks go to my doctoral advisory committee, Drs. Michael J. Conroy (Chair), James T. Peterson, Rebecca Moore, Laurie Fowler, and Nathan Nibbelink. Collectively, their advice, support, mentorship, and guidance helped me navigate the challenging waters that eventually routed me to the successful completion of the degree requirements for a Doctor of Philosophy. Mike and Jim often advised me in tandem and helped me to better understand the importance of quantitative techniques and their application in natural resource management. They taught me to challenge the statistical norms broadly used in the ecological sciences, including null hypothesis testing, the use of indices, and the general apprehension many natural resource scientists have towards the (explicit) use of models. They introduced me to the field of decision theory and helped me to develop my own philosophy towards its application in natural resource management. Mike steered me away from cynicism (when it crept in), and reminded me to remain focused on the big picture and our contributions (even small ones) towards building a better one. Jim's astute guidance challenged me to question my own assumptions, think critically, and be prepared to defend my conclusions. He also showed me that excellence in teaching can still be accomplished at a research-focused university despite the ever growing demands on faculty. Rebecca Moore is another excellent teacher. She introduced me to the field of environmental economics and, in turn, an alternate view (i.e., outside of the environmental science community) regarding how humans value the environment. In spite of her demanding teaching load, I studied under her for two semesters (via independent study) before she sent me off to the economics department to continue my tutelage in her field. I came away with a toolbox full of optimization and valuation techniques; but, more importantly, I am now armed to better communicate the beneficial effects of natural resource management to the public and policy-makers.   Last, but most certainly not least, Nate and Laurie's relentless optimism and support of my work kept me motivated on the darkest of days. I quickly learned that framing natural resource decision problems requires in-depth analysis and review of relevant policy. Laurie's background and input were imperative to this part of my work. She also supported my attendance at a course where I received formal training in conflict analysis and facilitation which greatly improved my skills as a decision coach. Meanwhile, Nate was always there to gently remind me that every natural resource decision problem is spatial.

The collaborative nature of this work dictates that it would not have been possible without the commitment and participation of members in both the brown bear and sea otter working groups. I could spend pages discussing the contributions of each individual member, but I will do my best to keep it short. From the sea otter working group, Jim Bodkin and Heather Coletti provided invaluable insight into sea otter system dynamics; while Suzann Speckman and Michael Shephard contributed perspectives on U.S. Fish and Wildlife Service and National Park Service management and monitoring regimes respectively. Jim and Heather worked collectively

to get me into the field where I spent a month living on a boat in Katmai National Park conducting near shore marine mammal and bird surveys. This remains one of the most memorable experiences of my life; and, from it, I learned that one can only benefit from experiencing a system before attempting to model it. In spite of a highly contentious political environment, Jim Lawler, Michael Shepherd, and Grant Hilderbrand provided the institutional commitment necessary for the brown bear working group to make it through the steps of the structured decision process. Harry Reynolds, Tammy Wilson, Josh Schmidt, Brad Schults, Troy Hammon, Bill Leacock, Sherri Anderson, Marci Johnson, and others generously provided valuable time, data, and feedback. Tammy, Grant, and Josh went above and beyond by providing their time and feedback on multiple occasions when I had been ruminating over an issue for too long and needed an outside perspective. Not only was Tammy's input instrumental to the brown bear work but she also opened her home to me when I found myself stranded in Alaska on more than one occasion. She later became a mentor of sorts as I navigated my way into a federal job, graciously sharing her own time and experiences. Finally, I would be remiss if I did not give specific mention of Harry Reynolds and his contributions. Harry is currently retired after spending 30 years as a bear biologist with the Alaska Department of Fish and Game (ADFG), so his participation as a working group member was purely voluntary. Not only did he share his wealth of knowledge regarding brown bear system dynamics in Alaska, he also provided important insight into ADFG management perspectives. More than that, his continued commitment to brown bear conservation after spending his entire career in public service was inspiring to say the least.

My father and his brother, my Uncle Richard, encouraged me to think critically from a young age. When there was no easy answer to my questions, they did not offer one and instead encouraged me to investigate such questions on my own. I believe it was their influence that eventually led me to a career in science. In addition to my father and Uncle, the love and support provided by my entire family was instrumental in allowing me to achieve my academic goals. My father, stepmother, and mother provided support throughout my graduate studies, delighted in my achievements, and shared in my frustrations. My brothers and sisters (by blood and marriage), Tony and Cherie, Joey and Lindsay, Nicholas, Paula and Brian, and Rebecca and Todd, listened, laughed, shared holidays, offered advice and encouragement, and, most importantly, instilled in me the value of family above all else. Their children, my nieces and nephews, inspire my continued dedication to a life in public service.

I write this final acknowledgement knowing full well that the recipient will never read or comprehend the role that she played in shaping the person I am today. Though she is intelligent, loving, and truly empathetic, there are limits to her canine faculties. That said, she deserves mention, perhaps more than anyone. Skyler and I became a pair when we were both babies. She was a 6-week-old puppy and I a 19-year-old college sophomore. We discovered the woods together, spending our weekends exploring our favorite wilderness areas, especially Cuyahoga Valley National Park. When I began working as an undergraduate research technician, she became my field assistant. She was my running partner, first in the unrelenting Cleveland winters and then in the stifling southern heat. When I decided to leave my close-knit family to pursue a Master's degree 800 miles away from anyone or anything that was familiar, it was she who gave me the courage. Her companionship meant that I was never truly alone. She moved with me countless times during my graduate studies and was there when I found a human partner whom she happily accepted into our lives. During my doctoral studies, Skyler adopted a slower, gentler pace. Her failing hips meant that our runs turned into walks, and she was happy to curl-up under my desk snoring most of the day while I worked. She most certainly did not know how thankful I was to have her greet me, at the age of fourteen, after the successful defense of my dissertation. Yet, sensing my excitement, she found the energy to bound about the house, embodying the pure joy and relief that I felt. Not long ago, she moved with me yet again, so that I could pursue a career with the US Fish and Wildlife Service. I picture her next me still at future rites of passage… a wedding, children, life's surprises, joys, and disappointments. I can't imagine them without her by my side. But the realities of nature and probability dictate that our time together is limited. Thank you for being my loyal friend and companion, Skyler Bleu. This work is dedicated to you.

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CHAPTER 1 : STRUCTURED DECSION MAKING AND ADAPTIVE MANAGEMENT AS TOOLS FOR NATURAL RESOURCE DECISION MAKERS

In this introductory chapter, I provide background on structured decision making (SDM) and adaptive resource management (ARM) and highlight challenges that are relevant to the research chapters. Because there is considerable variation in how the term “adaptive management” is used within the natural resource management community, I will first discuss various “co-opted” definitions of the term and will then provide the working definition used within the decision theoretic school of adaptive management. Next, I describe the elements of structured decision making and ultimately define adaptive management as an iterative form of SDM. I then discuss appropriate applications of SDM and ARM and describe the types of uncertainties and conflicts these processes can be used to address. Finally, I present challenges and discuss reasons for real or perceived failures to applications of SDM and ARM.

STRUCTURED DECISION MAKING AND ADAPTIVE MANAGEMENT DEFINED

Different schools of thought regarding adaptive management have led to considerable confusion regarding the true definition of the concept. To some, the term “adaptive” simply implies flexibility, such that a particular management plan is subject to change (Wilhere 2000). More commonly, “trial and error” approaches - which entail the implementation of a particular action until unsatisfactory consequences are revealed - are described as adaptive management. Trial and error approaches are, by nature, reactive (also called “learning by doing”) and often don’t include monitoring of outcomes. Thus, detection of deficient management schemes in “trial and error” adaptive management can be slow.   Another co-opted use of the term adaptive management occurs when certain components of adaptive management, such as stakeholder involvement, are confused with the process itself. Stakeholder involvement is certainly an important component of the adaptive management process, but the act of involving stakeholders in a decision making process does not in and of itself imply the practice of SDM or ARM.

There are two primary schools of thought which “true” adaptive management protocols tend to follow: the resilience- experimentalist (RE) school and the decision-theoretic (DT) school (McFadden et. al. 2011). The decision theoretic school is more heavily influenced by decision theory and is the school that has informed my research to the greatest extent. DT adaptive management involves the application of a structured decision process within a framework of iterative decision making that involves monitoring and the explicit reduction of structural uncertainty over time. Elements of the structured decision process include 1) defining the decision problem, 2) identifying and structuring stakeholder objectives, 3) developing a set of management alternatives, 4) evaluating the consequences of alternatives relative to objectives (usually via modeling), and 5) selecting an optimal decision action (Clemen and Reilly 2001, Williams 2011, Conroy and Peterson 2013). The 5-step structured decision making (SDM) process is a useful framework for evaluating a very broad range of decision problems, ranging from the re-organization of agency structure to the decision to list a species as “endangered” pursuant to the Endangered Species Act (ESA).

Adaptive management includes all of the components of SDM, but is applied to sequential (in time or space) decision problems that are hampered by structural uncertainty (Williams et al. 2002, Williams 2011; Conroy and Peterson 2013). In adaptive management frameworks, uncertainties about system dynamics are explicitly represented as competing models of alternative hypotheses. Monitoring programs are designed to discern which of the alternative scenarios produce better predictions and to evaluate the success of management schemes (Nichols and Williams 2006). Future decisions can then be *adapted* based on the new understanding of how the system works. Because the central motivation of adaptive management (as defined above) is to increase returns by reducing uncertainty about how a system responds to management, adaptive management must include the following three elements: 1) explicit, *a priori* predictions of management consequences given alternate models of system dynamics, 2) sequential (in time or space) decision-making, and 3) monitoring (Conroy and Peterson 2013). Any decision process that does not have these three elements, along with the five elements of SDM, is not adaptive management.

In the resilience-experimentalist (RE) school, there is a high emphasis placed on obtaining a shared understanding among stakeholders during the entire decision process (McFadden et. al. 2011). Additionally, proponents of this school require active learning about ecosystem resilience via experimental perturbation of ecosystem dynamics. In contrast, the DT school focuses communication with stakeholders during the early design and development stages of the process (steps 1-3 above). The process for the DT school often leads to less complex ecological models that are centered on the decision problem, while the RE school leads to complex models that include all potentially significant details of the ecosystem (McFadden et. al. 2011). Note that the model I develop in chapter five (the sea otter Bayesian belief network) more closely resembles models designed using RE theory; while models developed in chapters two through four strictly adhere to the DT school.

A recurrent theme in both adaptive management schools is the ongoing monitoring of measurable objectives while also implementing selected, optimal actions. With active learning and continuous monitoring, uncertainty decreases and forecast management outcomes can be more easily predicted (Nichols and Williams 2006). As the number of iterations increase in the AM process, more informed decision making is enabled.

ELEMENTS OF STRUCTURED DECISION MAKING AND ADAPTIVE RESOURCE MANAGEMENT

Stakeholder Involvement

An important early step in the SDM process, is to engage relevant stakeholders and ensure their involvement in the decision making process (Wondolleck and Yaffe 2000; Williams 2011). There are a number of reasons to include stakeholders in natural resource decision processes. First, natural resource decisions often involve trust resources. Thus, the public typically has a vested interest in decision outcomes. Trust resources also often have multiple users, and multiple uses of the same resource can lead to competition and conflict. Involving multiple user groups as stakeholders in SDM processes ensures that their interests and values will be reflected in the ultimate product. By including potential adversaries in decision-making processes, those who may have initially opposed implementation efforts can sometimes be converted into supporters. Stakeholder driven processes also foster transparency which facilitates buy-in by the public and policy-makers. Furthermore, a transparent process grants more legitimacy to decisions.

Although the number and identity of stakeholders can vary greatly, common representatives in natural resource decision processes include resource managers, policy makers, and special interest groups (e.g. watershed association groups or NGOs; Schreiber et al. 2004). While many interest groups could be stakeholders, not all relevant interest groups should be stakeholders. Stakeholder analysis is a process that can be used to assess the relative importance of potential stakeholders (Conroy and Peterson 2013). Generally, the group that elicited the decision analyst's expertise – those who are most familiar with the decision problem - can provide useful input to help with stakeholder analysis. Stakeholders that are essential to include in the process are those entities that have 1) a strong ability to affect the decision, or 2) will be strongly affected by the decision outcome. Criteria '1' dictates that decision-makers must participate in the process. It is paramount that all relevant decision-makers are included at the outset of SDM processes (Conroy and Peterson 2013). Stakeholders that do not meet either of these criteria are not essential to the process.

Outside of stakeholders, other representatives in the SDM processes include knowledge experts, facilitators, and decision analysts (Conroy and Peterson 2013). Stakeholder input is generally more important in the early design and development phases of the process, including identifying objectives and decision alternatives, and, later, associating (relative) values with predicted decision outcomes. It is of particular importance that stakeholders are involved in defining the decision situation so that they are in agreement about the scope, objectives, and management alternatives of the relevant resource issue (Clemen and Reilly 2011). In the absence of such an agreement, the likelihood of management program failure increases dramatically (Williams 2011).

Knowledge experts are generally more important in later stages of the SDM process including model development. Their input guides the decision analyst in modeling system dynamics and in describing alternate beliefs about system dynamics (e.g., conflicts about science). While stakeholders may also have knowledge about system dynamics, there is a danger in allowing participants to act as both knowledge experts and stakeholders. Because SDM is a value driven process, it is important that the decision analyst is able to clearly distinguish between conflicts about system dynamics (i.e., structural uncertainty that can be resolved via ARM) versus conflicts about values (i.e., trade-offs that should be assessed via multi-attribute utility theory). If a participant plays both the role of a stakeholder and a knowledge expert, their objectivity as a knowledge expert may become compromised (often unwittingly) and conflicts about objectives may end-up being misrepresented as conflicts about science. Different tools are available for addressing both types of conflict, and a decision analyst must be able to recognize which tool to apply. Therefore, I advocate that decision analysts assure that participants understand the alternate roles of stakeholders and knowledge experts and encourage participants to decide, at the outset of the process, which role they want to play..

Defining the Problem

After assessing who to involve in a SDM process, the first stakeholder-driven task is to define the decision problem. A problem statement should propose an action (or set of choices) that is predicted to lead to outcomes that fulfill objectives (Conroy and Peterson 2013). This can be accomplished by asking stakeholders to consider in the following "We (stakeholders) want to do X to achieve Y over time Z and in place W considering B." The purpose of this process is to turn a vague task into an affirmative action statement that ties actions to measurable outcomes. It also helps to define the spatial, temporal, and organizational bounds of the decision problem.

Identifying and Structuring Objectives

Structuring objectives involves the identification and separation of fundamental and means objectives (Clemen and Reilly 2001, Conroy and Peterson 2013). Fundamental objectives are those that relate to the decision-maker's core values and thus are not usually negotiable. In contrast, means objectives are actions that need to be accomplished in order to achieve the fundamental objectives.

Decision Alternatives

After identifying and structuring objectives, the next step in a decision process is to formulate possible alternatives for the policy. By construct, a decision involves an irrevocable allocation of resources by the decision maker. Alternatives should also be feasible, relevant to the decision scope, and they must represent specific actions that can be linked directly to some system response or management objective (Conroy et. al. 2008; Conroy and Peterson 2013). Feasibility implies that the alternative could be implemented if selected (Conroy et al. 2008). For example, actions that are outside of the jurisdiction of the management agency should not be included in the decision set. Moreover, actions contained within the decision set should be mutually exclusive and collectively exhaustive. The mutually exclusive criteria means that, should alternative “A” be selected, then alternatives “B” and “C” are eliminated as options. The collectively exhaustive criteria implies that all actions available to the decision-maker should be included the decision set, including non-action alternatives, or alternatives that might seem unpopular to stakeholders at the outset (Conroy et al. 2008). Lastly, the learning component of ARM ultimately relies on the ability to measure the success of management actions. Therefore, decision actions must be linked to measurable system responses in the model.

Evaluating Consequences with Models

Once the scope of the decision problem has been defined (i.e., decision statement, objectives, and management alternatives), alternate policies can be evaluated by predicting resource outcomes with respect to the objectives for each option. In SDM and ARM, models are commonly used to do this by explicitly linking potential management actions to resource consequences (Schreiber et al. 2004; Williams 2011, Conroy and Peterson 2013). Models incorporate uncertainties in ecosystem processes and causal relations by representing alternative hypotheses of system structure and function (Williams et al. 2002). Alternative hypotheses are embedded in competing models that predict resource changes through time. At any given time, available evidence can be used to assess confidence in competing models, allowing for the formal learning component in the ARM process.

Sensitivity Analysis

Before implementing an optimal decision, sensitivity analysis should be performed to evaluate the sensitivity of decision optimization to changes in model components and to changes in values on objectives. Specifically, three categories of sensitivity tests can be useful heuristics to assess the influence of model parameters and values to decision-making. First, one-way (or x-way) sensitivity analysis is used to determine the relative influence of each model component on the expected value of decisions and model outcomes (Peterson and Evans 2003, Conroy and Peterson 2013). To accomplish this, model parameters are systematically varied from minimum to maximum levels and associated changes in the expected value of the decision or model outcome are recorded. Second, response-profile analysis can be used to evaluate changes in the optimal decision that occur when parameters are varied from minimum to maximum levels. If a model parameter is identified to be both influential and important to decision optimization (via response-profile sensitivity analysis) it is a key uncertainty. Monitoring in adaptive management processes should focus on reducing key uncertainties (Nichols and Williams 2006). Third, for decision problems that have multiple objectives, indifference sensitivity tests can be used to evaluate the sensitivity of decisions to the relative weighting schemes on objectives (Conroy and Peterson 20013). Indifference tests help stakeholders evaluate whether or not they have placed appropriate weights on objectives.

Monitoring and Iterative Learning

The learning component that is arguably the most important defining feature of ARM is reliant upon monitoring programs that are designed to speak directly to management objectives (Yoccoz et al 2001; Williams et al. 2002; Nichols and Williams 2006). Learning occurs via comparison of model based predictions with observed resource states. This enables updating of beliefs about alternative representations of system dynamics and responses to management.

Because alternative scenarios are examined *a priori*, monitoring programs can be explicitly designed to reduce uncertainty and measure the system's reaction to management (Williams et al. 2002; Nichols and Williams 2006). Monitoring data can then be used to discern which of the alternative scenarios produce better predictions allowing managers and decision-makers to learn over time. Management is adjusted at each decision iteration in response to both changing resource status and learning, each of which is informed by monitoring data.

Monitoring in the absence of active decision-making has been equated with adaptive management (Moir and Block 2001). In general, learning in the absence of active management is done very poorly, requiring at least 10-20 years of monitoring to reduce uncertainty associated with a particular system component. Further, a distinction has been made between passive and active adaptive management (McCarthy 2006; Williams 2011b). The main difference between the two is the degree to which objectives emphasize the reduction of uncertainty. In passive adaptive management, management goals are the primary objective of the decision making process, while active adaptive management explicitly pursues the reduction of uncertainty via management interventions. Ultimately, when ARM is restricted to parts of the whole cycle, management schemes are much more likely to result in failure (termed the "Anna Karenina Principle" by Moore 2001).

UNCERTAINTY AND DECISION-MAKING

The use of a formal decision making process (SDM) allows for accounting of uncertainties related to decision-making, while ARM allows for the reduction of a certain kind of uncertainty (i.e., structural uncertainty, see definition below). There are multiple types of uncertainty that can affect natural resource decisions (Williams et. al. 2002; Conroy and Peterson 2013). Environmental stochasticity involves the uncertainty related to environmental factors beyond the control of the decision maker leading to stochastic or non-deterministic outcomes. For example, an extreme weather event could potentially have a severe impact on an expected outcome. Partial controllability is the uncertainty associated with the realization of a decision. For example, an 8% harvest rate may be dictated, but instead a 10% harvest rate is realized. Because we rarely if ever observe the true state of the system and instead rely on a sample of the population, statistical uncertainty can influence our ability to effectively determine current conditions and evaluate the results of our conservation actions. Statistical uncertainty manifests itself in estimates of the parameters or variables of interest and can lead to bias, imprecision or both. Structural uncertainty presents itself in the underlying assumptions about how a system will respond to a decision. Structural uncertainty is the type of uncertainty that can be reduced via adaptive management.

While the uncertainties outlined above are often addressed, or at least recognized, by the conservation biology community, the challenge of linguistic uncertainty is frequently overlooked. Linguistic uncertainty arises from the use of ambiguous, vague, context-dependent and/or under-specific language (Regan et al. 2002). Linguistic uncertainty is common and can greatly complicate policy interpretation and decision making (Regan et al. 2002).

In my observations, of the four categories of linguistic uncertainty identified above, decision alternatives suffer most from ambiguity and under-specificity. Ambiguity arises when a word has more than one meaning, and we are not sure which meaning was intended by the user (Regan et al 2002). For example, in the case of *Enhance permitting regulations*, the term "enhance" is ambiguous. It is not clear whether permitting regulations should be increased, improved, or intensified nor is it clear at what level(s) enhancement should occur. Under-specificity implies unwanted generality and occurs when the decision alternative does not provide the desired level of specificity. In the case of *Enhance permitting regulations*, we are left wondering: what types of permits?; which specific regulations?; what levels of regulations should be considered?; and so on.

In contrast, (in my experience) policy interpretation suffers most from vagueness and ambiguity. Vagueness arises when a word has an unclear meaning. For example, the terms “healthy” and “natural” are often used to describe population or ecological objectives. This is often not the fault of the decision-maker as the values dictated by statutes are often left purposely vague by legislators. In the *Chevron* case (1984), the Supreme Court held that in the absence of clear Congressional intent on an issue, courts should defer to an agency’s interpretation of a statute that it administers, so long as the agency is not acting in an arbitrary or capricious manner. This deference has practical importance as it allows more freedom to agencies to define their role and abilities under any particular statute. However, it also presents a challenge as agency managers and decision-makers must define what is meant by “healthy” and “natural.” In Chapter 2, I provide an example of how the SDM process facilitated the transformation of vague and ambiguous legislative objectives into measurable attributes.

ADAPTIVE MANAGEMENT APPLICATIONS: WHY DO SOME PROGRAMS SUCCEED WHILE OTHERS FAIL?

I posit that failures in the use of adaptive management tend not to be a fault of the process, but rather result from either a co-opted use of the term adaptive management or a misapplication of the tool. McFadden and Tyre (2011) conducted an extensive review and analysis of adaptive management applications from 2000 to 2009 across various schools of thought (DT, RE and Other). To accomplish this, they conducted a literature review and categorized ARM articles into six “success” categories (Table 1.1). They further subdivided each category into the three schools of thought (DT, RE and other).

The “implement” category is the only category in which learning, the cornerstone of ARM, was documented. This is the category that I would align with success, because if learning does not occur then adaptive management (DT or RE) has not truly been implemented. McFadden and Tyre (2011) found that articles that fell outside of two of the primary accepted paradigms of ARM (DT or RE) were very rarely in the “implement” or “framework” categories. Moreover, far more DT applications were categorized as “implement” successes than were RE applications. Their work also identified a number of “framework” DT applications. That is, those applications for which a decision framework was created but not implemented. Framework applications may reflect the lack of capacity for people trained in adaptive management. For example, practitioners of ARM are often funded by management agencies to develop a decision framework and an ARM protocol for a specific management problem. However, if there is no agency capacity to carry-on the work after the decision analyst leaves, the program may never move from the framework to the implement stage.

Ruhl-Fischman (2010) reviewed case law involving successes and failure of adaptive management programs according to judicial rulings. They found that one of the major failings of ARM from a judicial review perspective is a focus on the iterative process of ARM at the expense of addressing substantive management criteria required by law. An important criterion in the ESA is the “no jeopardy” standard which explains that federal agencies must ensure that their actions are not likely to jeopardize any endangered species or habitat.

Two cases concerning the operation of infrastructure on the Sacramento San-Joaquin River Delta exemplify the importance of substantive criteria in judicial decisions regarding ARM programs. The listing of Delta smelt (*Hypomesus transpacificus)* by the US FWS and salmonid species by the National Oceanic and Atmospheric Administration (NOAA) Fisheries Service gave rise to two sets of ARM plans (one for the smelt and one for the salmonids) that generated two different lawsuits and, ultimately, two different decisions by the same judge. The judge upheld the salmonid adaptive management protocol but remanded the smelt protocol under the judicial standard that an agency must provide reasonable certainty that it will meet a statutory requirement. The explanation for these disparate results was that the smelt protocol failed to provide enforceable, precise criteria that would reinitiate ESA consultation to revise management actions. While the smelt protocol did include a risk assessment matrix containing criteria that, if met, would trigger a working group to meet and consider a range of management changes, this did not provide enough substantive criteria for the judge to rule in favor of the protocol. In contrast, the salmonid protocol explicitly defined substantive criteria that would serve as a trigger for revising the current management action to a well-defined set of alternatives. Using the DT school of ARM, a well-defined set of management alternatives, and associated predicted outcomes, are examined *a priori* to program implementation. Therefore, I would argue that the failure of the smelt plan was a consequence of it not truly being an adaptive management protocol.

Outside of the misuse of the term adaptive management leading to perceived failures of the tool, I would attribute failures to a lack of capacity to carry programs from the design stage to the implement stage. Remaining failures can be attributed to misapplications of the tool. In cases where recurrent decisions are plagued by reducible (structural) uncertainty, adaptive management is the correct approach. This will not be the case for every decision problem. A more appropriate approach is to evaluate the context of a particular decision problem and then choose the appropriate tool for addressing the problem.

CHAPTER INTRODUCTION

In Chapters 2 through 4, I use a structured decision process to develop two separate, integrated modeling and decision support programs for the management of brown bears in Katmai National Park and Preserve (coastal, southwest Alaska) and Noatak National Preserve (interior, arctic Alaska). In Alaska, brown bears occur in large numbers on lands managed by the National Park Service (NPS) and other federal agencies and also are managed by the Alaska Department of Fish and Game and regulated as a game species by the Alaska Board of Game and the Federal Subsistence Board. I explore the implications of this complex jurisdictional framework in Chapter 2 and further assess its consequences in Chapters 3 and 4.

Brown bear decision models track the state of bears through time and are used to estimate the effects of management actions on bear populations, harvest success, human-bear incidents, and park visitation. Chapters 3 and 4 detail brown bear decision model parameterization, optimization, and sensitivity analysis. Sensitivity analysis identified key uncertainties that included factors that affected bear populations and human-bear incidents. The model estimates also were sensitive to relative values of harvest, bear population, and non-consumptive use objectives. Limiting the scope of the problem to NPS jurisdictional boundaries allowed for transparent decision making but may slow learning in an adaptive management framework.

In Chapter 5, I use a Bayesian belief network modeling approach to forecast sea otter population status in Katmai National Park, Alaska. The sea otter Bayesian Belief Network is a stochastic model that tracks sea-otter population density through time and is composed of environmental factors (e.g., habitat availability and prey density), population dynamics, and anthropogenic components. Sensitivity analysis was used to identify model parameters that are most influential to future sea otter population status, including predation, disease, and habitat capacity. Because NPS does not have management jurisdiction over the resources it monitors, separation of monitoring and decision-making precluded an adaptive process. Learning in a passive framework is predicted to occur much more slowly than would be possible given active manipulation of system dynamics (i.e., management) and monitoring that is explicitly linked to decision-making. Chapter 6 provides discussion of challenges and lessons learned from approaches developed in previous chapters and suggests directions for future research.

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Table 1.1.Categories created by McFadden and Tyre (2011) to assess the efficacy of various adaptive management programs.

Mention	ARM was used merely as a catch phrase
Theory	AM discussed in a general theoretical context but lacked a description of a specific case study
Suggest	Acknowledged AM as an appropriate approach for a particular mgmt problem but did not provide a complete analysis of a specific problem
Framework	Acknowledged AM as an appropriate approach and provided a decision-based framework for a particular mgmt problem
Implement	Same as framework plus a mgmt action was implemented, the outcome monitored, and the results incorporated into the next mgmt decision
Against	Deem AM an inappropriate approach for a mgmt problem

CHAPTER 2 : A STRUCTURED DECISION PROCESS FOR BROWN BEAR DECISION-MAKING ON NATIONAL PARK SERVICE LANDS IN ALASKA

INTRODUCTION

Brown bears bear are regulated as a game species both by the Alaska Board of Game (BOG) and the Federal Subsistence Board (FSB) and are regulated as a game species by the Alaska Department of Fish and Game (ADFG; Miller et. al. 2011). Brown bears occur in large numbers on lands managed by federal agencies, including the National Park Service (NPS). NPS involvement in wildlife management in Alaska has historically been limited to actions that do not involve sport or subsistence harvest (e.g. regulating access of bear-viewers and photographers; Van Daele et. al. 2001, Miller et. al. 2011; Hilderbrand et. al. 2013). However, the NPS has deemed recent actions by the state (namely implementation of liberal predator harvest regimes and predator control) to be in conflict with federal values; thus, the Service is reconsidering its role in harvest management on its lands (Hilderbrand et. al. 2013). By its nature, this problem involves tradeoffs between competing interests (sport hunting, subsistence hunting, and predator control) with other values such as wildlife viewing, with uncertainty about the impacts of harvest and other human activities on these respective values. Thus, federal and state resource managers face difficult decisions in establishing a balance between these conflicting values. These differences have inhibited the collaborative relationship required to achieve interagency management. The collaborative and integrative nature of structured decision making (SDM) is ideal for providing an explicit and transparent means for addressing interagency and cross-jurisdictional management issues. Consequently, a SDM approach could help the NPS and their cooperators conserve and manage bear populations while minimizing conflicts with other regulatory agencies and user groups.

SDM involves the use of explicit methods to identify and quantify conservation objectives and examine the effect of management decisions before implementation (Clemen and Reilly 2001, Conroy and Peterson 2013). It allows natural resource managers to incorporate multiple objectives and values of stakeholders, determine the relative influence of various sources of uncertainty, and estimate the value of collecting additional data (e.g., monitoring). SDM can be a useful heuristic in a variety of contexts, but it is particularly beneficial when decisions are complex, difficult, and uncertainty is high. In the context of managing multiple use resources, such as on DOI lands, management is complicated, involving the consideration of multiple stakeholder objectives and is potentially contentious. Uncertainty regarding the response of bear populations to management actions is also very high as there is a lack of information regarding the population dynamics of bears in Alaska (Van Daele et. al. 2006; Reynolds et. al. 2011).

Elements of the structured decision process include 1) defining the decision problem, 2) identifying and structuring stakeholder objectives, 3) developing a set of management alternatives, 4) evaluating the consequences of alternatives relative to objectives (usually with a model), and 5) selecting an optimal decision action (Clemen and Reilly 2001; Conroy and Peterson 2013). When applied, this process can be categorized into three sequential phases. Phase 1 involves framing the decision problem, identifying and structuring objectives, assessing the relative value of objectives (for multi-objective problems), revealing the means of achieving those objectives (i.e., via management actions), quantifying objectives, and developing a prototype decision model. Phase 2 involves revising and refining prototype models, identifying and compiling data sources, analysis of data, and parameterization of decision model(s). In

Phase 3, scenario evaluation and sensitivity analysis are used to evaluate model performance and outcomes. In this this chapter, I detail Phase 1 of the brown bear decision framework development process.

RELEVANT POLICY BACKGROUND

Our first task in Phase 1 of SDM was to engage relevant stakeholders for the purpose of factoring in their input in the decision process. Any person or entity with a vested interest in the decision outcome could be a stakeholder, but – to be effective – technical meetings (used to conduct most of the decision-making process) should remain relatively small (< 20 people; Conroy and Peterson 2013). This makes it is necessary to rate the relative importance of potential stakeholders in order to, a) include all *key* stakeholders, and, to b) keep the stakeholder working group small enough to remain efficient and effective. Key stakeholders are those entities who either have a strong ability to affect the decision (i.e. decision-makers) or who may be most strongly affected by a decision outcome (Conroy and Peterson 2013).

Because brown bears (and other predators such as wolves and coyotes) are a trust resource, the public – namely non-consumptive users (i.e., bear-viewers and photographers) and consumptive users (i.e., sport and subsistence hunters), have a vested interest in decision outcomes. The agencies responsible for making decisions about brown bear management have been entrusted (via various enabling policies) to consider the values of the public, along with other mandates, when evaluating various management scenarios. For example, the development of a recent compendium to management policies in Lake Clark National Park, Alaska involved seven public hearings held in various locations in or near the affected NPS units (NPS 2013). Further, during the open comment period on wildlife related restrictions in Lake Clark NP, the NPS collected nearly 60,000 written comments (primarily email) from the public. In this way, NPS and other trust agencies, by proxy, represent the public as stakeholders in decision processes.

To determine what entity had the legal authority and resources to implement brown bear decisions (i.e., the primary decision-maker), it was necessary to review relevant law and policy. The Alaska National Interest Lands Conservation Act (ANILCA; 1980) designated more than 100 million acres of federal lands in Alaska (in addition to the 100 million acres that was already under the jurisdiction of the federal government), effectively doubling the size of the country's national park and refuge system and tripling the amount of land designated as wilderness. Approximately half of federal lands in Alaska are designated primarily for fish and wildlife conservation (i.e., parks and preserves managed by the NPS and refuges managed by the US Fish and Wildlife Service, FWS), while the other half are managed by the Bureau of Land Management and USDA Forest Service for multiple use purposes including (but not limited to) timber production, fish and wildlife conservation, fish production, recreation, water reclamation, and mining.

Although more than 60% of land in Alaska is managed by the federal government, Section 805(D) of ANILCA states that "where hunting or trapping are authorized… non-conflicting state laws are adopted." Because state management policies were not deemed to be "conflicting" with federal values (until recently), the Alaska Board of Game (BOG) has been the primary decision-maker regarding brown bear harvest on federal and non-federal lands in Alaska since ANILCA was signed into law (Miller et. al. 2011). The BOG was historically comprised of administrative-level biologists from the ADFG but, more recently, has become a citizen's committee of Governor appointees that sets hunting regulations based – in part – on input from ADFG biologists and managers (Miller et. al. 2011).

Conflicting state and federal definitions of subsistence users in Alaska caused historical jurisdictional challenges for managing agencies (Van Daele et. al. 2001; also see *Ninilchik Traditional Council v. U.S*). The state of Alaska defines all Alaska residents as subsistence users under its subsistence statute (AS 16.05.258); whereas federal law (ANILCA) requires users to meet "rural-user" criteria to be eligible for a subsistence harvest permit (Hilderbrand et. al. 2013). In 1990, the Federal Circuit Court of Appeals ruled that the State's definition of rural was inconsistent with ANILCA's intent and dictated that the federal government assume responsibility for management of subsistence taking of fish and wildlife on federal public lands in Alaska (Van Daele et al. 2001). The Federal Subsistence Board (FSB), which is composed of members from five federal agencies in the Department of the Interior and the US Department of Agriculture, was established in response to the Federal Circuit's ruling to make decisions regarding subsistence use of wildlife on federal lands.

The passage of the Intensive Management Law in 1994 by the Alaska legislature further complicated interagency management. The law prioritized the consumptive use of ungulates by hunters over other resource values (Table 2.1) in response to reduced hunter availability of moose and caribou (thought to be caused by severe winters and high hunter harvest; Miller et. al. 2011). The law also directed that the ADFG may not adopt regulations that restrict the taking of wild ungulate meat unless it has already adopted "intensive management" strategies (i.e., control of large predators). Meanwhile, a provision in NPS Management Policies (the Service-wide implementation document of the NPS; 2006) explicitly prohibits predator control on NPS lands (Table 2.1) again triggering a controversy over federal and state jurisdiction.

To summarize, the BOG is the primary decision-maker regarding brown bear decisions for both residents and non-residents in Alaska provided that state law and/or harvest regulations do not conflict with federal statutes or policies where federal jurisdiction applies. The ADFG is responsible for implementing harvest regulations set by the BOG and for providing the BOG with relevant biological input. FSB regulations apply to rural residents of Alaska on federal public lands. When Alaska state laws and/or wildlife harvest regulations are conflicting with federal values, federal jurisdiction and policy is pre-emptive to state regulations. Federal values are extremely difficult to interpret given the linguistic uncertainty associated with most agency enabling legislation (see discussion of linguistic uncertainty under "decision scope" heading).

After passage of the Intensive Management Law, controversies surrounding the extent of predator reduction efforts in Alaska spurred the governor to requisition a study by the National Research Council (NRC) that assessed the ecological and economic impacts of wolf and brown bear intensive management schemes. The NRC recommended that predator management efforts by the state take a more cautious, research-based, conservative, experimental, and adaptive approach to wolf and bear management (NRC 1997). The BOG did not heed the recommendations of the NRC and increasingly liberal harvest regulations resulted in a greater than 200% increase in brown bear harvest between 2000 and 2010 (Miller et. al. 2011). Moreover, liberalizations of hunting regulations have occurred in an environment where impacts on the abundance of bears would be difficult to detect given the cost and feasibility challenges of adequately monitoring brown bear populations in Alaska (Reynolds et. al. 2011). In response to this series of events, NPS is considering whether ADFG brown bear harvest regulations are in conflict with NPS values, and, if so, where and how (Hilderbrand et. al. 2013). Decision-makers and managers from the Southwest Alaska Park Network (SWAN) and the Arctic Park Network decided to use a structured, adaptive approach (as suggested by the NRC in 1997) to determine deference (or not) to state harvest regulations in 2012 and contracted SDM coaches (the authors) to help guide the process.

Ideally, NPS, FSB, and ADFG (representing BOG) would have participated as stakeholders in the development of an integrated decision framework. Unfortunately, the ADFG declined numerous invitations from both NPS personnel and SDM coaches to participate in the process. Because NPS policy prohibits the Service from engaging in any form of predator control on its lands (Table 2.1), ADFG refusal to participate precluded their values from being directly included in the SDM process that potentially could have explored the relationship between brown bear predation and ungulate game availability. Such a process would require the inclusion of some form of predator control as a potential management action and enabling legislation of the participating federal agencies (NPS and FSB) prohibits the taking of one species for the purpose of increasing another species (note that this is a *value* statement rather than statement about science).

In addition to FSB, NPS SWAN, and NPS Arctic Network stakeholders, representatives from the US FWS Refuge systems in Alaska participated in the process to help develop a decision framework that would be portable to wildlife refuges in Alaska. Additional participants in the model development process were brown bear knowledge experts who provided guidance to decision coaches regarding brown biology and system dynamics. Expert affiliations included the Gobi Bear Fund, Audubon, NPS, and the University of Alaska. Agency representatives were considered to be stakeholders (who were by proxy representing the values of brown bear users), while other participants acted as knowledge experts. Two brown bear experts who were actively involved in model development were retired following full careers as bear biologists with the ADFG. In addition to bear knowledge, they were able to provide invaluable insight into the history and politics of brown bear decision-making in Alaska in the absence of official participation by the state.

Approximately 15 participants including stakeholders, knowledge experts, and SDM coaches comprised the brown bear SDM working group. At an initial informational workshop hosted in Anchorage, Alaska in March 2012, SDM coaches presented an overview of the SDM process and asked for an institutional commitment from participating agencies, and, in turn, commitment from stakeholder representatives for the longevity of the proposed project timeline (2-years to complete three phases). The initial workshop was also used to determine processes for operating within the brown bear core group. The group agreed to participate in monthly webinars (until Phase 1 was completed) in between a series of four workshops. SDM coaches created a listserv as a forum for working group communication and a members-only website containing workshop and webinar products to keep core members updated. Training workshops were delivered to both group cooperators and outside entities in Alaska (i.e., at the Alaska Chapter of the Wildlife Society) to help build capacity for SDM skills and enlist bottom-up support for the process.

DECISION SCOPE

Decision Problem

After assessing who to involve in the brown bear working group, the first stakeholder-driven task was to define the decision problem. A problem statement should propose an action (or set of choices) that is predicted to lead to outcomes that fulfill objectives (Conroy and Peterson 2013). We did this by asking the stakeholders to consider in the following "We (stakeholders) want to do <u>X</u> to achieve <u>Y</u> over time <u>Z</u> and in place <u>W</u> considering <u>B</u>." This purpose of this process is to turn a vague task into an affirmative action statement that ties actions to measurable outcomes. It also helps to define the spatial, temporal, and organizational bounds of the decision problem. The Deputy Regional Director of the Alaska Region of the

National Park Service was present during this process, and his familiarity with complex NPS policies regarding bear management was key in helping the group develop a problem statement.

Wildlife stewardship on NPS lands is guided by the Organic Act, the General Authorities Act, ANILCA, and NPS Management Policies. Because ANILCA mandates deference to state harvest regulations - unless regulations are in conflict with NPS values - considerable attention was given to determining what constitutes NPS values. NPS Management Policies (2006) (Section 1.4.6) define park resources and values, in part as:

"*the park's scenery, natural and historic objects, and wildlife, and the processes and conditions that sustain them, including, to the extent present in the park: the ecological, biological and physical processes that created the park and continue to act upon it…. and native plant and animals*."

Also included in the definitions of park resources and values are, "*appropriate opportunities to experience enjoyment of the above resources, to the extent that can be done without impairing them.*"

The Organic Act (1916) established the fundamental purpose of the NPS to:

"…conserve the scenery and the natural and historic objects and the wildlife therein and to provide for the environment of the same in such a manner and by such means as will leave them unimpaired for the enjoyment of future generations."

Linguistic uncertainty in these statute provisions, namely the use of the terms “natural” and “unimpaired” as biological objectives, is problematic to say the least. This type of uncertainty arises from the use of ambiguous, vague, context-dependent and/or under-specific language, is relatively common in conservation policy, and can greatly complicate policy interpretation, and in turn -- decision-making (Regan et al. 2002). While epistemic uncertainty (uncertainty in determinate facts) is often dealt with (or at least recognized) the importance of linguistic uncertainty is frequently overlooked by the conservation biology community. The SDM framework allowed us to identify problematic linguistic uncertainty at the outset of the process, and, later, we dealt with this uncertainty by associating explicit, measurable attributes with each management objective.

Another important component in the above statute provisions was the recognition of park resources as a source of enjoyment by the public (i.e., via consumptive and/or non-consumptive uses). However, note that enjoyment opportunities are identified as second to the “un-impairment” objective.

The final problem statement produced by the brown bear working group was to: “Manage habitat and consumptive and non-consumptive use of brown bears for current and future generations on Katmai National Park and Preserve and Noatak National Preserve to maintain populations, species assemblages, and ecosystem processes recognizing 1) natural variation, 2) sport and federally qualified subsistence harvest, 3) deference to non-conflicting state harvest regulations, and 4) realizing that bear populations extend beyond park boundaries.”

Temporal Dimensions

An infinite planning horizon was used for the decision problem (to ensure sustainability), but the model worked at an annual time-step to correspond with annual ADFG and FSB revision of harvest regulations. An annual time-step also corresponds to the frequency at which (some) monitoring data (used to update uncertain beliefs about system dynamics) is collected.

Spatial Dimensions

There is considerable evidence that availability of marine derived nutritional resources, particularly salmon, has a strong positive influence on brown bear demographic rates and densities (Hilderbrand et al. 1999, Hilderbrand et. al. 2004, Mowat and Heard 2006, Pierce et. al. 2013). Access to salmon, or lack thereof, has essentially resulted in bear populations that exhibit two different life history strategies in Alaska. Coastal dwelling bears, such as those inhabiting SWAN Park Units, occur in extremely high densities (e.g. 100 bears per km^2 in Katmai National Park and Preserve; Loveless et. al. unpublished), while brown bears in interior Alaska, including those in the Arctic Network, occur at much lower densities (e.g. 20 bears per km^2 in Gates of the Arctic National Preserve; Shults and Joly unpublished). Coastal brown bears also generally have larger skull sizes, produce larger litters and achieve heavier body weights than interior dwelling bears that do not have access to marine-derived dietary resources (Hilderbrand et. al 1999, Mowat and Heard 2006).

Human use of brown bears in these two categories is also quite different. Katmai National Park and Preserve contains one of the largest remaining populations of brown bears in the world (NPS 2012). This unique, high density population combined with the large numbers of brown bears that can be easily viewed at salmon spawning streams, attracts tens of thousands of bear-viewers and photographers every summer. Harvest in Katmai is limited to the Preserve (hunting is not permitted in National Parks). Though wildlife viewing in the Arctic Park Network may occur as a secondary purpose for visitation, the primary purpose of almost all visitation is angling or harvest of elk and caribou. Harvest of brown bears generally occurs opportunistically during multi-species hunts.

Finally, human-bear interactions in salmon-influenced versus interior-dwelling brown bear habitat are expected to be different. High-density bear populations and clumped, high quality food resources facilitate bear-to-bear habituation (Smith et. al. 2005). As a result, bears tolerate the presence of other bears at much closer distances than would be expected in low density populations where bears are isolated from one another (e.g., brown bear populations in northern Alaska). Bears that are habituated to other bears seem to be more tolerant of humans regardless of familiarity with humans (Smith et. al. 2005). Thus, as populations become less dense and individual bears become less likely to encounter other bears, it is hypothesized that negative human-bear interactions will become more likely.

Based on these differences, the brown bear working group decided it was necessary to develop two separate decision models, one for interior-dwelling and another for coastal-dwelling brown bear populations. Stakeholders from the SWAN Park Network delineated Katmai National Park and Preserve (KATM) as the spatial extent of the coastal bear decision model (~16,180 km^2; Figure 2.1). Stakeholders from the Arctic Network delineated the boundaries of Noatak National Preserve (NOAT) as the extent of the interior-dwelling bear decision model (25,305 km^2; Figure 2.2). While park boundaries were used to delineate the extent of decision models, we recognize that decisions will not be implemented uniformly in either KATM or NOAT. For example, harvest regulations in KATM only apply to the preserve (1,618km^2 compared to 14,164 km^2 in the park), but the model is used to predict park-level effects of decision actions. Moreover, we recognize that bears do not respect political boundaries. That said, this is a decision model, and NPS does not have jurisdiction outside of park boundaries. Recent precedence also suggested that establishing park “buffers” was not a feasible alternative

(Alaska Dispatch 2012), so we determined that using park and preserve boundaries as the spatial extent of decision models was the best available option. Sensitivity analysis will be used to assess whether decision optimization is sensitive to such decisions.

OBJECTIVE IDENTIFICATION AND STRUCTURING

Because management performance evaluation is dependent upon the elucidation of common objectives, management program failure is much more likely when stakeholder objectives are not identified *a priori* (Williams 2011). Therefore, an important early step in the decision process is the explicit formulation and structuring of objectives. Structuring objectives involves the identification and separation of fundamental and means objectives (Clemen and Reilly 2001, Conroy and Peterson 2013). Fundamental objectives are those that relate to the decision-maker's core values and thus are not usually negotiable, while means objectives are actions that need to be accomplished in order to achieve the fundamental objectives.

Stakeholder feedback from our initial workshop (in March 2012) was used to commence the process of identifying and structuring management objectives related to brown bears in NOAT and KATM. To ascertain the difference between fundamental and means objectives, workshop participants were asked to distinguish between objectives that were important to them without respect to how they are achieved (fundamental objectives) and those that could be used to help realize fundamental objectives (means objectives). The objective structuring process involved development of two separate means objectives hierarchies. The first organized objectives in terms of how they related to relevant law and policy (i.e., stakeholders considered what means could be used to achieve provisions in enabling legislation). The second was used to explore objectives in terms of biological drivers of system dynamics. Ultimately, these two means objective hierarchies were combined to help determine the overall fundamental objectives. After numerous sessions dedicated to refinement and revision of objectives, the following four fundamental objectives were settled upon: (1) optimize the structure and function of brown bear populations using NPS lands; (2) optimize sport and federally-qualified subsistence harvest; (3) minimize human-bear incidents; and (4) optimize non-consumptive use opportunities. Because objectives were not valued equally by stakeholders, multi-attribute utility theory was used to create a net objective function that optimized overall utility given weights on objectives (Conroy and Peterson 2013; see calculation of utilities below). Sport and subsistence harvest were initially considered as separate objectives with subsistence harvest valued higher than sport harvest. However, during a later stage of the decision process, model developers determined that separation of these two objectives was problematic so they were combined as one utility.

VALUING OBJECTIVES

Stakeholders (i.e., agency managers and decision makers) from the brown-bear working group (n= 7) were asked to rate the relative importance of each of four fundamental objectives (where 1 indicated the lowest importance, and 10 indicated the highest importance). The resulting responses indicated that the bear population objective was valued highest and the human-bear incident objective > sport and subsistence harvest objective > non-consumptive use objective. Mean scores for each objective (Table 2.2) were used as weights in the objective function. Note that knowledge experts were not involved in value elicitation.

Quantitative attributes associated with each objective were reflected as model components in the brown bear decision model and include the following: the future state of bears, % harvest success, # of visitor-use-days, and # human-bear incidents. Because each attribute is measured on a different scale (Table 2.3), proportional scoring (Clemen and Reilly

2001; Conroy and Peterson 2013) was used to convert attributes to a common scale. Attributes were rated from "worst" to "best" by assigning (non-proportional) scores to each level characterizing attributes. Individual utilities were calculated for each attribute as:

$$U(x_i) = \frac{[x_i - worst(x_i)]}{best(x_i) - worse(x_i)} \qquad [1]$$

where x_i is the measurement on the original attribute scale and *worst*(x_i) and *best*(x_i) are the least and most desired values of the attribute over the anticipated range. Individual utilities were combined into an objective function as a weighted sum of utilities:

$$U_i(x) = k_1 U(x_i) + k_2 U(x_i) + k_3 U(x_i) + k_4 U(x_i) \qquad [2]$$

where k_i is the relative importance of each attribute (Table 2.2).

IDENTIFICATION OF DECISION ALTERNATIVES

After identifying and structuring objectives, our next step was to formulate decision alternatives. A relatively long list of potential management actions was created and refined via stakeholder feedback. In the early design and development stages of Phase 1, we allowed creativity during decision formulation to encourage identification of novel solutions. Thus, we started by including every suggested alternative in the decision set. The initial list of potential alternatives contained four categories of decision types: 1) harvest decisions, 2) access control decisions, 3) incident-prevention decisions, and 4) habitat modification decisions. Decision alternatives within each category are mutually exclusive, while categories of actions are not (i.e. actions among categories may be implemented simultaneously). The term decision-set refers to combinations of non-mutually-exclusive actions while decision alternatives (or management actions) refer to actions from each category that collectively make-up a decision-set. Our initial list included approximately thirty-five (non-mutually exclusive) actions and 430 decision-sets.

In practice, decision alternatives must be feasible, relevant to the decision scope, and they must represent specific actions that can be linked directly to some brown bear population response or management objective. Moreover, a management action (by definition) should involve an irrevocable allocation of resources by the decision-maker. Feasibility implies that the alternative could be implemented if selected (Conroy et al. 2008, Conroy and Peterson 2013). For example, actions that are outside of the jurisdiction of the management agency should not be included in the decision set. Moreover, actions contained within the decision set should be mutually exclusive and collectively exhaustive. By mutually exclusive, we mean that should alternative “A” be selected, then alternatives “B” and “C” by default cannot be selected. The collectively exhaustive criteria implies that all actions available to the decision-maker should be included in the decision set, including no action alternatives or alternatives that might seem unpopular to stakeholders at the outset (Conroy et al. 2008). Lastly, we must be able to measure where we stand relative to our objectives after implementation of an action to determine the success of decision alternatives. Therefore, it is imperative that decision actions can be linked to measurable population responses in the decision model.

Based on the criteria above, we worked with stakeholders to revise and refine the overall decision-set. Construction of consequence tables - matrices describing the performance of decision alternatives on (fundamental) objectives (Conroy and Peterson 2013) - helped to facilitate this process. During consequence table exercises, we asked stakeholders to predict the generalized influence (positive, negative, or neutral) of decisions relative to fundamental objectives. This allowed us to eliminate certain decisions that were clearly inferior (Table 2.4). It also allowed us to identify alternatives that were strong at the outset (Table 2.4). Decision alternatives that would be implemented no matter what the state of the system (e.g. requiring visitors to use bear-proof food storage devices) and decisions that would never be implemented (e.g. predator control) were also eliminated. Although there are localized areas where brown bear habitat is being fragmented by human development, the remoteness and low density of human residents in and around NOAT and KATM have resulted in largely intact, high-quality bear habitat (Miller et. al. 2011). Additionally, it was difficult to identify direct linkages between potential habitat modification decisions and brown bear population responses (i.e., responses were generally several steps removed from actions). Therefore, the category of habitat modification actions was also removed from the model. In total, the number of decision alternatives was refined to include 13 non-mutually exclusive alternatives and 48 (4x4x5) decision-sets. Decision alternatives in harvest decision, incident-prevention, and access control decision categories are outlined in detail below.

Access Restriction and Incident Prevention Decision Alternatives

Human-bear management actions were grouped into two general categories: 1) *Access Restriction* actions that restrict or prevent human access to an area for non-consumptive uses; and 2) *Incident Prevention* actions that prevent human-bear incidents, especially in areas with increased potential for conflict. Access restriction actions are primarily implemented to prevent human-caused displacement of bears from prime habitat and/or food sources, while incident prevention is used to decrease the risk of human-bear incidents. These categories of actions are not mutually exclusive meaning that actions from each category may be implemented simultaneously to achieve multiple objectives.

Access restriction alternatives included in the model are the following:

1) Close public access
2) Specify access times
3) Restrict commercial use authorizations
4) No action

Incident prevention management alternatives included in the model are the following:

1) Aversive conditioning treatment
2) Increase enforcement efforts (e.g. # of ranger patrols)
3) Aversive conditioning treatment + increase enforcement efforts
4) No action

It should be noted that policies that are already being implemented and are not likely to be reversed (e.g. requiring bear-proof food storage, maintaining electric-fencing around camps, requiring that visitors maintain specified distances from bears, etc…) were not included in the decision model. However, increased enforcement may involve increasing ranger patrols to assure existing policies are adhered to by visitors and guides.

Harvest Decision Alternatives

The harvest category of actions is not mutually exclusive from access control or incident prevention categories. Brown bear harvest decision alternatives in the KATM and NOAT decision models include the following:

1) No harvest
2) Spring only harvest
3) Restrict concession hunts
4) Limit transport

5) Deference to state regulations given an 8% (KATM) or 4% (NOAT) harvest rate
6) Deference to state regulations given a 10% (KATM) or 6% (NOAT) harvest rate
7) Deference to State regulations given a 12% (KATM) or 8% (NOAT) harvest rate
8) Deference to state regulations given a 14% (KATM) or 10% (NOAT) harvest rate

Harvest decision actions (1-8) range from most to least prohibitive. Deference to state regulations with an 8% (KATM) or 4% (NOAT) harvest rate would result in a status quo harvest. Under this alternative, non-guided sport and subsistence harvest of brown bears by Alaska residents would be allowed. Additionally, a specified number of concessions authorized by the National Park Service (NPS) would allow non-resident sport hunters accompanied by guided hunting concessioners to harvest brown bears. Harvest success for actions 6 to 8 was estimated by increasing status quo harvest success by 2%. For example, deference to state regulations given a 10% harvest rate was calculated as status quo harvest + 2%. For the 12% harvest rate, 4% was added to calculate harvest success. Under the *restrict concession hunts* alternative, no guided hunting contracts would be authorized by the NPS. Restricting concession hunts would eliminate harvest of brown bears by U.S. citizens who are not residents of Alaska. Generally, spring and fall harvests of brown bear bears in NOAT are authorized every other year. Thus, harvest success for the spring only harvest alternative was predicted to be half of status quo harvest. In Katmai Preserve, more harvest occurs in fall hunts than in spring hunts. Thus, the spring only harvest alternative in the Katmai model was parameterized to reduce status quo harvest by 40%. Limiting transport of hunters into either Katmai Preserve or NOAT was modeled to reduce non-resident harvest by half. In addition, resident harvest is expected to occur at status quo levels under this alternative. Under the no harvest alternative, all non-resident and resident sport harvest opportunities would be eliminated.

QUANTIFYING OBJECTIVES WITH MEASURABLE ATTRIBUTES

A proper definition of explicit objectives is of great importance in quantitative decision analysis. In particular, objectives need to involve measurable attributes – states of nature or other elements that we can predict, observe, quantify, and compare to some standard (Conroy and Peterson 2013). That is, to be able to make decisions (e.g., evaluating trade-offs among competing choices), we first need to be able to predict (in advance of the decision) how a given action will lead to measurable objective outcomes. Once decisions are implemented, monitoring data is used to measure realized objective outcomes in order to assess whether objectives are being met.

During a second workshop (in October 2012) and in several follow-up webinars, stakeholder feedback was used to identify quantifiable attributes that are being (or that can be) estimated (using a model) and measured for each of the fundamental objectives identified by the brown bear core working group. This process allowed us to explicitly address the linguistic uncertainty identified during decision scope development and objective identification. For example, the term “unimpaired” was originally used in the bear population fundamental objective, but – because this term is ambiguous (i.e., it is open to more than one interpretation) - there is no attribute that can be used to measure impairment. The term “unimpaired” was replaced with the phrase “structure and function” and proxies for structure and function that are being or can be measured were identified (Table 2.5).

Indices were used in lieu of direct measures because monitoring bears in Alaska is a difficult and expensive task due to an extremely short survey window (15 days between den emergence and leaf-out), the remoteness and limited accessibility to bear habitat, and the large spatial extent of individual bear home ranges (which naturally disaggregates populations) (Reynolds et. al. 2011). For example, raw counts of bears at salmon spawning streams along with den occupancy estimates were used as indices of bear population size in KATM. Density estimation of bears in Gates of the Arctic National Park (which neighbors NOAT; Shults and Joly unpublished) was used as a proxy for bear population size in NOAT. These measures were combined with indicators of harvest pressure to determine the state of bears in KATM and NOAT prior to decision-making (Table 2.5). Other measurable attributes included visitor-use-days, harvest success, and human-bear incidents. Data collection and analysis procedures for each attribute are described in detail in Chapter 3.

PROTOTYPE MODEL DEVELOPMENT

Another purpose of the October workshop was to begin constructing a prototype model for brown bears that linked brown bear system dynamics to objectives and decision actions. Models are an important component to SDM processes because decision optimization requires prediction of effects of management actions on resource objectives (e.g., population state). Because knowledge about large-scale ecological processes and bear population responses to management are imperfect, uncertainty was incorporated via the use of alternative models representing different hypotheses of ecological dynamics and statistical distributions representing error in model parameters. Each model (hypothesis) was assigned a plausibility or probability. The optimal decision-set then was selected based on the current system state (i.e., the state of bears prior to decision-making) and a prediction of the expected future state taking into account various sources of uncertainty.

When management decisions recur over space or time (e.g., annual harvest regulations), model probabilities are updated through time by comparing model specific predictions to observed (actual) future conditions (Williams and Nichols 2001, Williams et al. 2002). The adjusted model probabilities then can be used to predict future conditions and choose the optimal (or satisficing) decision for the following time step. This cyclical adaptive feedback explicitly provides for learning through time and possibly, the resolution of competing hypotheses with monitoring data. Monitoring data serve two purposes: (1) they provide an estimate of the current system state and (2) they are used to update beliefs in each alternative model and/or parameter values (Williams and Nichols 2001, Williams et al. 2002). Thus, monitoring data are used to learn about system dynamics; thereby improving future decision-making. This approach is defined as adaptive resource management (ARM) and has been formally adopted by the Department of Interior for managing federal resources (Williams et. al. 2009).

NOAT and KATM model prototypes were initially constructed as influences diagrams to facilitate visualization of decisions and objectives relative to system dynamics. Model development involved numerous of interactive sessions between stakeholders, knowledge experts, and decision coaches. The working group created a number of prototypes as participants explored alternative means of describing system variables, defining and discretizing states for model components, depicting causal relationships, and identifying alternate means for measuring system components. During phase 2 of the SDM process (see Chapter 3), the prototype model structure was refined and model components and the relationships among them were parameterized.

SUMMARY

The United States is a vast and heterogeneous country so it is not surprising that national policies in resource management often conflict with local cultures or discrete community interests. Further, local or regional culture can have great influence within state and local management agencies for political accountability reasons. Thus, when federal and state management agencies address the difficult task of the long-term protection and management of resources under their respective jurisdictions, fundamentally different policy visions and goals frequently arise. This management task is further complicated when resources span agency jurisdictional lines.

While SDM is not a conflict management tool, it can be used to address specific types of conflict - namely, conflict about management objectives and conflicts about science. The early design and development phases of structured decision making (problem scoping and objective structuring) can be used to resolve conflicts about objectives, while the iterative process of adaptive management can resolve conflicts about science. The conflict between BOG and NPS involved conflicts about objectives (i.e., state versus federal values and sovereignty) and conflicts about science (i.e., efficacy of predator control on ungulate availability for game use). Or, more likely, conflicts about objectives were masquerading as conflicts about science.

The collaborative and integrative nature of SDM may be ideal for addressing interagency management issues, but it is not a solution for resolving deep-rooted conflicts such as state versus federal sovereignty. For resource problems involving volatile political situations, management success may rely more on balancing the complex social and political interactions of stakeholders than elucidating the relevant science.

Because the ADFG did not to participate in the brown bear SDM working group, we were not able to address either conflict, but – by limiting the scope of the decision problem to NPS jurisdictional boundaries - we were able to use the process to develop an explicit, transparent, and tractable means by which the NPS can decide when deference to state brown bear harvest regulations is optimal. That said, even given sub-optimal decision-making, the use of an SDM framework will allow for accountability by the NPS, while the use of an ARM approach to decision-making will allow for learning.

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Table 2.1. Conflicting policies contained in the Intensive Management Law passed by the state of Alaska in 1994 and the agency-wide National Park Service Management Policy Guide last amended in 2006 (NPS 2006).

Intensive Management Law (ADFG)	NPS Management Policy
"The Board of Game shall adopt regulations to provide for intensive management programs to restore abundance or productivity of identified big game prey populations as necessary to achieve human consumptive use goals of the board…"	"…the Service does not engage in activities to reduce the numbers of native species for the purpose of increasing the numbers of harvested species….nor does the Service permit others to do so on lands managed by the NPS"

Table 2.2. Summary of value elicitation survey responses. Brown bear SDM stakeholders were asked to rate the relative importance of each of four objectives (1 = lowest importance, 10 = highest importance). Mean scores were used as utility weights (k_i) in the objective function (equation 2).

	Bear Pop. Structure and Function	Sport and Subsistence Harvest	Human-bear Incidents	Non-Consumptive Use
Mean	10 (k_1)	4.6 (k_2)	6.3 (k_3)	3.7 (k_4)
Median	10	4	7	4
Minimum	10	3	4	2
Maximum	10	7	9	6

Table 2.3. Attributes used to measure decision utility.

Attribute	Attribute Scale	Range (worst to best)
Bears at t+ 1	Categorical	Perturbed - Baseline
Harvest Success	% Success	0% to 100%
Visitor-use-days	# of visitor-use days	0 to 18,000
Human-bear incidents	# of incidents	900 to 0

Table 2.4. Example results from a consequence table exercise that evaluated the general influence of harvest decisions on NOAT objectives. "+" indicates a positive influence, "-" indicates and negative influence, and "0" indicates a neutral influence. Decisions that were determined to have a neutral influence on all fundamental objectives (e.g. changing boundaries on hunt concession authorizations) were eliminated from the potential list of decision alternatives.

	Objectives			
Harvest Decisions	Bear pop. structure & function	Sport & subsistence harvest	Minimize human-bear Incidents	Non-consumptive use opportunities
Close to harvest	+	-	+	+
Prohibit baiting	0	0	0	0
Defer to state regulations	-	+	+	0
Prohibit guided combination hunts	+	0	0	0
Modify # of commercial sport guide permits	0	0	0	0
Change boundaries on hunt concession authorizations	0	0	0	0

Table 2.5. Measurable attributes associated with fundamental objectives in NOAT and KATM decision models.

Objective	Measurable Attribute	Units
Bear population structure and function	Current Bear State	Median age of bears harvested
Bear population structure and function	Current Bear State	# of bears harvested/year
Bear population structure and function	Current Bear State	Proportion of females harvested
Bear population structure and function (KATM)	Current Bear State (KATM)	Proportion of dens occupied
Bear population structure and function (KATM)	Current Bear State (KATM)	Maximum count of bears at salmon streams
Bear population structure and function (NOAT	Current Bear State (NOAT)	# bears/100km^2
Sport and fed. qualified subsistence harvest	Harvest Success	# successes/# permits
Non-consumptive Use	Visitor-use days	# of visitors per year
Minimize human-bear incidents	Human-bear Incidents	# of incidents per year

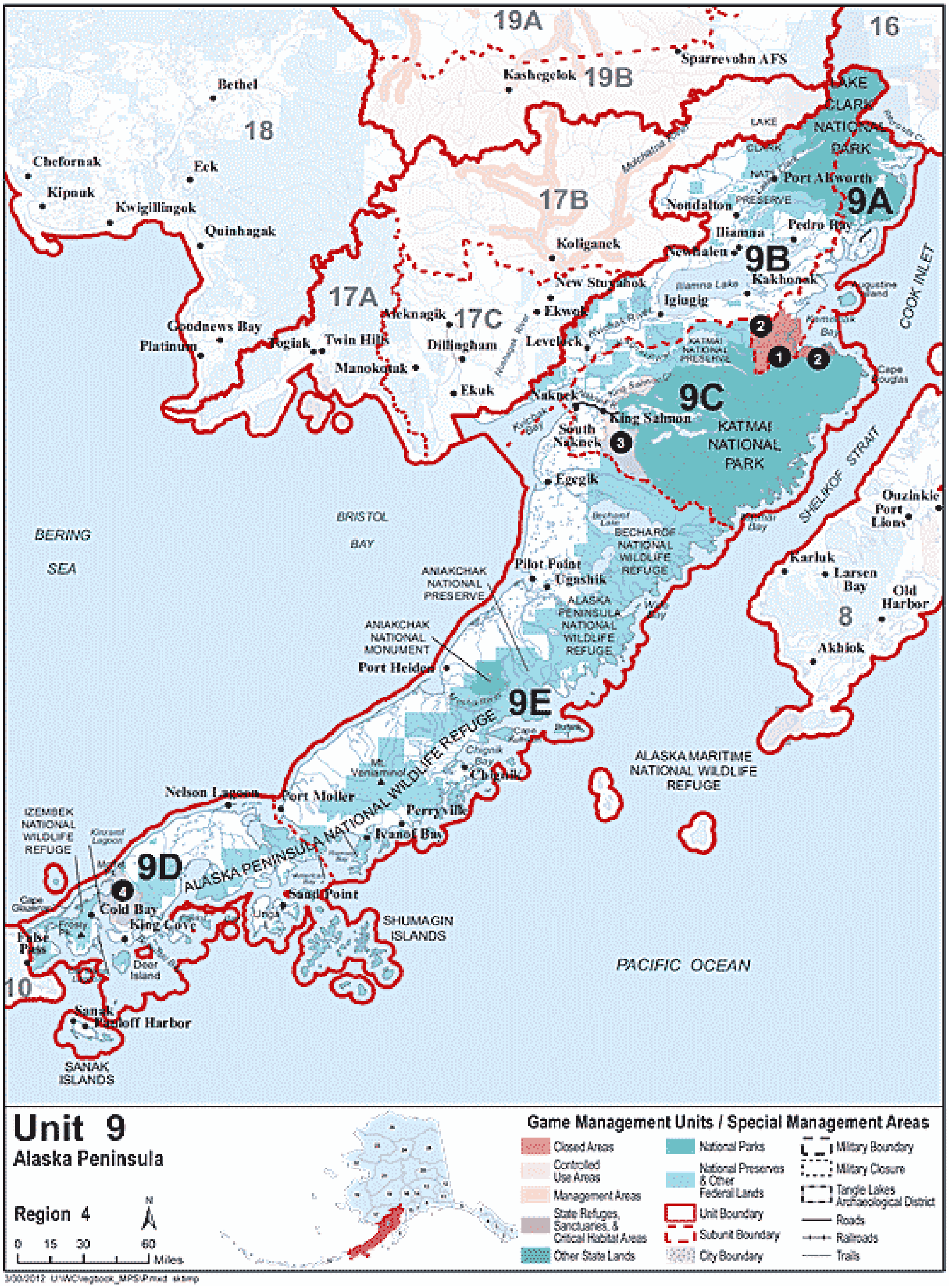

Figure 2.1. Game management unit 9 delineated by the Alaska Department of Fish and Game. GMU 9C contains Katmai National Park and Preserve. Map downloaded from ADFG on 02 February 2016 at http://www.adfg.alaska.gov/index.cfm?adfg=huntingmaps.gmuinfo&gmu=09.

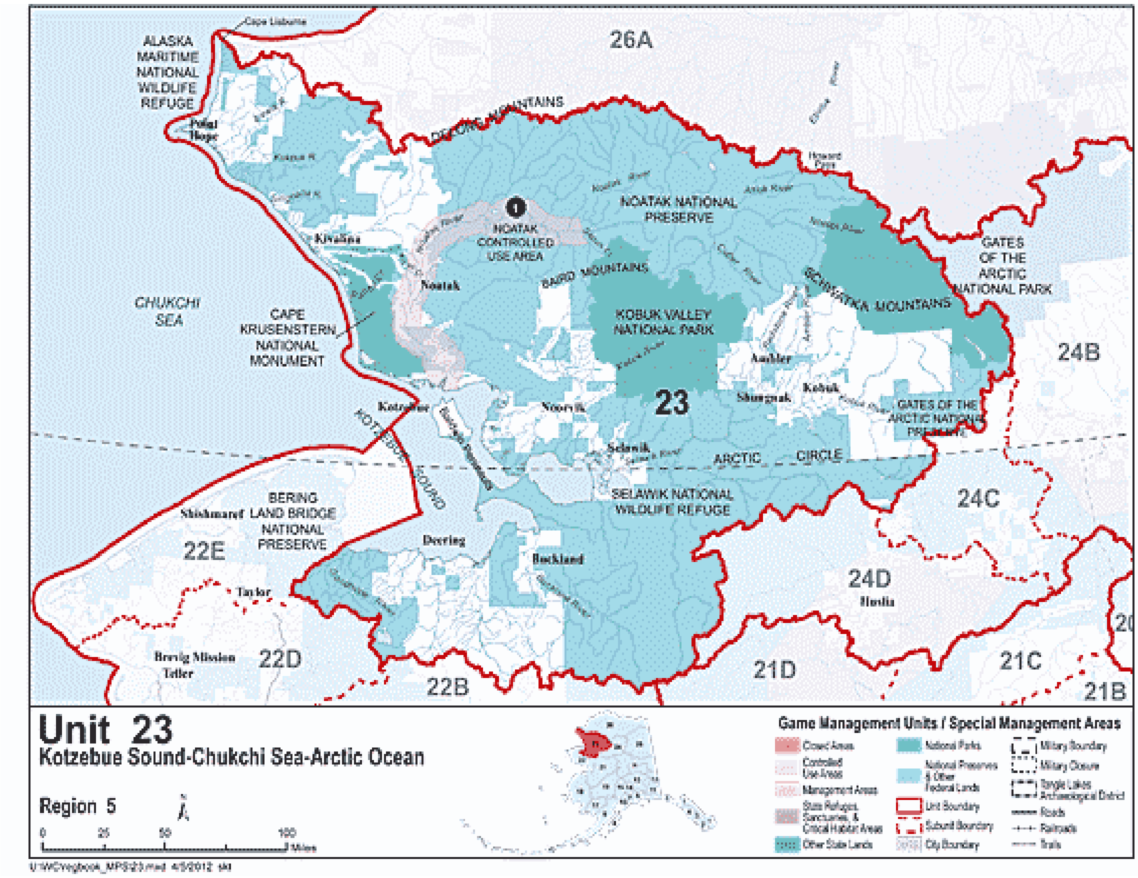

Figure 2.2. Game management unit 23 delineated by the Alaska Department of Fish and Game. Noatak National Preserve borders the north central border of GMU 23. Map downloaded from the ADFG on 18 February 2014 at http://www.adfg.alaska.gov/index.cfm?adfg=huntingmaps.gmuinfo&gmu=23.

CHAPTER 3 : PARAMETERIZATION OF BROWN BEAR DECISION MODELS IN NOATAK NATIONAL PRESERVE AND KATMAI NATIONAL PARK AND PRESERVE

INTRODUCTION

Although brown bear are regulated as a game species by the Alaska Board of Game (BOG) and are managed by the Alaska Department of Fish and Game (ADFG), they occur in large numbers on lands managed by the National Park Service (NPS) and other Department of the Interior (DOI) agencies in Alaska. Depending on the status of bears on parklands, NPS involvement in bear management can range from regulating access to full involvement with ADFG and the Federal Subsistence Board in regulating harvest (Van Daele et. al. 2001, Miller et. al. 2011). Data collected from inventory and monitoring (I&M) programs are oriented at assessing population distribution, abundance and trends, and where possible, demographic rates. Most brown bear abundance data have been derived principally from capture-mark-recapture (CMR; Miller et. al. 1997) and line transect sampling (Quang and Becker 1996, Becker and Quang 2009). Although both techniques have been widely employed across Alaska, there are concerns that small sample sizes have compromised the reliability of these methods, particularly in low density areas. Thus, more recently attention has been given to the use of occupancy sampling and modeling (MacKenzie et al. 2006; Lindberg and Schmidt 2007; Wilson unpublished data). As with many wide-ranging species occupying rugged landscapes at variable densities, it is likely that no single method will be ideal in all circumstances, and it can be expected that I&M for Alaskan brown bears will involve the integration of several data structures including those listed above.

To be of use to natural resource managers, inventory and monitoring data – collected by whatever means – must be gathered, quality checked, and managed in such a way that end users can retrieve and use the data and can be confident of underlying metadata. Although challenges to proper database management exist, they are well understood challenges, and with sufficient communication, cooperation, and technical assistance are readily surmountable. In our view, a somewhat different --- and arguably more difficult—challenge is assuring that the data that are gathered are used as efficiently as possible to address conservation needs. Ideally, this means that the data are collected in anticipation that they will be used for decision making, as opposed to gathered for vague purposes, and then coincidentally applied to decision making. Admittedly most situations fall somewhat between these extremes, but we are confident that focusing first on the objectives of management will lead to monitoring that is ultimately more responsive to management needs. We therefore advocate a structured decision making (SDM; Conroy and Peterson 2013) approach to inventory and monitoring, the ultimate goal of which is to inform decisions that are optimal with respect to specified management objectives. Such an approach requires clear distinctions between aspects of decision making that seem "subjective" (goals and objectives, decision alternatives, constraints and tradeoffs) and those that seem scientific or "objective" (biological hypotheses, monitoring data, predictive models). The key is for I&M data to be specifically collected to inform decision making, rather than viewed as a means of testing hypotheses (e.g., about positive or negative trends; Yoccoz et al. 2001, Williams et al. 2002, Nichols and Williams 2006).

The structured decision process can be categorized into three sequential phases. Phase 1 of the process involves framing the decision problem, identifying and structuring objectives, revealing the means of achieving those objectives (i.e., via management actions), and developing a prototype decision model (Williams et. al. 2002, Williams 2011). Phase 2 involves identifying and compiling data sources that can be used to parameterize the decision framework, decision model revision and refinement, parameterization and data analysis. In Phase 3 of the process, scenario evaluation and sensitivity analysis is used to evaluate model performance and outcomes. In this chapter, I describe Phase 2 of the process for brown bear decision models in Noatak National Preserve and Katmai National Park and Preserve.

GENERAL MODEL OVERVIEW

NOAT and KATM brown bear decision models are stochastic, dynamic models that track brown bear population state through time in Katmai National Park and Preserve (KATM) and Noatak National Preserve (NOAT). The goal of decision making for each park was to identify brown bear management policies that are optimal with respect to objectives that include both interests of consumptive and non-consumptive users and brown bear population status. Both models operate on an annual time step and predict the future state of bears given decisions and system dynamics. Although the spatial extent of each model is currently defined by NOAT and KATM boundaries, the models were constructed to be portable to similar bear management areas in Alaska. The model structure was comprised of two main components: (1) a component that estimates the current state of bears in each of two national park units (NOAT and KATM) and (2) a component that predicts the future state of bears given current bear state, system dynamics (e.g. salmon availability), and decisions.

NOAT and KATM decision models were constructed as in the form of probabilistic influence diagrams which model relationships among components using conditional dependencies. Models were graphically represented as influence diagrams that consisted of model components, referred to as nodes with each node consisting of environmental states that are mutually exclusive and collectively exhaustive. Directed arcs indicate causal relationships between model components with parent nodes influencing (pointing into) child nodes. Root nodes do not have any arcs pointing into them and, thus, are only informed by prior information.

System states and dependencies among states were parameterized (via meta-analysis) using published relationships (models) and empirical data (~13/20 dependencies). For example, monitoring data collected and maintained by the Alaska Department of Fish and Game (ADFG) and/or the National Park Service (NPS) Inventory and Monitoring Program was used to estimate a number of model parameters (e.g. salmon escapement). When data were completely lacking, relationships among model components were parameterized using expert judgment (~ 5/20 dependencies) or probability scaling (~2/20 dependencies; see explanation below).

NOAT and KATM decision models can be divided into four major subcomponents: (1) *the current bear state submodel*, (2) *the human-bear interactions submodel*, (3) *the salmon-bear interactions submodel* (KATM only), and (4) *the harvest submodel* (Figures 3.1, 3.2). Note that the salmon-bear interactions model is only relevant to bear populations that have access to salmon as a primary food source (e.g. Katmai bears). Also included in the model are three categories of decision actions and four fundamental objectives and associated utilities (see Chapter 2). Below, I describe data compilation and analysis procedures used to parameterize each of the four submodels in detail.

CURRENT BEAR STATE SUBMODEL

Brown bear population state is a binary attribute (i.e., bear state can be baseline or perturbed) that reflects both population size and composition. For example, an abundant population with many family groups (i.e., females with dependent cubs) would be "baseline;" while, a population with low abundance and few family groups would be perturbed. Any one characteristic (i.e. population size or composition) can get the state to "perturbed." Current bear state (prior to decision-making) is determined by a combination of harvest pressure (used as an index for composition) and bear population size indices (Figures 3.3, 3.4). Hunters target large bears, which results in more older and male bears being harvested (given baseline conditions; NPS 2012). If adult, male bears become unavailable to hunters (i.e. due to high harvest pressure), younger bears and more female bears are expected to comprise a larger proportion of take. Thus, the proportion of females harvested and the age of bears harvested, along with the number of bears harvested, are important indicators of harvest pressure. These indicators of harvest are collected in a summary node (harvest index) that, along with bear population size (adult density in NOAT and stream surveys and den occupancy in KATM), determine if bears are perturbed prior to decision-making. Data collection and analysis for each model component in the *current bear state submodel* are described in detail below.

Number of bears harvested, proportion of females harvested, and age of bears harvested

NOAT borders the north-central boundary of ADFG game management unit 23 (Table 2.2), while KATM comprises almost all of GMU 9C (Table 2.1). Brown bear harvest data (collected by ADFG) was used to determine harvest pressure parameters in each park unit. Note that sport harvest on NPS lands is limited to preserves; thus, only subsistence harvest occurs in Katmai National Park. Inter-annual variation in harvest data was used to reflect uncertainty in harvest parameter estimates (Tables 3.1, 3.2).

Average annual harvest in NOAT was 23 bears versus 8 bears in KATM (Tables 3.1, 3.2). On a per-acre area, NOAT has a higher brown bear harvest than any other area in the state’s Game Management Unit 23 (Figure 3.5). Females comprise a larger proportion of overall harvest in NOAT (41%) than in KATM (31%). Adult bears (age 6-12) comprise most of the harvest in both parks (Tables 3.1, 3.2). Note that harvest statistic reporting for KATM is slightly more recent and comprehensive because data from GMU 9C (Table 2.1) is easily retrieved from the online ADFG harvest statistic database. Because NOAT makes up only a small portion of GMU 23 (Table 2.2), harvest statistics for the preserve had to be requested from agency data managers.

Discretized state cut-off values for the *# of bears harvested* model component in NOAT and KATM reflect hypothesized minimum and maximum (i.e., a collectively exhaustive range) potential harvests (based on historical data; Tables 3.1; 3.2).

<u>Number of bears harvested states NOAT:</u>

- Low - 0 to 20 bears per year
- Baseline – 20 to 30 bears per year
- High – greater than 30 bears per year

<u>Number of bears harvested states KATM:</u>

- Low - 0 to 6 bears per year
- Baseline – 6 to 20 bears per year
- High – greater than 20 bears per year

<u>**Harvest Index**</u>

Expert judgment was elicited to determine the probability that bears are subject to high, medium, or no harvest threat given alternate combinations of bear abundance and harvest data measures. For example, given that the number of bears harvested is low (0-20 bears per year), females comprise less than 40% of the harvest, and few juveniles are harvested, experts hypothesized that harvest is unlikely to be a high or medium threat (Appendix 1). Alternatively, given that the number of bears harvested is high (> 30 bears per year), females comprise greater than 40% of the harvest, and many juveniles are harvested, experts hypothesized that harvest is likely to be a high threat; Appendix 1).

Bear Density (NOAT)

A 2010 survey of bears in the northern portion of Gates of the Arctic National Park and Preserve (GAAR; Figure 3.6) was used as a proxy for current bear population size in NOAT. Though divided by a political boundary, bears using GAAR are likely to use NOAT and anthropogenic and environmental factors are similar among parks in the Arctic Network (Harry Reynolds personal communication). The 2010 survey was also the most recent survey available. Conducted as part of the NPS Arctic Network Inventory and Monitoring Program, the survey used a stratified random sampling design and double counting techniques (to account for observability) (Shults and Joly unpublished report). 346 (230 - 463 95% CI) bears were observed in a 17,314 km^2 study area. This represents a density of approximately 20 adult bears per 1000 km^2.

Discretized state cut-off values reflect hypothesized minimum and maximum (i.e., a collectively exhaustive range) bear densities in NOAT (based on the GAAR survey):

- 0 to 8
- 8 to 16
- 16 to 24
- 24 to 32

Stream Surveys (KATM)

Bears in Katmai concentrate in large numbers around streams in the fall when salmon return to spawn. Thus, fall stream surveys have been used to document minimum levels of bear activity in Katmai since 1980 (NPS 2012). Bears are surveyed at "high concentration bear management areas" identified by the Katmai National Park and Preserve General Management Plan (1987) and include Kukaklek Lake, Northern Creek, Funnel Creek, Moraine creek, Moraine Forks, Spectacle Lake, Battle Creek, and Nanuktuk Creek. The number of bears observed at each site is recorded on three separate dates in late August/early September (Table 3.3). This number is combined for each of eight sites to infer the minimum level of bear activity in Katmai in a particular year. The maximum count of bears observed in 2011 (155 bears on 8/16/2011; Table 3) was used to populate the prior probabilities in the stream survey node. Uncertainty in this model component was incorporated using inter-annual variation across maximum estimates from years 2006, 2007, and 2011 (Table 3.3). A discretized range of state cut-off values reflect expected minimum and maximum (i.e., a collectively exhaustive range) bear counts based on historical data (Table 3.3).

- High – 225 to 150
- Medium – 150 to 75
- Low – 75 to 0

Den Occupancy (KATM)

Mark-recapture distance sampling (MRDS; Williams et. al. 2002) was used in 2007 to estimate brown bear density in Katmai National Preserve (Loveless et. al. unpublished report). This study estimated bear density to be 101 ± 18 (SE). However, more recent attempts to implement this survey design have failed due to an extremely short survey window (15 days between den emergence and leaf-out), the remoteness and limited accessibility to bear habitat, and the large spatial extent of individual bear home ranges (which naturally disaggregates populations) (Reynolds et. al. 2011). Because MRDS surveys are expensive and difficult to implement in remote Alaska, surveys of this kind are not likely to be implemented in the future. Instead, annual surveys that document occupied dens are being used as an alternate means of monitoring bears in KATM (Tammy Wilson, NPS unpublished report).

The overall site occupancy rate of denning bears was estimated to be 0.64 (SE = 0.17) in 2012 (Tammy Wilson, NPS unpublished report). This estimate was used to parameterize the prior probabilities of the den occupancy model component. Uncertainty was characterized using a beta distribution. Four continuous states that describe a collectively exhaustive range of potential occupancy rates ranging from 0 to 1 characterize this node.

Current bear state

The *current bear state* model component is characterized by two states: baseline and perturbed, and is predicted given combinations of harvest pressure and population size indices (Tables 3.4, 3.5). Probability scaling was used to calculate individual scores for each state characterizing harvest pressure and bear density model components. Note that probability scaling is a technique that reflects method used in proportional scoring (Conroy and Peterson 2013); however, it does not involve subjective utilities derived from stakeholders. Instead, it was used to estimate current bear state given estimates of harvest pressure and population size parameters.. Scores for each state were calculated as:

$$Score(x_i) = \frac{[x_i - worst(x_i)]}{best(x_i) - worse(x_i)} \qquad (1)$$

where x_i is the measurement on the original (non-probability) scale and *worst*(x_i) and *best*(x_i) are the least and most desired states characterizing the model component over the anticipated range. This results in probability scores of 0, 0.5, and 1.0 for harvest index states of high threat, medium threat, and no threat, respectively. Scores for bear density states of 0 to 8, 8 to 16, 16 to 24, and 24 to 32 were 0, 0.33, 0.67, and 1, respectively. The probability that current bear state is baseline (rather than perturbed), was calculated for all possible combination of states ($3 \times 4 = 12$ combinations) as:

$$P(Baseline_{xi}) = \frac{[Score(x_1)+Score(x_2)+Score(x_3)]}{3} \qquad (2)$$

The probability that current bear state is perturbed (rather than baseline), was calculated for all possible combinations of states as:

$$P(Perturbed_{xi}) = 1 - P(Baseline_{xi}) \qquad (3)$$

HUMAN-BEAR INTERACTIONS SUBMODEL

The human bear interactions submodel is largely the same in KATM and NOAT. Current bear state influences the selection of optimal access restriction and incident prevention decision actions (Figure 3.7). Access restriction decisions are also influenced by salmon escapement in KATM (see salmon-bear interactions submodel) but not in NOAT. Incident prevention decision actions directly influence the number of future human-bear incidents, while access restriction actions indirectly influence future human-bear incidents by decreasing human use in brown bear habitat (Figure 3.7). Visitor-use-days, the current state of bears, and incident prevention decision actions were collectively used to estimate the number of human-bear incidents that are predicted to occur after decision-making.

Access Restriction and Incident Prevention Decision Alternatives

Human-bear management actions are grouped into two general categories: 1) *Access Restriction* actions that restrict or prevent human access to an area; and 2) *Incident Prevention* actions that prevent human-bear incidents, especially in areas with increased potential for conflict. Access restriction actions are primarily implemented to prevent human-caused displacement of bears from prime habitat and/or food sources, while incident prevention is used to decrease the risk of human-bear incidents. These categories of actions are not mutually, exclusive meaning that actions from each category may be implemented simultaneously. Decisions within each category are mutually exclusive.

Access restriction alternatives include the following:

5) Specify access times
6) Close public access
7) Restrict commercial use authorizations
8) No action

Incident prevention management alternatives include the following:

5) Aversive conditioning treatment
6) Increase enforcement efforts (e.g. # of ranger patrols)
7) Aversive conditioning treatment + increase enforcement efforts
8) No action

It should be noted that policies that are already being implemented and are not likely to be reversed (e.g. requiring bear-proof food storage, maintaining electric-fencing around camps, requiring that visitors maintain specified distances from bears, etc…) were not included in the decision model. However, increased enforcement may involve increasing ranger patrols to assure existing policies are adhered to by visitors and guides.

Aversive Conditioning

Deterrents are used relatively infrequently to immediately modify a bear's undesirable behavior (e.g. to prevent a bear from entering a campground). This technique, called hazing, should be differentiated from the aversive conditioning decision alternative. An aversive conditioning treatment is a management method that attempts to permanently modify undesirable behavior in bears by continually and consistently administering deterrents (Hopkins et. al. 2010). A number of studies have evaluated effects of aversive conditioning treatments on black bears, but most programs have failed to continually and consistently apply deterrents (Smith et. al. 2005, Hopkins et. al. 2010). Effects of long-term aversive conditioning treatments on brown bears remain largely unexplored.

Human-bear interactions

During human-bear interactions, bears are aware of people viewing them and either tolerate them while exhibiting no stress-related response (termed a bear-sighting) or respond with behavior that may or may not lead to an incident (Hopkins et. al. 2010). Bear incidents may involve a conflict (i.e. exhibition of overt stress or predatory behavior and/or physical contact with a human), or episodes where bears cause property damage or obtain anthropogenic food. Conflicts may result in the harming or killing of a bear in defense of life and property (DLP; Hopkins et. al. 2010).

KATM Visitation

KATM contains one of the largest remaining populations of brown bears in the world (NPS 2012). This uniquely dense population, along with the large numbers of brown bears that can be easily viewed at salmon spawning streams, attracts many bear-viewers and photographers every summer. Commercial Use Authorization (CUA) reports are filed by recreational guides that accompany bear-viewers and photographers into the park and preserve. Among other details, CUAs document the purpose of visitation (e.g. bear-viewing) and visitor-use-days. These data were used to estimate the annual number of non-consumptive (i.e. bear-viewing, photography, etc…) visitor-use-days in Katmai from 2007 – 2012 (Table 3.6). Visitation has remained relatively stable over the past six years, averaging approximately 12,606 recreational visitor-use-days per year. CUA data were used to determine a discretized set of state values that encompass a collectively exhaustive range of expected visitor-use-days (by non-consumptive users):

- 0 to 3000
- 3001 to 6000
- 6001 to 9000
- 9001 to 12000
- 12001 to 15000
- 15001 to 18000

NOAT Visitation

There are no roads, trails, campgrounds or regularly attended ranger stations in NOAT, and users typically access the preserve by small aircraft (though some residents access the park by boat using the Noatak River). Recreational use is largely limited to residents, and to parties of fisherman, hunters, or river travelers from other areas of the state. Although wildlife viewing may be a secondary purpose of visitors, the primary purpose of most visitation is angling or hunting (NPCA 2006). The western Arctic Range is home to the largest herd of caribou in North America, and more bear harvest occurs in NOAT than in any other region in GMU 23 (NPCA 2006). This is due to the proximity of this area to Kotzebue (15 miles from the preserve) with its jet-supported airport provides easy access for non-locals flying in to hunt in the region (National Parks Conservation Association 2013). Transport reports are filed by licensed air transporters who fly visitors into NOAT. Visitor-use-days in NOAT reflect the number of visitors that are transported into the park by licensed air transporters (Table 3.7).

<u>Human-bear incidents in Katmai National Park and Preserve</u>

Bear Management Report Forms (BMRFs) are created by park personnel as a means of reporting bear incidents that commonly occur in Katmai (Sherri Anderson personal communication). It should be noted that BMRFs can only be created for incidents that personnel witness or are made aware of after the incident occurs. Thus, the number of BMRFs created should be considered as a minimum estimate of incidents.

The number of BMRFs that occurred from year 2000 to 2012 ranged from 72 to 728 (Table 3.8). The number of BMRFs increased steadily from the year to 2000 (when 72 incidents were reported) to 2007 (when 657 incidents were reported) and then remained stable until 2011 (Table 3.8). The average number of BMRFs from 2007 – 2011 was 667. The increase in BMRFs from 2000 – 2007 may reflect a range of factors including, but not necessarily limited to, implementation of management actions designed to decrease human-bear incidents (e.g. bear-proof food storage devices and electric fencing were installed in popular viewing areas), an increased number of bears (that corresponded to an increase in salmon escapement) using Brooks

River, construction projects that may have limited distances between people and bears, and improvement in reporting by park staff (Sherri Anderson personal communication). The average number of BMRFs that were created in 2012 and 2013 declined to 378 (Table 3.8). The reason for this decline is not apparent but does correspond to a large turnover in staff and may be a reflection of under-reporting (Sherri Anderson personal communication). Additionally, salmon escapement – and, in turn, bear activity at streams - has been steadily declining since 2008.

The human-bear incident node represents the number of human-bear incidents that are predicted to occur after decision-making. BMRF data (Table 3.8) was used to determine five discretized states that encompass a collectively exhaustive range of annual human-bear incidents:

- 0 to 150
- 151 to 300
- 301 to 450
- 451 to 600
- 601 to 750

Human-bear Incidents in Noatak National Preserve

Because there are no regularly attended ranger stations in NOAT, reporting (and subsequent recording) of human-bear incidents in the preserve has not occurred since 2003. Prior to 2003, there are limited reports of incidents (Table 3.9). Given that more than 3,500 people live within 15 miles of the edge of the preserve, it is expected that reporting (even when it occurred) largely underestimated the level of local human-bear incidents (National Parks Conservation Association 2013).

Visitor-use-days and human-bear incidents

Incident-rates for NOAT and KATM were calculated by dividing the number of incidents by visitor-use-days (Equation 4; Table 3.10). Dependencies between visitation and human-bear incidents in each model were calculated by multiplying visitor-use-days by the mean incident rate (9.8 incidents ⁄ 377 visitors = 0.03 incident rate in NOAT; 572 incidents ⁄ 12, 606 visitors = 0.05 incident rate in KATM; equation 5). Note that the NOAT incident rate is extremely uncertain due to the lack of recent human-bear incident data and apparent under-reporting in historical data.

Current bear state and human-bear incidents

A number of factors may influence how bears react to humans including human-related factors (e.g. a person's activity at the time of an encounter), environmental factors (e.g. season, presence of prey items), and bear-related factors (e.g. sex, age, familiarity with humans; Herrero et. al. 2005, Hopkins et. al. 2010). Habituation, defined by Whittaker and Knight (1998) as the waning of a response to repeated, neutral stimuli, is especially important in determining the outcome of human-bear interactions.

Bear-to-human habituation occurs when bears are frequently exposed to humans and may lead to bears becoming more tolerant of people (Jope 1985; Hopkins et. al. 2010). However, increased human use in bear habitat leads to more frequent and (potentially dangerous) interactions with people, especially in circumstances when bear-to-bear habituation is not common (Smith et. al. 2005). Human-to-bear habituation occurs when humans have frequent, innocuous encounters with bears, and can result in people acting casual around bears, increasing the potential for human-bear conflict.

High-density populations and clumped, high quality food resources in KATM facilitate bear-to-bear habituation (Smith et. al. 2005). As a result, bears tolerate the presence of other bears at much closer distances than would be expected in low density populations in which individual bears are isolated from one another (e.g. bears in NOAT). Bears that are habituated to other bears seem to be more tolerant of humans regardless of familiarity with humans (Smith et. al. 2005). Thus, as populations become less dense and individual bears become less likely to encounter other bears, negative human-bear interactions may become more likely.

Given the negative relationship between bear density and overt reaction distances (i.e., bears in low density populations are more likely to charge from further distances), human-bear interactions in KATM were modeled to be twice as likely when current bear state is perturbed. Low bear density in NOAT precludes bear-to-bear habituation; thus, human-bear incidents were modeled to be half as likely to occur in Noatak when the current state of bears is perturbed.

<u>Incident prevention decisions and human-bear incidents</u>

Expert (n = 5) responses to 4-step uncertainty elicitation questions (Spiers-Bridge et. al. 2010) were used to parameterize the dependency between incident prevention decisions and human-bear incidents. During the 4-step process, experts were asked to predict the number of human-bear incidents they expected to occur given implementation of a particular management action. They were also asked to create an interval around, and to assess their level of confidence in, each estimate. Parameters were estimated by finding the normal distribution that best fit the conditions provided by experts (i.e., a median value and upper and lower % confidence limits; Table 3.11). Uncertainty was reflected using both the level of confidence provided by each expert (i.e., via estimation of parameter estimates) and the variation of judgments across experts (i.e., by averaging parameter estimates across experts).

KATMAI SALMON-BEAR INTERACTIONS SUBMODEL

Access restriction actions are primarily implemented to prevent human-caused displacement of bears from prime habitat and/or food resources (such as salmon streams). Thus, along with the state of bears prior to decision-making, optimization of decisions that restrict human access to bears is influenced by salmon escapement (Figure 3.8). Access restriction actions indirectly effect recruitment by influencing visitor-use-days. Salmon escapement and visitor-use-days collectively influence recruitment. Note that the salmon-recruitment submodel does not occur in the NOAT decision model (i.e., salmon are not a uniquely important food source for interior-dwelling brown bears).

Salmon escapement (KATM only)

Marine derived meat is known to be an important component of Katmai brown bear diets (Hilderbrand et. al. 1999); however, salmon populations are highly variable with large differences in the number of fish that return to salmon spawning grounds each year (Figure 3.9). Thus, availability of salmon to bears is also variable and is at least partially dependent upon annual escapement. Angling pressure could influence the accessibility of salmon to bears, but fishing regulations are outside of the scope of the decision problem so they were not considered.

The Alagnak and Naknek River drainages comprise the majority of land area draining into Bristol Bay. Thus, escapement data from these systems was used to provide an estimate of salmon numbers entering Katmai that are available to brown bears each year. Using these data (Figure 3.9), state cut-off values for the salmon escapement model component were defined as follows:

- Minimal: 0 to 1. 5 million
- Moderate: 1.5-3 million

- Unlimited: 3 – 8 million

Recruitment (KATM only)

Brown bears have one of the lowest reproductive rates of any terrestrial mammal (Bunnel and Tait 1981, Hilderbrand et. al. 1999). Estimates of survival for adult females in SW Alaska are high (ranging from 0.9 – 0.97) and are thought to be less important to recruitment than low survival rates for cubs (ranging from 0.48 – 0.67) and yearlings (0.73 – 0.89; Seller and Aumiller 1994, Kovach et. al. 2006). Average litter sizes for coastal brown bears were reported to range from 1.8 -2.5 cubs (McLellan 1994), but substantial mortality of cubs occurs following den emergence resulting in the loss of up to 37% of cubs emerging from dens (Sellers and Aumiller 1994). Weaning of dependent cubs generally occurs between the ages of 18 to 30 months.

In addition to high cub mortality, long reproductive intervals contribute to low recruitments rates for brown bears. Kovach et. al. (2006) estimated the age of adult females at first weaning in SW Alaska to be 8.9 years, while minimum time between weaning was 4.5 years. Birth intervals for bears using McNeil River in Alaska were reported to range from 3.7 to 4.8 years (Sellers and Aumiller 1994). Recruitment rate, measured using successful litters (i.e. those that raised young to the end of the second summer), was estimated to be 0.34 yearlings per adult female per year.

The recruitment model component in the decision model represents the average number of two-year-olds produced per female per year. State cut-off values were defined using a discretized range of values based on empirical estimates of recruitment for bears in southwest Alaska (Sellers and Aumiller 1994, Kovach et. al. 2006, Van Daele et. al. 2012). This node is characterized by four continuous states that describe a collectively exhaustive range of potential recruitment rates:

- 0 to 0.15
- 0.16 to 0.30
- 0.31 to 0.45
- 0.46 to 0.60

<u>Salmon escapement and recruitment (KATM only)</u>

It is well established that availability of meat, particularly salmon, has a strong positive influence on brown bear demographic rates and densities (Hilderbrand et al. 1999, Hilderbrand et. al. 2004, Mowat and Heard 2006, Pierce et. al. 2013). For example, bears that had access to salmon (or other high quality dietary subsidies) were found to have larger skull sizes, produce larger litters, achieve heavier body weights, and occur in higher densities than interior dwelling bears that did not have access to marine-derived dietary subsidies (Hilderbrand et. al 1999, Mowat and Heard 2006). There is, however, a trade-off between the risk of infanticide (due to cannibalism by adult males) and access to salmon streams for females with dependent young (Ben-David et. al. 2004, Rode et. al. 2006). Females with spring cubs may avoid salmon streams that are densely occupied by males, but the same behavior is not expected by females with yearlings (or older) or females with no cubs (Ben-David et. al. 2004).

In long-lived species with low reproductive rates, such as brown bears, nutritional quality largely determines reproductive rate (Bunnel and Tait 1981, Naves 2003). Moreover, because brown bear reproduction occurs during winter dormancy, reproductive success is tightly linked to the availability of high-quality food resources in late summer and early fall (time-periods that correspond to salmon returning to Katmai streams to spawn).

The dependency between the salmon escapement and recruitment model components was parameterized using probability elicitation. Knowledge experts (n = 5) were asked to provide probabilities of various levels of recruitment given minimal, moderate, or unlimited salmon escapement. Uncertainty was characterized by averaging probabilities among experts.

<u>Human impacts on salmon-bear interactions (KATM only)</u>

In addition to the number of salmon returning to Katmai each year, anthropogenic use of park resources may also affect both the availability and accessibility of salmon to bears (Hildebrand et. al. 2004). Availability is primarily influenced by harvest of salmon (i.e. salmon harvested by humans are not available for brown bears), but decisions regarding fishing regulations were determined to be outside of the scope of the decision context. Thus, the model addressed accessibility issues (e.g. reductions in access to salmon by bears displaced by wildlife-viewing activities) that may be caused by human use.

A number of studies suggest that wildlife-viewing activities may displace bears from fishing sites, effectively reducing the number of fish they can consume (Hilderbrand et. al. 2004). For example, bears apparently delayed their use of a salmon stream on Brooks River in response to an extended visitor season in 1992 (Olson 1997). Moreover, Rode et. al. (2006) reported reduced use of salmon streams on the Douglas River by adult male bears when bear-viewing was experimentally introduced. Conversely, females with dependent young in the same study increased their use of bear-viewing sites, apparently exhibiting a preference for humans over infanticidal adult males. Thus, the literature suggests there are both positive and negative effects of human recreational activity on bear access to salmon.

As a group, experts (n = 5) were asked to provide a graphical representation of the functional relationship they believed to best characterize the dependency between salmon escapement and visitor-use-days (Figure 3.10). Given a baseline recruitment rate of 0.35 2-year-olds per female per year (i.e., when visitation = 0), experts hypothesized that a relatively high-level of visitation (i.e., up to 45,000 visitor-use-days) would have a small positive impact on recruitment (i.e., because females with cubs might gain access to salmon streams they would otherwise avoid). Once visitor-use days reaches a level of approximately 45,000 users, experts predicted that bears would begin to be displaced by anthropogenic activity resulting in a negative influence on recruitment (Figure 3.10).

Access restriction decisions and visitor-use-days (KATM and NOAT)

Expert (n = 5) responses to 4-step uncertainty elicitation questions (Spiers-Bridge et. al. 2010) were used to parameterize the dependency between access restriction decisions and human-bear incidents. During the 4-step process, experts were asked to predict the number of visitor-use-days they expected to occur given implementation of a particular management action. They were also asked to create an interval around - and to assess their level of confidence in - each estimate. Parameters were estimated by finding the normal distribution that best fit the conditions provided by experts (i.e., a median value and upper and lower % confidence limits; Tables 3.12, 3.13). Uncertainty was reflected using both the level of confidence provided by each expert and the variation of judgments across experts.

HARVEST SUBMODEL

The current state of bears influences harvest success and the future state of bears. Harvest decisions directly influence harvest success and adult female survival (Figure 3.11). Adult female survival and the current bear state collectively determine the future state of bears in NOAT. In KATM, future bear state is also influenced by recruitment. Decision optimization is also influenced by values associated with fundamental objectives (utility values).

Harvest decisions and harvest success

KATM and NOAT harvest decision alternatives include the following:

1) No harvest
2) Spring only harvest
3) Restrict concession hunts
4) Limit transport
5) Defer to state regulations (8% harvest rate for KATM; 4% harvest rate for NOAT)
6) Defer to state regulations (10% harvest rate for KATM; 6% harvest rate for NOAT)
7) Defer to state regulations (12% harvest rate for KATM; 8% harvest rate for NOAT)
8) Defer to state regulations (14% harvest rate for KATM; 6% harvest rate for NOAT)

Model dependencies between harvest decisions and harvest success were parameterized, in part, using brown bear harvest data from the ADFG harvest statistics database (Tables 3.14). Uncertainty associated with predicted estimates of harvest success for each alternative was incorporated using inter-annual variation in historical harvest data.

Harvest decision actions (1-8) range from most to least prohibitive. The *defer* harvest regulation reflects deference to existing ADFG harvest regulations (i.e., no action by the National Park Service). Deference to existing regulations could result in a range of harvest rates depending on annual Board of Game (BOG) regulations. Historic (baseline) rates in KATM range from 8-10%, while in NOAT (where there are fewer bears) harvest regulations generally dictate a 4% harvest rate. Under this alternative, non-guided sport and subsistence harvest of brown bears by Alaska residents would be allowed. Additionally, a specified number of concessions authorized by the National Park Service (NPS) would allow non-resident sport hunters accompanied by guided hunting concessioners to harvest brown bears. Harvest success (when defer rate is 8% in KATM or 4% in NOAT) was determined using the number of bears that have been harvested, on average (for the most recent 6-years), by both residents and non-residents. Harvest success rates were modeled to increase proportionally with increasing defer rates. For example, given a 23.6% total harvest success rate (based on historical data) and the defer decision with a 14% harvest rate, harvest success was predicted to be 29.6% (23.6% + 6% above historic rates). Under the *restrict concession hunts* alternative, no guided hunting contracts would be authorized by the NPS. Restricting concession hunts would eliminate harvest of brown bears by U.S. citizens who are not residents of Alaska. Harvest success for this alternative was determined by using resident-only harvest success. Generally, spring and fall harvests of brown bear bears in Katmai Preserve are authorized every other year, but slightly more harvest occurs in fall versus spring hunts. Thus, the spring only harvest alternative in the Katmai model was parameterized by reducing status quo harvest by 40% (Grant Hilderbrand, NPS personal communication). Limiting transport of hunters into Katmai Preserve was modeled to reduce non-resident harvest by half. Resident harvest is expected to occur at status quo levels under this alternative. Under the no harvest alternative, all non-resident and resident sport harvest would be eliminated.

<u>Adult female survival</u>

Because brown bears are long-lived species with low reproductive rates, human-induced mortality is important in determining population viability. In populations that are not subject to over-harvest, survival of adult female brown bears is quite high (> 90%; Sellers and Aumiller 1994, Kovach et. al. 2006). The adult female survival model component is characterized by state-cut-off values that represent a discretized range of potential survival rates ranging from 0 to 1. Baseline survival for bears using Katmai and Noatak NPs was estimated using a range of estimates reported for female brown bears (not subject to intensive harvest) in SW Alaska

(~0.93) and may decline as a result of human-induced mortality. Uncertainty associated with the survival parameter was characterized using a beta distribution.

Harvest Decisions and adult female survival

Expert (n = 5) responses to 4-step uncertainty elicitation questions (Spiers-Bridge et. al. 2010) were used to parameterize the dependency between harvest decisions and adult female survival. During the 4-step process, experts were asked to predict adult female survival given implementation of a particular management action. They were also asked to create an interval around, and to assess their level of confidence in, each estimate. Parameters were estimated by finding the beta distribution that best fit the conditions provided by experts (i.e., a median value and upper and lower % confidence limits). Uncertainty was reflected using both the level of confidence provided by each expert (i.e., to estimate parameters) and the variation of judgments across experts (i.e., estimated parameters were averaged across experts).

Because deference to BOG regulations could result in a range of harvest rates, we modeled the influence of four *defer* harvest decisions on adult female survival (Tables 3.15, 3.16). Highly productive brown bear populations, such as the one in Katmai, are thought to be able to sustain an 8 to10% compensatory harvest (Harry Reynolds, personal communication), while interior–dwelling populations are thought to be able to sustain approximately half that rate (i.e., 4% compensatory harvest). After this point, harvest is thought to be additive. Harvest rates greater than 8% in KATM and greater than 4% in NOAT were modeled to have an additive influence on adult female survival.

Future bear state

The future state of bears is directly influenced by recruitment (KATM only), adult female survival, and current bear state. Probability scaling was used to calculate individual scores for each node state using equation 1 (Table 3.17). The probability that the future state of bears is baseline (rather than perturbed), was calculated for all possible combination of states using equation 2. The probability that the future bear state is perturbed (rather than baseline), was calculated for all possible combinations of states using equation 3.

SUMMARY AND CONCLUSIONS

Monitoring is most useful when it is conducted in such a way that it informs decision-making (Yoccoz et. al. 2010). Phase 2 of the structured decision process allowed us to identify and assess data sources that are being - or can be - collected to inform decision-making. At the outset of the process, a number of data sources were identified, e.g. berry productivity, that were determined to be outside of the decision scope and therefore not relevant to the decision problem. Sensitivity analysis (conducted in Phase 3; see Chapter 4) further facilitates identification of important monitoring targets by identifying key uncertainties (i.e., those uncertainties that are important to both decision optimization and future bear state).

Phase 2 also allowed us to combine multiple sources of information (i.e., monitoring data, expert judgment and published relationships) into an explicit, integrated decision framework. This involved a review and meta-analysis of brown bear literature so that the model reflects the most current understanding of brown bear system dynamics in interior and coastal Alaska. Though empirical data are always preferred over expert judgment, expert elicitation provided a means of obtaining a transparent "best guess" (where data was lacking) that can be updated over time via the learning component of the adaptive management process.

Finally, the explicit and transparent nature of the structured decision process facilitates defense of decision-making in highly contentious management environments (see Chapter 2). Even when decision problems are not fraught with conflict, accountability should be an important goal of agencies tasked with managing trust resources for the public. The SDM process assures transparency, and, thus accountability, while adaptive management facilitates learning, and - in turn – efficient and effective use of public funds (i.e., directs monitoring to inform decision-making).

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Table 3.1. Brown bear harvest statistics reported by the Alaska Department of Fish and Game for Noatak National Preserve from 2003 to 2009.

Year	No. Harvested	Median Age	% Females
2003	21	7.9	10
2004	19	9.5	50
2005	38	9.6	45
2006	25	7.6	40
2007	22	7.9	65
2008	10	7.3	40
2009	24	7.4	35
Mean	**22.7**	**8.2**	**40.7**

Table 3.2. Alaska Department of Fish and Game brown bear harvest statistics for Game Management Unit 9C (KATM) from 2000 to 2011.

Year	No. harvested	% Juveniles	% Seniors	% Adults	% Females
2011[1]	31	0	0	100	35.5
2010[1]	5	20	0	80	60
2009[1]	4	0	25	75	25
2008[1]	9	0	22.2	77.8	0
2007[1]	13	7.7	23.1	69.2	23.1
2006[1]	9	0	11.1	88.9	44.4
2005	4	25	50	25	25
2004	15	6.7	0	93.3	20
2003	14	0	0	100	14.3
2002	23	8.7	0	91.3	21.8
2001	12	8.3	16.7	75	16.7
2000	12	0	0	100	16.7
6-year Mean[1]	**11.8**	**4.6**	**13.6**	**81.8**	**31.3**

[1]Data used to calculate prior probabilities for harvest index parent nodes.

Table 3.3. Proportional scaling was used to estimate the current state of bears in Noatak National Preserve for all combinations (ranging from worst to best) of harvest index and bear density parameters.

Model Component	Scale	Range (worst - best)
Harvest Index	Threat level	High threat - No threat
Bear Density	Bears/km^2	0 - 32

Table 3.4. Proportional scaling was used to estimate the current state of bears in Katmai National Park and Preserve for all combinations (ranging from worst to best) of harvest index and bear density parameters.

Model Component	Scale	Range (worst - best)
Harvest Index	Threat level	High threat - No threat
Stream Surveys	# of bears	Low - High
Den occupancy	Proportion of occupied dens	0 - 1

Table 3.5. Visitor-use-days reported by guides on commercially authorized trips to Katmai National Park and Preserve for the primary purposes of bear-viewing and photography from 2007 – 2012.

Year	Visitor Use Days
2007	12583
2008	14613
2009	10957
2010	12475
2011	12176
2012	12830
Mean	**12606**

Table 3.6. Visitors transported into Noatak National Preserve by licensed air transporters.

Year	Visitors Transported
2010	300
2011	355
2012	478
Mean	**377.7**

Table 3.7. Annual number of bear management report forms (BMRFs) that were created by park personnel as a means of describing brown bear incidents in Katmai National Park and Preserve from year 2000 to 2013.

Year	# BMRFs[1]
2000	72
2001	156
2002	126
2003	206
2004	260
2005	364
2006	419
2007	657
2008	629
2009	684
2010	635
2011	728
2012	416
2013	340

[1]Bear Management report Forms

Table 3.8. Human-bear incidents reported in Noatak Nation al Preserve from 1996 – 2003.

Year	Incident
1996	90
1997	150
1998	200
2000	110
2002	10
2003	30
Mean	**98**

Table 3.9. Incident rate in Katmai National Park and Preserve from 2007 – 2012.

Year	Incident Rate (BMRFs/Visitor-Use)[1]
2007	0.05
2008	0.04
2009	0.06
2010	0.05
2011	0.06
2012	0.03
Mean	**0.05**

[1] $Human\ bear\ incidents = Visitor\ use\ days \times Incident\ rate$

Table 3.10. Annual number of human-bear incidents hypothesized to occur in Katmai National Park and Preserve given implementation of incident prevention management actions.

Decision	# Human-bear incidents (SD)
Avers. Cond. + Inc. Enforc.	284.9 (111.5)
Aversive Conditioning	378.6 (124.2)
Increased Enforcement	347.1 (121.4)
No Action	515.4 (164.8)

Table 3.11. Number of visitor-use-days predicted to occur given implementation of various access restriction management actions Katmai National Park and Preserve and Noatak National Preserve.

Decision	KATM Visitor-Use-Days (SD)	NOAT Visitor-Use-Days (SD)
Close Park	497 (365.5)	14.7 (10.8)
Specify Access Times	9276.97 (1024.9)	274 (30.3)
Restrict Commercial Use	6869.6 (1723.5)	201.6 (52.7)
No Action	13467.02 (2701.6)	377.7 (91.1)

Table 3.12. Alaska Department of Fish and Game harvest statistics for brown bears in Game Management Unit 9C (KATM) from 2006 to 2011. Successes are the number of bears harvested in a given management year.

Year	# Hunters	Residents	Non-residents	Total Success	Resident Success	Non-resident Success
2011	51	35	16	31	19	12
2010	35	30	5	5	3	2
2009	33	30	3	4	3	1
2008	51	40	11	9	6	3
2007	48	39	9	13	8	5
2006	51	40	11	9	3	6

Table 3.13. Predicted (median) adult female survival rate and associated alpha and beta parameters given the implementation of harvest management actions in Katmai National Park and Preserve.

	Adult Female Survival		
Decision	Median	α	β
No Harvest	0.93	255.26	20.2
Spring Only	0.92	261.36	21.3
Restrict Concessioners	0.92	261.36	21.3
Limit Transport	0.91	270.11	26.19
Defer Rate 8%	0.9	318.5	33.62
Defer Rate 10%	0.88	369.47	48.3
Defer Rate 12%	0.86	414.73	65.1
Defer Rate 14%	0.84	454.56	83.84

Table 3.14. Predicted (median) adult female survival rate and associated alpha and beta parameters given the implementation harvest management actions in Noatak National Preserve.

	Adult Female Survival		
Decision	Median	α	β
No Harvest	0.91	313.1	32.3
Spring Only	0.89	344.73	40.7
Restrict Concessioners	0.89	344.73	40.7
Limit Transport	0.89	344.73	40.7
Defer Rate 4%	0.87	392.8	56.4
Defer Rate 6%	0.85	693.47	122.19
Defer Rate 8%	0.83	749.9	153.42
Defer Rate 10%	0.81	798.6	186.16

Table 3.15. Model components used to estimate the state of bears after decision-making.

Model Component	Scale	Range (worst - best)	Probability Score
Recruitment[1]	no. of 2 y.o. per female per yr.	0 to 0.6	0, 0.008, 0.167, 0.5, 0.83, 1
Adult Female Survival	Survival Rate	0 to 1	0, 0.5, 0.75, 1
Bears at t	Categorical	Perturbed or Baseline	0, 1

[1]Recruitment model component is unique to the Katmai model and is not in the Noatak model.

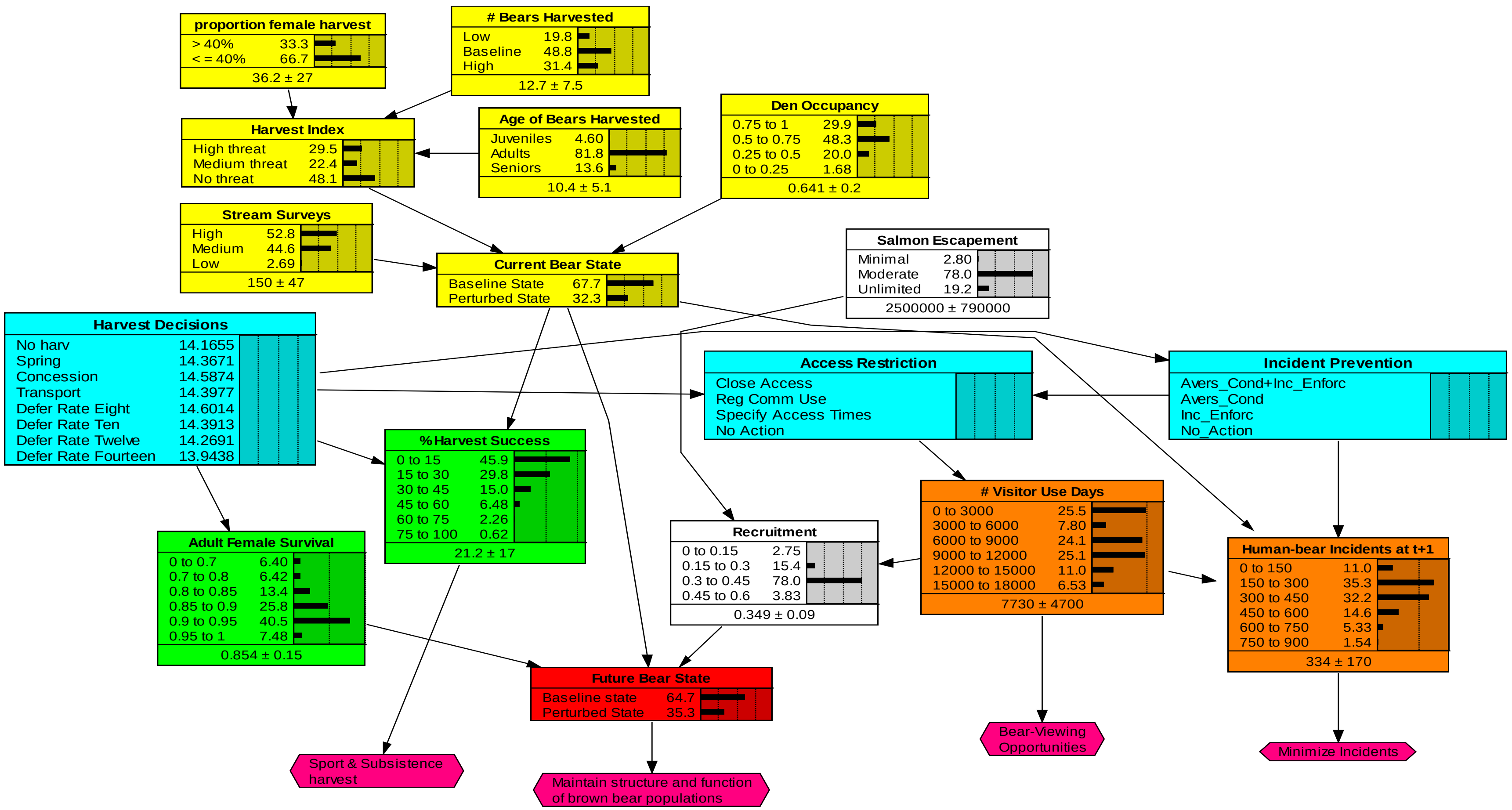

Figure 3.1. Brown bear decision model for Katmai National Park and Preserve. The model is composed of 4 submodels: (1) the current bear state submodel (yellow boxes), (2) the human-bear interactions submodel (orange boxes), (3) the salmon-bear interactions submodel (white boxes), and (4) the harvest submodel (green boxes). Directed arcs indicate causal relationships with parent nodes influencing (pointing into) child nodes. Decisions and utilities are represented in blue and pink respectively.

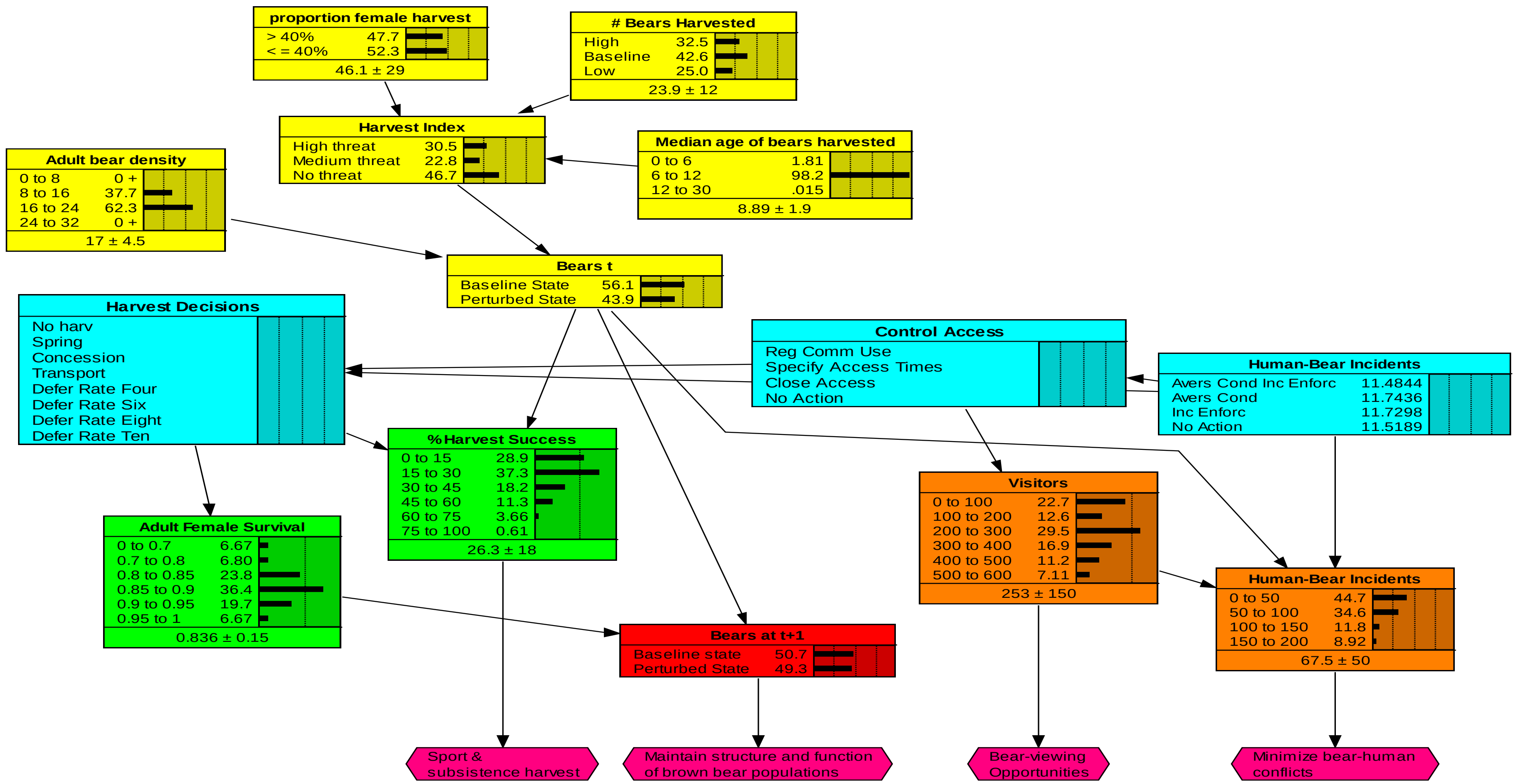

Figure 3.2. Brown bear decision model for Noatak National Preserve. The model is composed of 3 submodels: (1) the current bear state submodel (yellow boxes), (2) the human-bear interactions submodel (orange boxes), and (3) the harvest submodel (green boxes). Directed arcs indicate causal relationships with parent nodes influencing (pointing into) child nodes. Decisions and utilities are represented in blue and pink respectively.

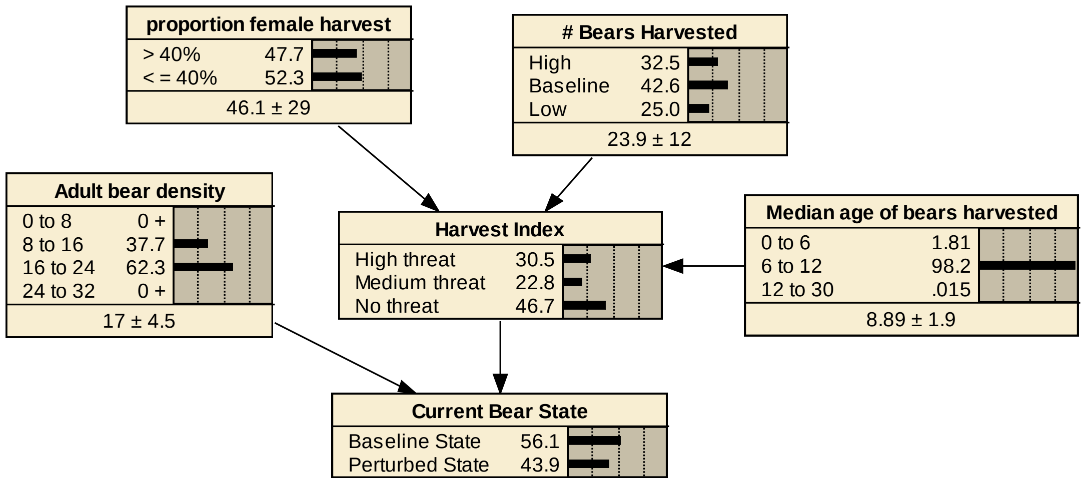

Figure 3.3. Current bear state in NOAT is predicted by a combination of observed harvest pressure and bear density. Directed arcs indicate causal relationships between model components with parent nodes influencing (pointing into) child nodes.

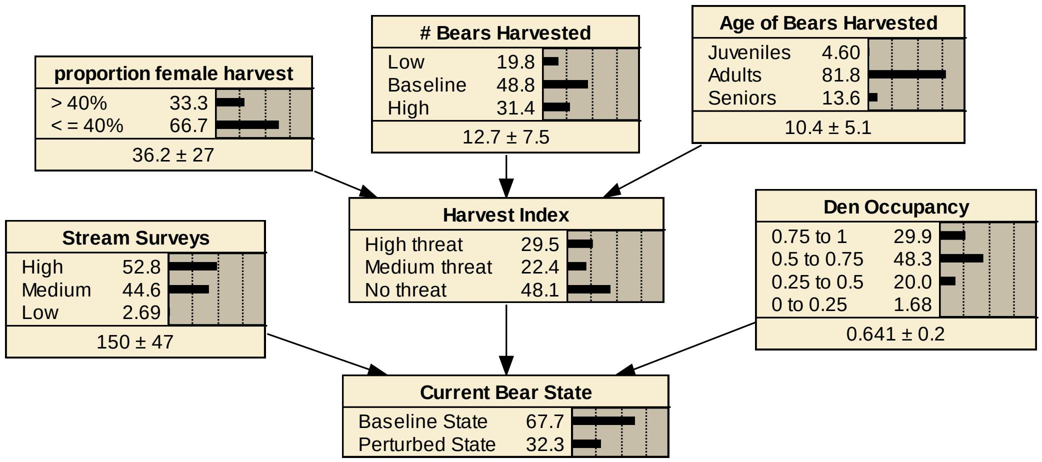

Figure 3.4. Current bear state in KATM is estimated using a combination of harvest pressure and two indices of bear population size – raw counts of bears at salmon spawning streams and den occupancy. Directed arcs indicate causal relationships between model components with parent nodes influencing (pointing into) child nodes.

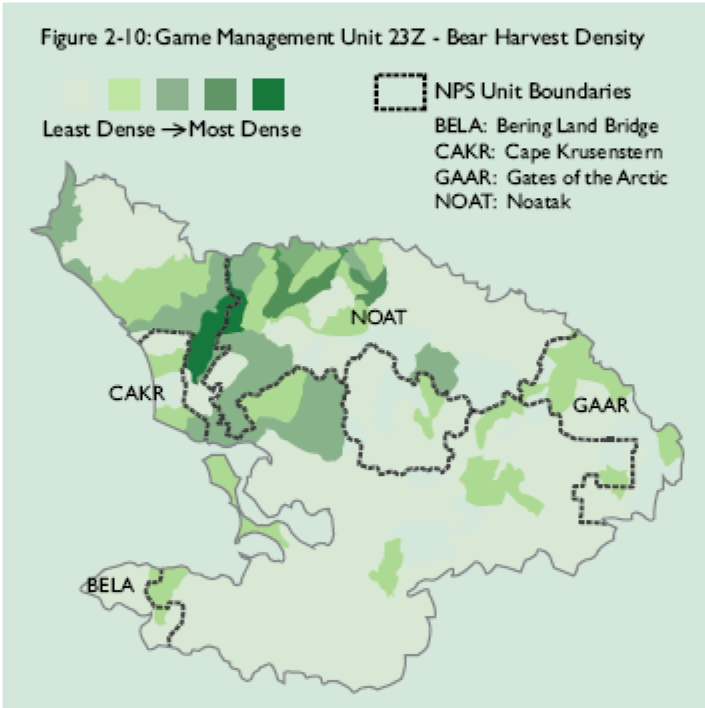

Figure 3.5. Game Management Unit 23Z delineated by the Alaska Department of Fish and Game. Noatak National Preserve (NOAT) borders the north-central boundary of GMU 23Z. High harvest density occurs in the NE border of NOAT. Map from the National Parks Conservation Association. Downloaded on 19 February 2014 from http://www.npca.org/assets/pdf/AlaskaReport.pdf.

Figure 3.6. National park lands in the Arctic National Park Network. A 2010 survey of bears in Gates of the Arctic National Park and Preserve reported and estimate of approximately 20 bears per 1000 km^2 (Shults and Joly unpublished report). Map from the National Park Service. Downloaded on 19 February 2014 from http://science.nature.nps.gov/im/units/arcn/about.cfm.

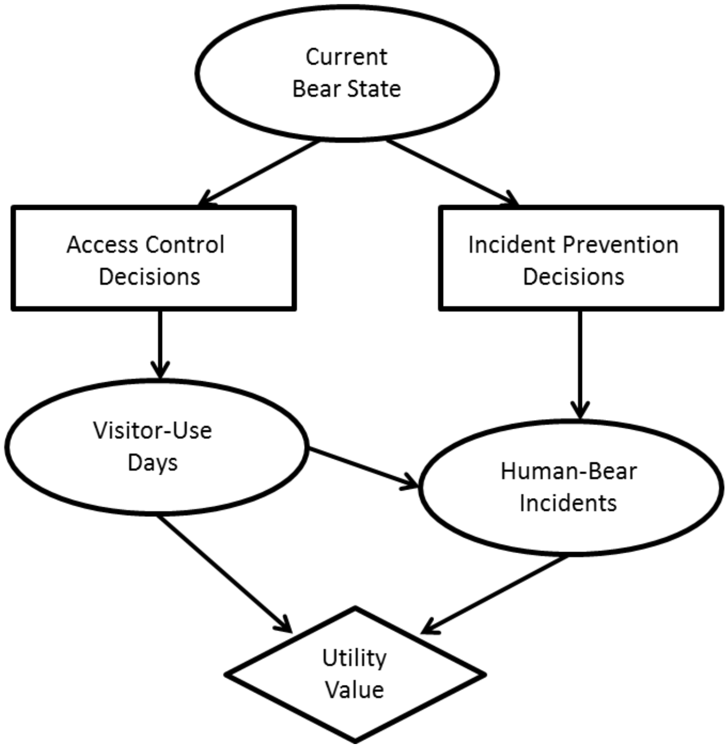

Figure 3.7. Human-bear interaction model components in the KATM and NOAT brown bear decision models. Note that current bear state is not a root node. It was estimated using harvest index and abundance index parameters. Directed arcs indicate causal relationships between model components.

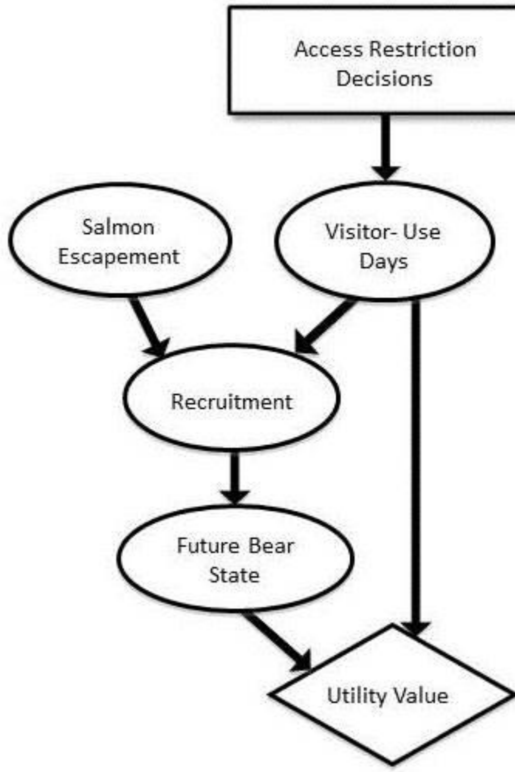

Figure 3.8. Model components in the salmon-bear interactions submodel Katmai National Park and Preserve submodel. Directed arcs indicate causal relationships between model components.

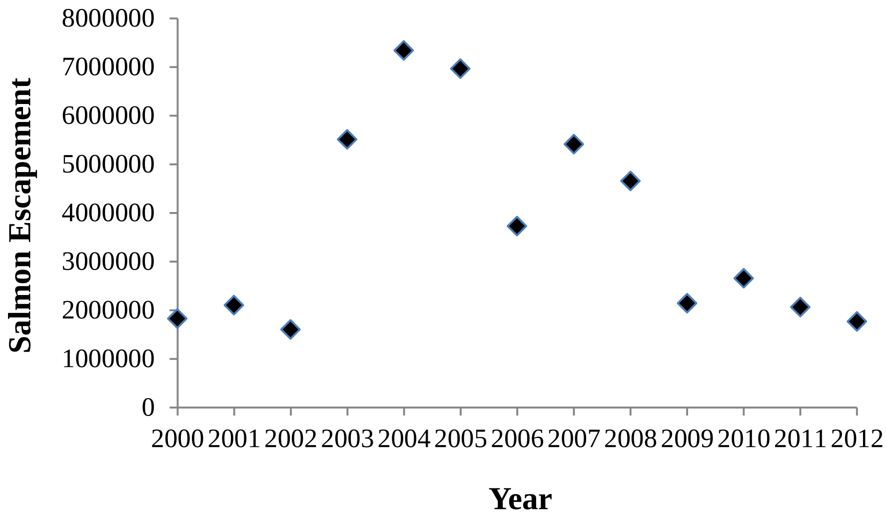

Figure 3.9. Total number of salmon returning to the Alagnak and Naknek Rivers from 2000 to 2012 (raw data provided by ADFG).

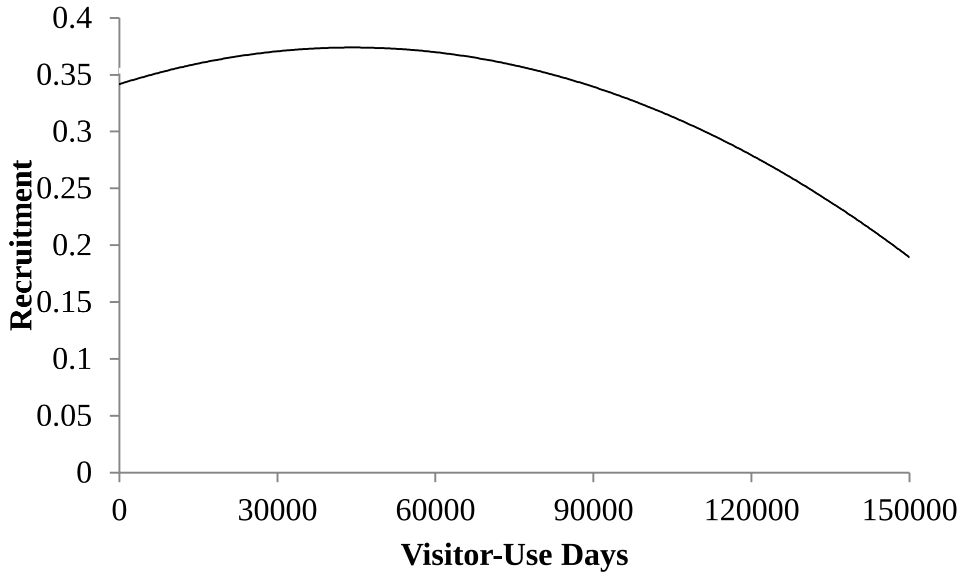

Figure 3.10. Hypothesized relationship from a group elicitation exercise in which experts were asked to graphically describe the functional relationship between recruitment (# 2 year-olds produced per female per year) and visitor-use-days.

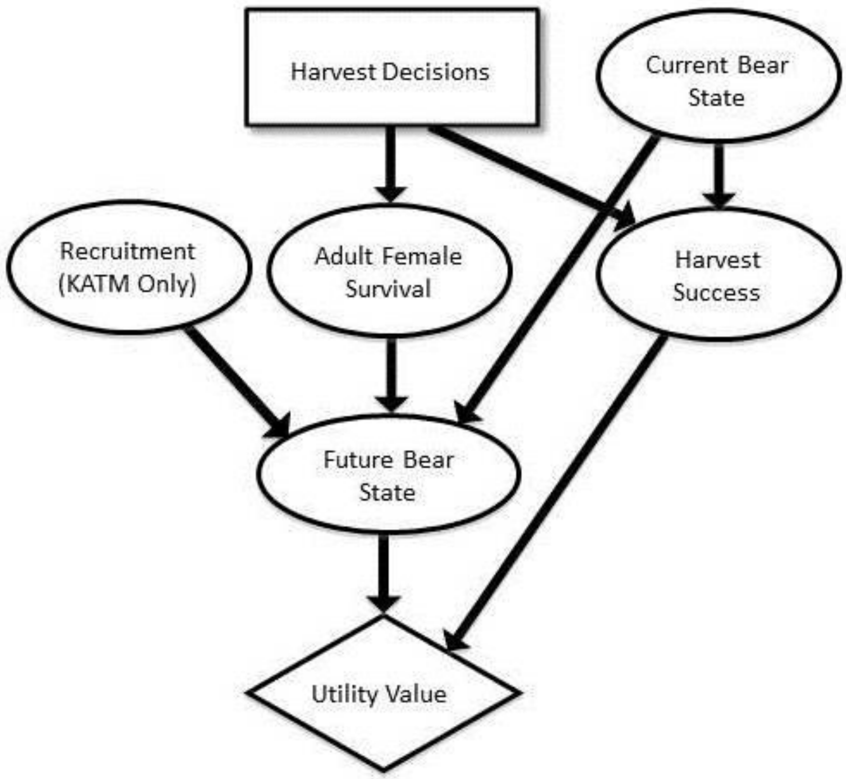

Figure 3.11. Harvest decision model components in KATM and NOAT brown bear decision models. Note that current bear state is not a root node. It was estimated using harvest index and abundance index parameters. Directed arcs indicate causal relationships between model components.

Appendix 3.1. Conditional probability table describing the dependency between harvest pressure and indicators of bear population size to the current state of brown bears in Katmai National Park and Preserve and Noatak National Preserve.

Parent Nodes			Bears at t	
Harvest Index	Den Occupancy	Stream Surveys	Baseline State	Perturbed State
High threat	0.75 to 1	High	0.666667	0.333333
High threat	0.75 to 1	Medium	0.5	0.5
High threat	0.75 to 1	Low	0.333333	0.666667
High threat	0.5 to 0.75	High	0.555556	0.444444
High threat	0.5 to 0.75	Medium	0.388889	0.611111
High threat	0.5 to 0.75	Low	0.222222	0.777778
High threat	0.25 to 0.5	High	0.444444	0.555556
High threat	0.25 to 0.5	Medium	0.277778	0.722222
High threat	0.25 to 0.5	Low	0.111111	0.888889
High threat	0 to 0.25	High	0.333333	0.666667
High threat	0 to 0.25	Medium	0.166667	0.833333
High threat	0 to 0.25	Low	0	1
Medium threat	0.75 to 1	High	0.833333	0.166667
Medium threat	0.75 to 1	Medium	0.666667	0.333333
Medium threat	0.75 to 1	Low	0.5	0.5
Medium threat	0.5 to 0.75	High	0.722222	0.277778
Medium threat	0.5 to 0.75	Medium	0.555556	0.444444
Medium threat	0.5 to 0.75	Low	0.388889	0.611111

Medium threat	0.25 to 0.5	High	0.611111	0.388889
Medium threat	0.25 to 0.5	Medium	0.444444	0.555556
Medium threat	0.25 to 0.5	Low	0.277778	0.722222
Medium threat	0 to 0.25	High	0.5	0.5
Medium threat	0 to 0.25	Medium	0.333333	0.666667
Medium threat	0 to 0.25	Low	0.166667	0.833333
No threat	0.75 to 1	High	1	0
No threat	0.75 to 1	Medium	0.833333	0.166667
No threat	0.75 to 1	Low	0.666667	0.333333
No threat	0.5 to 0.75	High	0.888889	0.111111
No threat	0.5 to 0.75	Medium	0.722222	0.277778
No threat	0.5 to 0.75	Low	0.555556	0.444444
No threat	0.25 to 0.5	High	0.777778	0.222222
No threat	0.25 to 0.5	Medium	0.611111	0.388889
No threat	0.25 to 0.5	Low	0.444444	0.555556
No threat	0 to 0.25	High	0.666667	0.333333
No threat	0 to 0.25	Medium	0.5	0.5
No threat	0 to 0.25	Low	0.333333	0.666667

CHAPTER 4 : OPTIMIZATION AND SENSITIVTY ANALYSIS OF BROWN BEAR DECISION MODELS IN NOATAK NATIONAL PRESERVE AND KATMAI NATIONAL PARK AND PRESERVE

INTRODUCTION

The structured decision process can be categorized into three sequential phases. Phase 1 of the process involves framing the decision problem, identifying and structuring objectives, revealing the means of achieving those objectives (i.e., via management actions), and developing a prototype decision model (Williams et. al. 2002, Williams 2011). Phase 2 involves identifying and compiling data sources that can be used to parameterize the decision framework, decision model revision and refinement, parameterization and data analysis. In Phase 3 of the process, scenario evaluation and sensitivity analysis are used to evaluate model performance and outcomes. In this chapter, I describe Phase 3 of the process for brown bear decision models in Noatak National Preserve (NOAT) and Katmai National Park and Preserve (KATM).

First, I provide a brief review of NOAT and KATM general model structures. I then discuss valuation of objectives and optimization techniques. Of course, before adopting any policy, model behavior and sensitivity should be explored (Clemen and Reilly 2001, Peterson and Evans 2003, Conroy and Peterson 2013). During this process I assessed sensitivity of decision optimization to changes in model parameter values and utility weighting schemes used in the multi-attribute objective function. Model components that are important to both decision optimization and the model outcome (i.e., future bear state) are identified as key uncertainties (Peterson and Evans 2003). Because utility measures are highly subjective – and they have a substantial influence on the selection of optimal decisions (see discussion below) – I explored how decision optimization would change using economically derived utility weights. Finally, I assessed the potential consequences of implementing optimal decisions (derived using both static and dynamic optimization techniques) by forward simulating brown bear state given alternate policies.

GENERAL MODEL OVERVIEW

NOAT and KATM brown bear decision models are stochastic models that track brown bear population state through time in Katmai National Park and Preserve (KATM) and Noatak National Preserve (NOAT). Brown bear population state is a binary attribute (i.e., bear state can be baseline or perturbed) that reflects both population size and composition. For example, an abundant population with many family groups (i.e., females with dependent cubs) would be "baseline;" while, a population with low abundance and few family groups would be perturbed. Any one characteristic (i.e. population size or composition) can get the state to "perturbed." The goal of decision making for each park was to identify brown bear management policies that are optimal with respect to objectives that include interests of consumptive and non-consumptive users and brown bear population status. Both models operate on an annual time step and predict the future state of bears (i.e., baseline or perturbed) given decisions and system dynamics. Although the spatial extent of each model is currently defined by NOAT and KATM boundaries, the models were constructed to be portable to similar bear management areas in Alaska. The model structure contained two main components: (1) a model that estimates the current state of bears in each of two national park units (NOAT and KATM) and (2) a model that predicts the future state of bears given current bear state, system dynamics (e.g. salmon availability), and decisions.

NOAT and KATM decision models were constructed in the form of Bayesian Belief Networks (BBN) - which model relationships among components using probabilistic (conditional) dependencies (McCann et. al. 2006, Marcot et. al. 2006). Bayesian belief networks are graphically represented as influence diagrams that consist of model components, referred to as nodes with each node consisting of environmental states that are mutually exclusive and collectively exhaustive. The directed arcs indicate causal relationships between model components with parent nodes influencing (pointing into) child nodes. Root nodes do not have any arcs pointing into them and, thus, are only informed by prior information.

Two types of optimization were used to solve for optimal policies. First, we solved for the optimal policy, in the modeling shell Netica, by predicting returns based on a single time step with a single decision epoch. Next we solved for the optimal decision using dynamic programming (via the MDP Toolbox; R Core Team 2013). The latter optimization approach also worked at a 1-time step transition but the returns were based on a 100-year time horizon and optimal policies were identified recurrently through time.

The primary difference in structure between the 1-time-step-BBN and the 100-year forecasting model is that the latter assumed that current bear state is known (i.e., based on the current bear state model) prior to decision-making. In the BBN model, current bear state is uncertain and that uncertainty is represented probabilistically. The deterministic assumption regarding bear state (in the 100-year forecasting model) allowed us to avoid having to use a much more complex decision space, a partially observable Markov decision process, and we felt that this added complexity was unnecessary for our purposes. Otherwise, parameters and dependencies between parameters are the same. Model structure and parameterization is discussed in detail in Chapter 3 and is summarized in Table 4.1.

VALUATION OF OUTCOMES AND OPTIMIZATION

The utility, which describes the managers' value system, is the annual measure of what the manager receives from a system in return for investments. Value elicitation of decision makers in NOAT and KATM was used to determine the relative importance of each of four fundamental objectives (where 1 indicated the lowest importance, and 10 indicated the highest importance). Elicitation responses indicated that the bear population objective was valued highest and that the incident-prevention objective > sport and subsistence harvest objective > non-consumptive use objective (Table 4.2). Mean scores for each objective were used as weights in the objective function (equation 4.2).

Quantitative attributes associated with each objective are reflected as parameters in NOAT and KATM decision models and include the following: future bear state, harvest success, number of visitor-use-days, and number of human-bear incidents. Because each attribute is measured on a different scale (Table 4.3), proportional scoring (Clemen and Reilly 2001; Conroy and Peterson 2013) was used to convert attributes to a common scale. First, attributes were rated from "worst" to "best" by assigning (non-proportional) scores to each level characterizing attributes.

Individual utilities were calculated for each attribute as:

$$U(x_i) = \frac{[x_i - worst(x_i)]}{best(x_i) - worse(x_i)} \tag{4.1}$$

where x_i is the measurement on the original attribute scale and *worst*(x_i) and *best*(x_i) are the least and most desired values of the attribute over the anticipated range. Individual utilities were combined into an objective function as a weighted sum of utilities:

$$U_i(x) = k_1U(x_i) + k_2U(x_i) + k_3U(x_i) + k_4U(x_i) \qquad (4.2)$$

where k_i is the relative importance of each attribute (Table 4.2).

The 1-time-step optimal decision was determined by examining the expected value of each management alternative (Peterson and Evans 2003). The expected value is the sum of the probability-weighted values of all possible combinations of future bear state, harvest success, visitor-use-days, and human-bear-incidents. To solve for the recurrent optimal decision, the objective function was recast as a Markov decision problem and was solved using dynamic programming (Williams et. al. 2002; Moore and Conroy 2006, Conroy and Peterson 2013). Given current bear state (known to be either baseline or perturbed), dynamic, stochastic programming was used (via the Markov Decision Process Toolbox (R Core Team 2013) to maximize the present value of the perpetual utility stream from all future actions. This process involves using backward induction (via Bellman's equation; Williams et. al. 2002; Conroy and Peterson 2013) to identify a recurrent reward each year over an indefinite time horizon. Note that the purpose of recasting the decision problem as a Markov decision problem was to evaluate how decision optimization differed when the optimal solution was solved recurrently (vs. using 1-time returns), so the more complex model (KATM) was used for this exercise.

MODEL BEHAVIOR AND SENSITIVITY STRUCTURE

Like all models, NOAT and KATM brown bear decision models are a simplified approximation of reality so model behavior and sensitivity must be evaluated. As a coarse assessment, model components and associated dependencies were evaluated to ensure that they produced outcomes that were within the range of what has been observed empirically or for which there are strongly prevailing hypotheses in the ecological community. To do this, each model component was varied from its minimum to its maximum state and associated changes to dependencies were evaluated to see if model components produced any obviously unrealistic states. This assessment revealed that NOAT and KATM models reasonably approximated brown bear dynamics for interior-dwelling (i.e., NOAT) and coastal (i.e., KATM) brown bear populations in Alaska. Calibrating models with empirical data is an important next step in model assessment. This will be an easier task in KATM where data are more abundant and accessible than in NOAT where data is extremely limited.

Three categories of sensitivity tests were used to assess the influence of model parameters and values to decision-making. One-way sensitivity analysis was used to determine the relative influence of each model component on the expected value of decisions and model outcomes (i.e., future bear state) (Peterson and Evans 2003, Conroy and Peterson 2013). To accomplish this, node states were systematically varied from minimum to maximum levels and associated probabilities for future bear state were recorded. This same exercise was used to assess the influence of model components on the expected value of the optimal decision-set. A second type of sensitivity test – called response-profile analysis – was used to evaluate how the optimal decision changed when current bear state was varied from baseline to perturbed. Finally, indifference sensitivity tests were used to evaluate the sensitivity of the decision to the relative weighting of multiple objectives. Both NOAT and KATM decision models had four attributes associated with each of four fundamental objectives which were assigned unequal weights (bear structure and function > incidents > harvest success > human-bear incident prevention). Weights are, by nature, subjective, so indifference tests are important tools that can help stakeholders determine if their objectives have been properly weighted (Conroy and Peterson 2013). To assess the sensitivity of decisions in each category (i.e., harvest, access control, and incident-prevention) to changes in utilities, decision categories that were not being evaluated were fixed using the estimated optimal decision for that category. For example, to assess the sensitivity of harvest decisions to changes in utilities, access control and incident-prevention decisions were fixed using estimated optimal decisions for those categories.

Sensitivity of the Katmai Decision Model

One-way sensitivity analysis revealed that future bear state was most sensitive to current bear state, recruitment, and adult female survival (Figure 4.1). This is not surprising given that these parameters were used to directly estimate future bear state. Probability that future bear state would be baseline was 1.5 times higher when levels of these model components were systematically changed from their lowest to highest states. For example, given that all other parameters are held constant, there is a 0.388 probability that future bear state will be baseline when recruitment is set at its lowest state (0 - 0.15). The probability of a baseline, future bear state increases to 0.721 when recruitment is set at its maximum state (0.45 - 0.60).

Sensitivity of the future bear state model component to harvest index, stream surveys, and den occupancy (i.e., parameters used to estimate current bear state) can be attributed to the direct relationship between current and future bear state (Figure 4.1). The apparent sensitivity of future bear state to human-bear incidents is less intuitive because it is largely the result of back propagation that can occur when conducting sensitivity analysis using directed acyclic graphs. Human-bear incidents were parameterized to be twice as likely to occur given that current bear state is perturbed (Table 4.1; see chapter 3); thus, high incident occurrence is directly related to a perturbed bear state. The influence of visitors on future bear state reflects the hypothesized relationship between visitors and recruitment (see chapter 3).

The expected value of the optimal policy was most sensitive to future bear state, human-bear incidents, and harvest success (Figure 4.2). These model components are the attributes that are directly associated with utility values, so it is understandable that the expected value of the decision is sensitive to them. Visitor-use-days are also directly associated with utility values, but the weight on the non-consumptive use utility was much lower than on other utilities (i.e., a weight of 3.7 out of 10). Additionally, visitor-use was parameterized to negatively influence human-bear incidents (i.e., human-bear incidents increase as visitation increases), and the incident reduction objective was valued twice as highly as the non-consumptive use objective. One might expect to see the same sort of relationship between the harvest success utility and the bear population utility, but harvest success in the model is a measure of hunter happiness and does not affect future bear state. Rather, harvest effects on bear state are mediated through harvest decision actions, and, in turn, survival which is used to predict future bear state.

Response profile sensitivity analysis was used to assess how trade-offs between harvest and bear population objectives influenced the estimated optimal decision. For example, when it is known with 100% certainty that current bear state is perturbed, the optimal decision is deference to state regulations given that state regulations dictate a an 8% harvest rate for KATM (Table 4.4). Given that current bear state is completely unknown (i.e., a 50% probability that it is either baseline or perturbed) or is known to be perturbed, the optimal decision is to restrict concession hunts (i.e., eliminate non-resident harvest). Similarly, adult female survival and harvest success were important to decision optimization. Optimal policies changed twice over the range of harvest success (i.e., from 0% to 100%) and adult female survival (i.e., 0 to 1). Although the human-bear incident model component had a strong influence on the value of the optimal decision, the optimal decision alternative remained unchanged regardless of the state of human-bear incidents. Because the objective function minimizes human-bear incidents without a cost constraint, the optimal decision is always to take the most restrictive action (i.e., aversive conditioning plus increased enforcement).

Another way to assess trade-offs between multiple competing objectives is to systematically change utility weighting schemes and evaluate the influence of alternate utility weights on the estimated optimal policy (Conroy and Peterson 2013). Harvest success and bear utilities were important to harvest decision optimization. Given the weight that stakeholders provided (weight “1” in Figure 4.3) the optimal harvest decision is to restrict concession hunts (i.e., eliminate non-resident harvest). If harvest is not valued at all, the optimal decision is to eliminate all bear harvest (Figure 4.3). Harvest must be valued seven times more than it is currently weighted for the most liberal harvest decision (i.e., deference to the state with a 14% harvest rate) to be optimal (Figure 4.3). Similarly, estimated optimal policies favor more liberal harvest decisions when the bear utility weight is reduced (Table 4.5). For example, when bears are not valued at all (i.e., the utility weight is equal to zero) the optimal decision is the most liberal harvest decision (i.e., deference to the state with a 14% harvest rate). Optimal decisions become more restrictive as the weight on the bear utility increases. The bear utility must be valued 100 times more than it is currently weighted for the optimal decision to be no harvest (Table 4.5).

Access restriction decisions were sensitive to non-consumptive-use, bear, and incident-prevention utilities (Figures 4.4- 5; Table 4.6). For example, when the non-consumptive use utility weight was zero, the optimal action was to close access to the park (Figure 4.4). As the weight on the non-consumptive use value increases, access restriction actions become more liberal (Figure 4.4). A similar, but lesser, effect is evident for incident-prevention and bear utilities and access restriction decisions (Figure 4.5, Table 4.6). As the weight on either the incident-prevention (Figure 4.5) or the bear utility (Table 4.6) increases, the optimal decision changes from no action to specifying access times. Regardless of how high bear or incident-prevention utilities are weighted, specifying access times is the most restrictive action identified as optimal (given that all other utilities and model components are held at base levels). Incident prevention decisions were not sensitive to the ranking scheme on any utility.

Sensitivity of the Noatak Decision Model

Future bear state in the NOAT decision model was most sensitive to current bear state and adult female survival (Figure 4.6). When all other parameters are held at baseline levels, the probability that future bear state will be baseline becomes twice as likely when either parameter is changed from its minimum to its maximum state. Given that these two parameters are used to estimate future bear state, their influence is not surprising. Adult bear density and harvest index were also influential to future bear state as they are used to estimate current bear state, which, in turn, is used to estimate future bear state. Similar to the KATM model, the influence of human-bear incidents on future bear state is a reflection of backwards propagation that can occur in directed acyclic graphs. Incidents were parameterized to be less likely to occur when current bear state is perturbed (i.e., we hypothesized that fewer bears would result in fewer human-bear interactions that could escalate to incidents). Thus, (many) bear incidents in the Noatak model are indicative of a baseline current bear state.

The expected value of the optimal decision in the Noatak model was most sensitive to future bear state and harvest success (Figure 4.7). Current bear state, adult female survival, and human-bear incident model components also had a substantial influence on the expected value of decision-making. Three out of five of these model components (future bear state, harvest success, and human-bear incidents) are attributes that are directly associated with utility values, so it is understandable that the expected value of the decision is sensitive to them. The other two influential model components, adult female survival and current bear state (Figure 4.7), are used to estimate future bear state. Similar to the KATM decision model, the visitor-use model component (also directly associated with a utility) was not influential to either future bear state or the expected value of decision-making (Figures 4.6, 4.7). Again, the weight on the non-consumptive use utility was much lower than on other utilities (i.e., a weight of 3.7 out of 10), and visitor-use was parameterized to negatively influence incident-prevention (i.e., more incidents occur when visitation is high) which was valued twice as highly as the non-consumptive use objective.

The Noatak decision model had a similar, but more sensitive, response profile than the KATM model. Given that current bear state is known to be baseline (with 100% certainty), the optimal decision is deference to the state given an (expected) harvest rate of 4% (Figure 4.8). When current bear state is known to be perturbed (with 100% certainty) the optimal decision is to eliminate all brown bear harvest. The optimal harvest decision was also sensitive to changes in the harvest success model component. The optimal decision changed from No Action to

Restrict concession Hunts to Limit transporters over the range of harvest success rates (0 to 100%) when all other components were fixed. Note that restricting concession hunts, limiting transporters, and spring only harvest actions were modeled to have the same influence on adult female bear survival but have increasingly negative effects on harvest success (spring only > restricting concession hunts > limiting transport). So, harvest success in the NOAT model drives selection between these three decision alternatives).

Although the KATM incident-prevention decision was stochastically dominant (i.e., the most restrictive action was always optimal), NOAT incident-prevention decisions were sensitive to the visitor-use model component. As visitor-use increased, the optimal incident prevention decision changed from increased enforcement to aversive conditioning (Figure 4.9). This difference in optimization between park units can be attributed to two factors: 1) a lower overall incident occurrence in NOAT (i.e., ~ 10-50 incidents per year in NOAT versus ~ 450 incidents per year in KATM) and 2) a higher incident rate in NOAT than in KATM (10% in NOAT versus 3% in KATM). Similarly, visitation in NOAT is extremely low compared to KATM, so the optimal access restriction action is always no action. Access restriction actions are primarily designed to reduce anthropogenic disturbance to bear activity and it was hypothesized that non-consumptive use activity in NOAT will not be high enough to warrant implementation of access restriction actions.

As with KATM, NOAT harvest decision optimization was highly sensitive to harvest success and bear utility ranking schemes. The optimal harvest decision given the brown bear working group ranking scheme (i.e., where the utility weight is equal to 1) is to limit transport (Figure 4.10). No harvest is the optimal decision when harvest success is not valued at all (i.e., utility rank is equal to zero). The harvest utility weight must be ranked seven times higher than it is currently scored in order for the optimal decision to be deference to the state with a 10% harvest rate (i.e., the most liberal harvest decision in the NOAT model). Harvest decision optimization was also sensitive to the bear utility weight (Figure 4.11). The optimal decision changed four times, from the most liberal to the most restrictive decision, over the range of ranking schemes explored (ranks from 0 to 2).

Access restriction decision optimization was somewhat sensitive to the non-consumptive use utility weight. When the non-consumptive use utility was not valued at all (i.e., the utility rank was zero) the optimal decision is to specify access times. When the utility weight was increased to 0.25 (i.e., 0.75 less than the brown bear working group valued non-consumptive use) the optimal decision is no action. Again, visitor-use in NOAT is predicted to remain low enough that access restriction actions are not likely to be warranted. However, visitor-use was hypothesized to affect human-bear incidents – that is, incidents become more prevalent as visitor-use increases – so, visitor use (the model component not the utility) is important to incident-prevention decision optimization (Figure 4.9). Similar to the KATM model, incident-prevention decision optimization in the NOAT model was not sensitive to utility ranking schemes on any objective.

DECISION OPTIMIZATION

Management actions in *access control*, *incident-prevention*, and *harvest decision* categories are mutually exclusive, but actions among categories are not. So, optimal policies will be a combination of three decisions (one from each decision category). Three decision categories containing $8^{x}4^{x}4$ actions dictate that we considered 128 potential policies. Given the weighting scheme provided by decision-makers, the optimal static policy in KATM is deference to state harvest regulations with an 8% harvest rate, no access control decision, and aversive conditioning plus increased enforcement (for incident-prevention). The optimal policy in NOAT is to limit transport (i.e., reduce non-resident harvest by half), no access control decision, and increased enforcement (for incident-prevention). Both policies are highly sensitive to the estimate of the current state of bears. In KATM, abundance indices and harvest data used to estimate the current state of bears indicated a higher probability of baseline than perturbed (0.677:0.323). This estimate is consistent with incidental observations made by park managers who are not currently concerned that bear abundance or population composition is compromised in KATM (Troy Hammond, NPS KATM personal communication). Bear managers do, however, want to be able to detect when current bear state shifts enough to warrant non-deference to state Board of Game regulations. The model predicts that implementation of the optimal policy in KATM will result in a slight decline in the probability that future bear state will be baseline (0.677 to 0.633). Monitoring data can be used to assess how this model prediction performs and the dependency between decision actions and future bear state can be updated accordingly. However, the estimate of current bear state is highly uncertain as it was estimated using indices for harvest and abundance, so reducing the uncertainty associated with parameter estimates that influence decision making (such as current bear state) will also contribute to learning, and in turn, improve decision-making over time.

The more restrictive policy in NOAT (as compared to KATM) is indicative of the extreme uncertainty regarding bear dynamics in the Arctic Park Network. Given the density estimate used (which is seven-years-old and was implemented in a different park) combined with harvest indices, current bear state is essentially completely unknown (0.561 Baseline: 0.439 perturbed). Again, this model prediction is consistent with incidental observations of NPS brown bear biologists (Brad Shults NPS Arctic Network personal communication). Much of the subsistence harvest in NOAT may be attributed to conflicts between bears and residents that live in the rural Noatak community (located 15 miles from the preserve border). Bears taken in defense of life and property (DLP) are almost never reported as such because subsistence harvest reporting does not require interaction with law enforcement (while reporting a DLP does; Marci Johnson, NPS Arctic Network personal communication). There may be more complex interactions between harvest and human-bear incidents that we have not captured in the model. However, this uncertainty could be reduced over time if monitoring detects declines in subsistence harvest that correspond to more aggressive incident-prevention decision actions. The expected value of the optimal decision, future bear state, and decision optimization were sensitive to the human-bear incident model component, thus, along with current bear state, it is a key uncertainty in NOAT (Figures 4. 6, 4.7, and 4. 9). Our hope is that the decision model will facilitate a transparent defense for implementing monitoring programs designed to reduce the uncertainty regarding the occurrence of human-bear incidents and current bear state in and around NOAT. The same is true for current bear state in KATM.

1-Time-Step Versus Perpetual Returns

Optimization under dynamic decision-making at KATM favored extremely restrictive harvest policies given current weights on objectives. The optimal policy was no harvest (i.e., the most restrictive harvest decision), no access control action, and aversive conditioning plus increased enforcement. Outside of the harvest decision, the optimal policy identified using dynamic programming was the same as the optimal policy identified using one-time returns. It was initially puzzling, however, that optimal dynamic policies were not dependent on current bear state. That is, the optimal policy was the same given that current bear state was either baseline or perturbed. We guessed that restrictive policies were favored in the dynamic model because such a high premium was placed on bears being "baseline" or getting to "baseline" given the utility weighting scheme provided by NPS managers. Our hypothesis was corroborated when the model returned state-dependent optimal decisions after the bear utility weight was reduced. The bear utility had to be substantially reduced so that is was half of what the harvest utility weight was (i.e., it was multiplied by 0.2) to get state-dependent optimal policies. Given that current bear state is known to be baseline or perturbed, the optimal policy (using the reduced bear utility weight) is the same as that identified using 1-time returns (Table 4.4; baseline = deference to the state with an 8% harvest rate + no access restriction + aversive conditioning and increased enforcement; perturbed = restrict concession hunts + no access restriction + aversive conditioning and increased enforcement).

To assess the consequences of implementing different optimal policies, we forward simulated bear population state and harvest success for 100 years given two scenarios. First, we assessed the consequences of the non-state dependent policy (i.e., no harvest + no access restriction + increased enforcement and aversive conditioning). In this scenario, the optimal policy does not change with initial bear state. Forward simulating bear state and harvest success for 100 years given this policy resulted in zero harvest success and a relatively stable probability that bear state would be baseline (100 yr. average = 0.723; Table 4.7).

Next we assessed the consequences of implementing the state-dependent policy. In this scenario, policies were allowed to vary depending on the state of bears. The "baseline" policy was to restrict concession hunts + no access restriction + aversive conditioning and increased enforcement, while the "perturbed" policy was deference to an 8% state harvest regulation + no access restriction + aversive conditioning and increased enforcement. Again, the probability of a baseline future bear state remained relatively stable (100 year average = 0.693) - as did harvest success - but harvest success was 25% versus 0% in the non-state dependent policy (Table 4.7).

This simulation exercise demonstrated that the trade-off between state and non-state-dependent policies for bears is essentially nothing. By implementing the non-state-dependent policy the manager gains a very small (~0.03) increase in the probability that future bear state will be baseline but loses a very large return by eliminating harvest success. Alternatively, the state-dependent policy satisfies both the bear objective and the harvest success objective. This indicates that the utility weights that resulted from elicitation should be modified to reflect the ranking scheme that achieved the state-dependent policy (i.e., the bear utility was ranked too high).

AN ECONOMIC APPROACH TO UTILITY VALUATION

Decision optimization in both KATM (static and dynamic) and NOAT models was extremely sensitive to weights on utilities in the multi-attribute objective function. One of the primary drivers of decision optimization in SDM, along with system dynamics, is the estimation of the utility function; yet, little attention has been paid to value estimation methods in the natural resource decision literature. As was done in this study, elicitation of values from decision-makers and/or managers for a range of predicted outcomes is generally conducted in order for an analyst to parameterize the utility function in a decision model. This can be particularly problematic when attributes in the utility function are measured in disparate units. We addressed this problem by asking decision-makers to rank objectives relative to one another and then we used those ranks as unit less multipliers to weight utilities in the objective function.

One major assumption of this technique is that the values of the public (and other stakeholders) are well-understood by decision-makers and managers from whom values were elicited.

An alternate approach is to borrow from the field of environmental economics and conduct original valuation studies that monetize either the most significant, or some targeted set, of values associated with the decision problem (Bockstael et. al. 2000, Adamowicz 2004). Monetizing all attributes automatically puts them on the same scale, but management agencies rarely have the time or resources to perform such assessments. Moreover, monetary value is not always the appropriate unit on which to base policy formulation. For example, endangered species may have no economic value but relevant statutes may dictate that policy-makers develop recovery plans for them.

Policy relevant to the brown bear decision problem (discussed in detail in Chapter 2) does not dictate that an economic approach to objective valuation is inappropriate; therefore, we assessed whether using an economic approach to valuation versus the "manager-elicitation" approach would influence decision optimization. As is true for many decision problems, we did not have the time or resources to conduct an original valuation study. Instead, we used benefit transfer (Loomis and Rosenberger 2006, Johnston and Rosenberger 2010) of values estimated in a previous study to make economic inferences about the value of harvest, brown bear, and non-consumptive use objectives in KATM and NOAT in Alaska. We were unable to identify a study from which values could be transferred for the human-bear incident-prevention objective, but decision optimization was not sensitive to this value so we considered it as constant in this exercise.

Miller et. al. (1998) used a contingent valuation approach to estimate the relative value of Alaska brown bears to resident and non-resident voters and hunters. Their approach involved directly questioning people through surveys about the economic value they would be willing to pay for hypothetical bear viewing opportunities. They also asked survey respondents (including Alaska resident voters, resident hunters, and non-resident hunters) to document their expenditures from over-night wildlife viewing and hunting trips. Because the NPS manages resources for all residents of the United States, estimates were averaged over resident and non-resident values (hunting values were much higher for non-residents; Table 4.8). Total social value was estimated by Miller et. al. (1998) as the number of trips taken by survey respondents times the average gross value of the trip, for viewing, hunter, and total benefit values (Table 4.8). These values were used to replace non-consumptive-use, harvest success, and bear utility weights respectively in the objective function (k_i in equation 2). The weights obtained from this exercise were quite similar to the ones obtained via elicitation of NPS decision-makers and managers (Table 4.8), so it is not surprising that decision optimization did not differ for either park.

It should be noted that, thus far, value has been considered without a cost constraint. Moreover, an economist would likely not agree with the approach of using the "total benefit" value derived for brown bears as the bear structure and function utility weight. Because the bear structure and function utility is both a measure of bear abundance and bear composition, a more appropriate approach would be to design a study that estimated willingness to pay for certain kinds of viewing and hunting opportunities. For example, when bear state is *perturbed* in our model, they contain fewer family groups; thus, one could design questions to reveal preferences regarding how much visitors value seeing dependent cubs with sows versus independent males. An alternate, and more cost-effective approach, would be to eliminate the bear utility from the model while adding a sustainability constraint. Assuming that decision-makers and stakeholders value sustainability, the problem would need to be solved for perpetual returns over a sufficiently long time frame to capture the value of future returns, and – in turn – the value for sustainability (i.e., hunter happiness tomorrow will depend on bears being available for harvest).

SUMMARY AND CONCLUSIONS

Optimal, state-dependent policies for KATM were 1) perturbed: restrict concession hunts (i.e., eliminate non-resident harvest) + no access control + aversive conditioning and increased enforcement; and 2) baseline: deference to an 8% state harvest regulation + no access restriction + aversive conditioning and increased enforcement. In NOAT, the "baseline" policy was deference to a 4% harvest rate + no access control + aversive conditioning and increased enforcement, while the "perturbed" policy was no harvest + no access control + aversive conditioning. Differences in optimal policies between parks reflect differences in coastal versus interior-dwelling brown bear dynamics. Coastal dwelling bears, such as those in KATM, occur in extremely high densities (e.g. 100 bears per km^2 in Katmai National Park and Preserve; Loveless et. al. unpublished), while brown bears in interior Alaska (e.g. in NOAT), occur at much lower densities (e.g. 20 bears per km^2 in Gates of the Arctic National Preserve; Shults and Joly unpublished). Coastal brown bears produce larger litters and achieve heavier body weights than interior dwelling bears that do not have access to marine-derived food resources (Hilderbrand et. al 1999, Mowat and Heard 2006). Moreover, harvest in KATM is limited to the Preserve (hunting is not permitted in National Parks). The more restrictive "perturbed" harvest policy in NOAT (no harvest) versus KATM (eliminate non-resident harvest) reflects the lower density and, in turn, a lower resilience to increased harvest pressure.

Human use of brown bears in KATM and NOAT also is different. Katmai National Park and Preserve contains one of the largest remaining populations of brown bears in the world (Hilderbrand et. al. 2013). This uniquely dense population, along with the large numbers of brown bears that can be easily viewed at salmon spawning streams, attracts tens of thousands of bear-viewers and photographers every summer. More restrictive incident-prevention decisions in KATM reflect more opportunities for incident occurrence in KATM than in NOAT.

Human-bear interactions in KATM and NOAT are also much different. High-density populations and clumped, high quality food resources facilitate bear-to-bear habituation in KATM (Smith et. al. 2005). As a result, bears tolerate the presence of other bears at much closer distances than would be expected in low density populations where bears are isolated from one another (e.g. NOAT). Bears that are habituated to other bears seem to be more tolerant of humans regardless of familiarity with humans (Smith et. al. 2005). The density of bears in NOAT is so low that bears are not expected to be habituated to other bears or humans; thus, as bear density declines (or bears become "perturbed") in NOAT, human-bear incidents were modeled to become less likely. Likewise, as visitor-use increased and/or bear density increased (or bears being "baseline" increased) incidents were modeled to become more likely. The sensitivity of incident-prevention decisions to bear state and visitor-use in NOAT can be attributed to these hypothesized effects. Although, the KATM incident-prevention decision is more restrictive than in NOAT it is not state-dependent (because incident-occurrence is expected to be high regardless of bear state). Adding a cost constraint to the objective function would more realistically reflect the ability of park managers to reduce incidents in both parks.

Key uncertainties identified using sensitivity analysis included factors that affected bear populations (harvest and bear abundance indices) and human-bear incidents in both parks.

Indices of abundance were the best available data in KATM while a dated density estimate from another park was used as a proxy for bear abundance in NOAT. The use of indices for detecting changes in population size is problematic to say the least (Williams et. al. 2002). One of the purposes of this project was to aid the NPS in identifying key uncertainties that could be reduced via the NPS Inventory and Monitoring Program. Given that optimal policies are dependent on bear state, measures that determine bear state - especially in NOAT where bear state was estimated to be extremely uncertain - are paramount to achieving optimal decision outcomes. The reporting system in KATM for human-bear incidents provided a relatively good estimate of incidents; while incident-reporting in NOAT has not occurred since 2003. Therefore, we had to make very uncertain assumptions to estimate incident-occurrence rate in NOAT. Reducing this uncertainty would allow for better predictions, and – in turn, better decision-making over time.

Optimal decisions were also highly sensitive to relative values of harvest, bear population, and non-consumptive use objectives. To get state-dependent policies, the bear population utility had to be reduced so that it was half as valuable as harvest. Model simulations revealed that the consequences of keeping a non-state dependent policy would be detrimental to achieving the harvest success objective while providing an extremely minimal increase in return for the bear population objective. We explored benefit transfer (i.e., monetizing utilities) as a more objective means of obtaining relative weights for utilities in our multi-attribute objective function. This exercise revealed that NPS decision-makers and managers (involved in the value elicitation exercise) understood the relative value of consumptive and non-consumptive park users relatively well (assuming that relative values estimated in the study have not changed since its implementation). However, monetizing a “bear population structure and function” objective presents a challenge. A better approach (if using an economically-derived objective function) would have been to monetize harvest and non-consumptive use values with a sustainability constraint to prevent overharvest of bears.

The brown bear decision problem is highly politicized, and - in such cases – monetizing values (where appropriate) may facilitate communication between managers, policy-makers, and the public (Adamowicz 2004). Clearly, this will not always be the case. As with any decision problem, we advocate that the decision analyst evaluate the context of each decision problem and then choose the appropriate tool(s) for addressing that problem.

The learning component is arguably the most important defining feature of adaptive resource management (ARM; Williams et. al. 2002, Conroy and Peterson 2013) and is the important next step in the brown bear decision process. Learning in an ARM framework is reliant upon monitoring programs that are designed to speak directly to management objectives (Yoccoz et al 2001). After a management decision is implemented, monitoring data can be used to compare model predictions to the true state of the system. By comparing monitoring results to model predictions, decision-makers can discern over the long run which model beliefs produce better predictions and favor those beliefs in future decisions (Williams et. al. 2011, Conroy and Peterson 2013). This is the adaptive part of the decision-making process and provides both a formal learning component and an explicit method by which to transfer learned information among managers over time and space.

The NOAT and KATM brown bear decision frameworks provide an explicit, transparent, and tractable means by which the NPS can decide when deference to state brown bear harvest regulations is optimal. The SDM process also allowed us to identify key uncertainties which can be reduced via NPS inventory and monitoring efforts to improve decision-making over time. That said, even given suboptimal decision-making, the use of an SDM framework will allow for accountability by the NPS, while the use of an ARM approach to decision-making will allow for learning.

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Table 4.1. Definitions, states, and sources of information for components of the quantitative decision models used to evaluate brown bear decision alternatives in Katmai National Park and Preserve (KATM) and Noatak National Preserve (NOAT) in Alaska.

Model Component	Definition and source	Component state	Component Value
Proportion of females harvested	The average annual contribution of females harvested in NOAT and KATM from 2007 to 2011 estimated from Alaska Department of Fish and Game harvest statistics database.	> 40% < 40%	KATM mean (SD) 23.93% (25.4) NOAT: mean (SD) 40.8% (16.7)
No. bears harvested	Average annual number of bears harvested in NOAT and KATM from 2007 to 2012 estimated from ADFG harvest statistics database.	KATM Low = 0 to 7 Baseline = 8 to 14 High = 15 to 30 NOAT Low = 0 to 20 Baseline = 21 to 30 High = 31 to 50	KATM mean (SD) 11.3 (5.4) NOAT mean (SD) 24 (8.9)
Age of bears harvested	Average median age of bears harvested from 2007 to 2012 estimated from ADFG harvest statistics database.	Age Ranges Juveniles = 0 to 6 Adults = 6 to 12 Seniors = 12 to 30	KATM mean (SD) 10.4 (5.1) NOAT mean (SD) 8.2 (1.05)
Harvest Index	Summary node that predicts the probability of harvest threat given no. of bears harvested, female contribution to harvest, and median age of bears harvested. Expert judgment.	High threat Medium threat No threat	Categorical
Salmon Escapement[1]	Average annual number of salmon returning to Alagnak and Naknek river drainages estimated from ADFG salmon escapement database using data from years 2010-2012	Salmon Escapement Levels (millions) Minimal = 0 to 1.5 Moderate = 1.5 to 3 Unlimited = 3 to 8	Mean (SD) 2,530,281 (538,986)

Recruitment[1]	Recruitment is the number of 2 year olds produced per female per year. Dependencies between recruitment, salmon escapement, and visitor-use were predicted using expert judgment.	<u># of 2 y.o. per female per year</u> 0 to 0.15 0.15 to 0.30 0.31 to 0.45 0.46 to 0.60	<u>Mean (SD)</u> 0.349 (0.09)
Stream Surveys[1]	Maximum count of bears observed at salmon spawning streams in late August/early September of 2011. Uncertainty was incorporated using historical variation in counts. Data from NPS.	High = 225 to 150 Medium = 151 to 75 Low = 76 to 0	<u>Maximum Count (SD)</u> 155 (41.1)
Den Occupancy[1]	Site occupancy rate of denning bears in 2012 estimated using mark-recapture distance sampling. Data from NPS Southwest Alaska Park Network	0 to 0.25 0.25 to 0.50 0.50 to 0.75 0.75 to 1.0	<u>Occupancy Rate (SE)</u> 0.64 (0.17)
Adult Bear Density	Density estimate from stratified random sample survey design for brown bears using the northern portion of Gates of the Arctic National Park and Preserve. Data from the NPS Arctic National Park Network.	<u>Bears per 1000 km^2</u> 0 to 8 8 to 16 16 to 24 24 to 32	<u>Bears per 1000 km^2</u> 16.45 (1.44)
Adult female survival	Adult female survival given implementation of various harvest decisions. Predicted using expert judgment.	<u>Adult Female Survival Rate</u> 0 to 0.70 0.70 to 0.80 0.80 to 0.85 0.85 to 0.90 0.90 to 0.95 0.95 to 1.00	<u>KATM Ranges</u> Survival: 0.93 to 0.84 α: 255.3 to 454.4 β: 20.2 to 83.8 <u>NOAT Ranges</u> Survival: 0.91 to 0.81 α: 313.1 to 79.9 β: 32.3 to 186.6

Harvest Success	Baseline harvest success was estimated as the number of successful hunts divided by the number of permits distributed. Dependencies between harvest success and harvest decisions were parameterized using data from the ADFG harvest statistics database. Baseline harvest in KATM is the defer 8% decision and baseline harvest in NOAT is the defer 4% decision.	Harvest Success (%) 0 to 15 16 to 30 31 to 45 46 to 60 61 to 75 76 to 100	KATM Baseline (SD) 24.9% (18.3) NOAT Baseline (SD) 43.7% (9.9)
Visitors	Baseline visitation in KATM was estimated as the average visitor-use-days from 2011 to 2013. Baseline visitation in NOAT was estimated as the number of individuals transported into the Preserve by authorized transporters. Data was provided by NPS Artic and Southwest Alaska Park Networks. Expert judgment was used to predict changes in baseline visitation given implementation of various decision alternatives.	KATM Visitor-Use-Days 0 to 3000 3000 to 6000 6000 to 9000 9000 to 12000 12000 to 18000 NOAT Visitors Transported 0 to 100 100 to 200 200 to 300 300 to 400 400 to 500 500 to 600	KATM Range (SD) 497 (365.5) to 1346 (2701) NOAT Range (SD) 14.7 (10.8) to 377.7 (91.1)
Human-bear Incidents	Baseline incidents for each park were estimated using data from the NPS bear incident reporting database. An incident rate was calculated for each park by dividing annual incident occurrence by annual visitation. The dependency between visitation and human-bear incidents was parameterized using incident rates. In KATM, incidents were parameterized to be twice as likely given that the current bear state is perturbed. In NOAT, incidents were parameterized to be half as likely given that current bear state is perturbed. Expert judgment was used to predict changes in baseline incident occurrence given	KATM Human-bear Incidents 0 to 150 150 to 300 300 to 450 450 to 600 600 to 750 750 to 900 NOAT Human-bear Incidents 0 to 50 50 to 100 100 to 150 150 to 200	KATM Baseline (SD) 347.1 (101.4) NOAT Baseline (SD) 103.1 (33)

	implementation of various decision alternatives.		
Current Bear State	Current bear state was estimated using a combination of harvest threat and bear abundance indices.	<u>States</u> Baseline Perturbed	Categorical
Future Bear State	Future bear state was predicted given decisions, recruitment, adult female survival, and current bear state.	<u>States</u> Baseline Perturbed	Categorical

[1]Model component unique to KATM decision model

[2]Model component unique to NOAT decision model

Table 4.2. Results of value elicitation in which brown-bear SDM working group members were asked to rate the relative importance of each of four objectives (1 = lowest importance, 10 = highest importance). Mean scores were used as utility weights (k_i) in the objective function.

	Bear Pop. Structure and Function	Sport and Subsistence Harvest	Human-bear Incidents	Non-Consumptive Use
Mean	10 (k_1)	4.6 (k_2)	6.3 (k_3)	3.7 (k_4)
Median	10	4	7	4
Minimum	10	3	4	2
Maximum	10	7	9	6

Table 4.3. Attributes used to measure decision utility.

Attribute	Attribute Scale	Range (worst to best)
Bears at t+ 1	Categorical	Perturbed - Baseline
Harvest Success	% Success	0% to 100%
Visitor-use-days	# of visitor-use days	0 to 18,000
Human-bear incidents	# of incidents	900 to 0

Table 4.4. Expected value of the optimal policy for harvest alternatives given baseline, unknown, and perturbed bear state. Expected values for optimal decisions are highlighted.

Current Bear State	No Harvest	Spring Only Harvest	Restrict Concession Hunts	Limit Transport	Defer Rate 8%
Baseline	15.415	15.7	16.025	15.812	16.092
Unknown	13.0804	13.236	13.399	13.222	13.384
Perturbed	10.746	10.772	10.773	10.632	10.675

Table 4.5. Harvest decisions with the highest expected value are listed given bear utility weights ranging from 0 to 100. A weight of one is equal to value that the brown bear working group assigned to the utility. The optimal decision changes six times over the range of utility ranks evaluated.

Bear Utility Weight	Optimal Decision
0	Defer 14%
0.2	Defer 12%
0.3	Defer 8%
0.5	Restrict Concession Hunts
1	Restrict Concession Hunts
5	Spring Only
100	No Harvest

Table 4.6. Access control decisions with the highest expected value given bear utility weights ranging from 0 to 100. A weight of one is equal to value that the brown bear working group assigned to the utility. The optimal decision changed once over the range of utility ranks evaluated.

Bear Utility Weight	Optimal Decision
0	No Action
1	No Action
2	No Action
3	No Action
4	Specify Access Times
5	Specify Access Times
6	Specify Access Times
7	Specify Access Times
8	Specify Access Times
9	Specify Access Times
100	Specify Access Times

Table 4.7. Consequences to future bear state and harvest success (forward simulated for 100 years) given implementation of alternate state-dependent and non-state dependent policies. The non-state dependent policy (i.e., no harvest + no access restriction + aversive conditioning and increased enforcement) remained the same regardless of bear state. The state-dependent policies were allowed to vary depending on the state of bears. In the state-dependent simulation, the "baseline" policy was restrict concession hunts + no access restriction + aversive conditioning and increased enforcement, while the "perturbed" policy was deference to an 8% state harvest regulation + no access restriction + aversive conditioning and increased enforcement.

	Minimum probability of baseline future bear state	Maximum probability of baseline future bear state	Average Harvest Success
Non state-dependent	0.692	0.753	0
State-dependent	0.663	0.731	25.4

Table 4.8. Total social benefit (million $US 1991) for trips taken annually by Alaska voters, resident hunters, and non-resident hunters from Miller et. al. 1998* and utility weights elicited from decision-makers in this study. Social benefit was calculated as the estimated number of trips taken times the average gross value of the trip.

		Hunter Trips			
	Viewing Trips	Residents	Non-residents	Mean	Total Benefit
Miller et. al. 1998	4.93*	1.93*	13.68*	7.805*	12.735*
Elicited utility weights	3.7	N/A	N/A	6.3	10

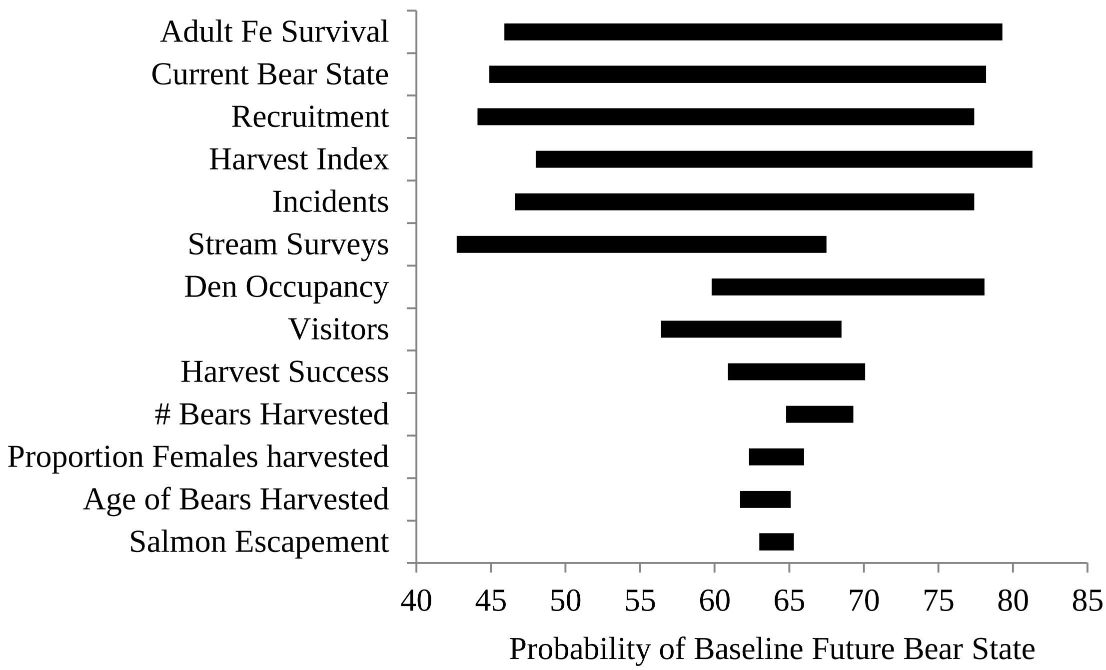

Figure 4.1. One-way sensitivity analysis with model components listed from greatest (top) to least influential to the probability of future bear state. For each component, the bar length represents the extent to which the probability of future bear state varies in response to changes in the value of that component, with all other components held at base values.

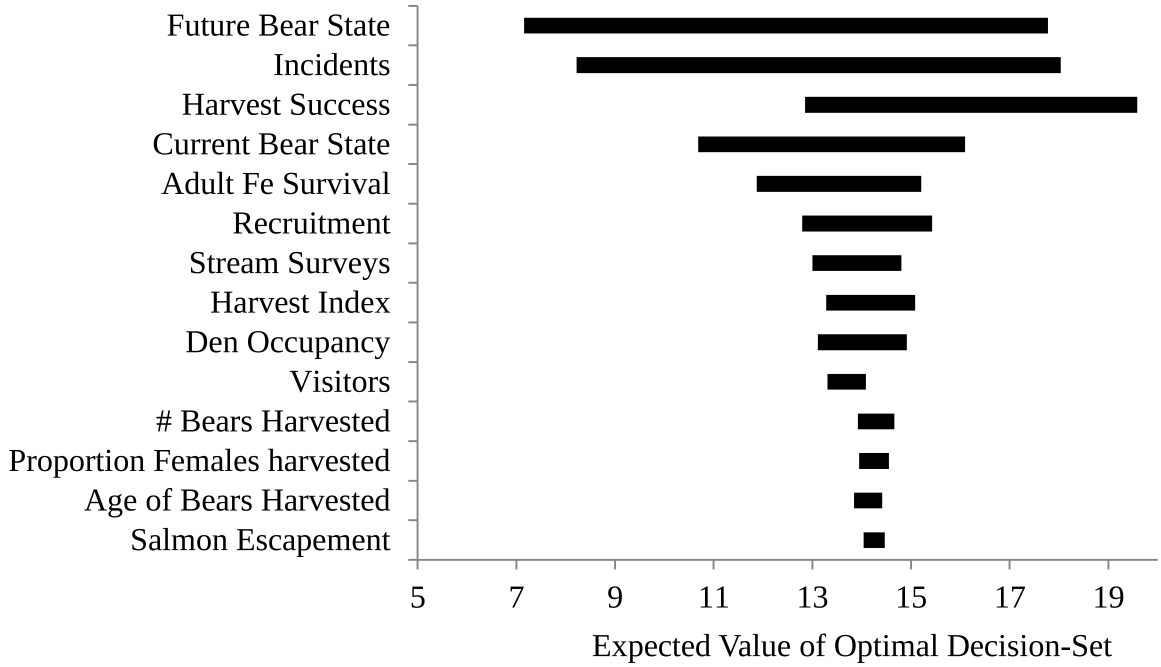

Figure 4.2. One-way sensitivity analysis with model components listed from greatest (top) to least influential to the expected value of the optimal decision. For each component, the bar length represents the extent to which the expected value of the decision varies in response to changes in the value of that component, with all other components held at base values.

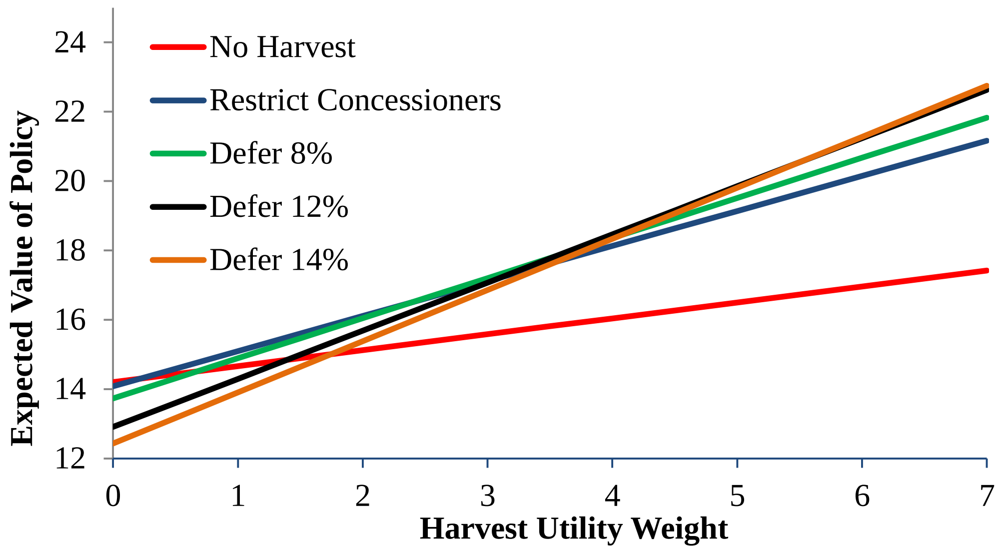

Figure 4.3. Expected value of policies given harvest success utility weights ranging from 0 to 7. Access control and incident-prevention decisions with the highest expected utility were selected as stable to assess how harvest decisions changed over the range of harvest success utility weights. A weight of one is equal to the value that the brown bear working group assigned to the utility. Points where lines cross indicate ranks where the decision-maker is indifferent to overlapping decisions. For example, given a weight of 0.25, the decision-maker is indifferent to *No Harvest* and *Restrict Concessioners* decisions.

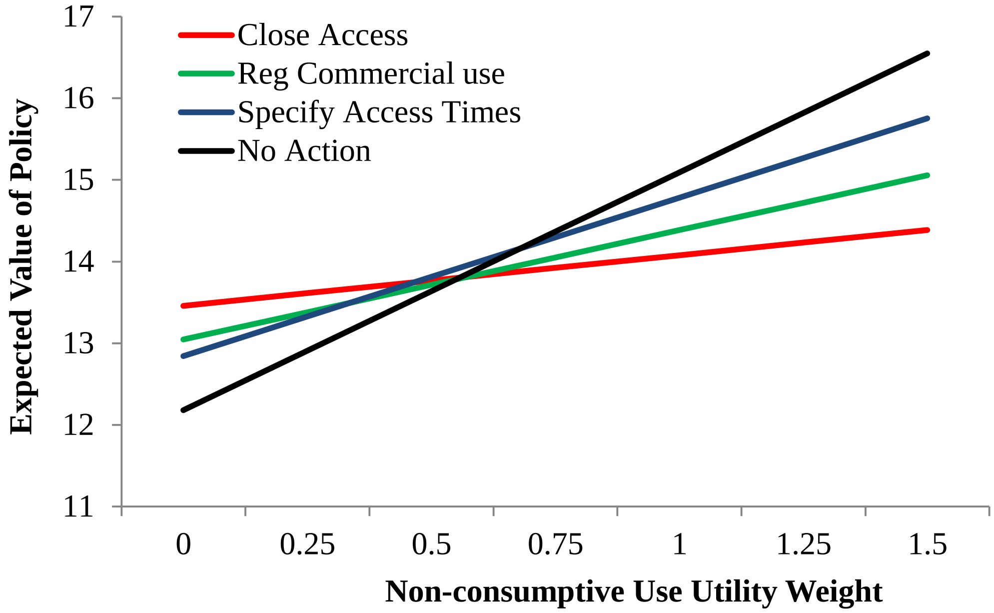

Figure 4.4. Expected value of policies given non-consumptive utility weights ranging from 0 to 1.5. Harvest success and incident-prevention decisions with the highest expected utility were selected as stable to assess how access control decisions changed over the range of non-consumptive utility weights. A weight of one is equal to the value that the brown bear working group assigned to the utility. Points where lines cross indicate ranks where the decision-maker is indifferent to overlapping decisions. For example, given a weight of 0.05, the decision-maker is indifferent to *No Action* and *Specify Access Times* decisions.

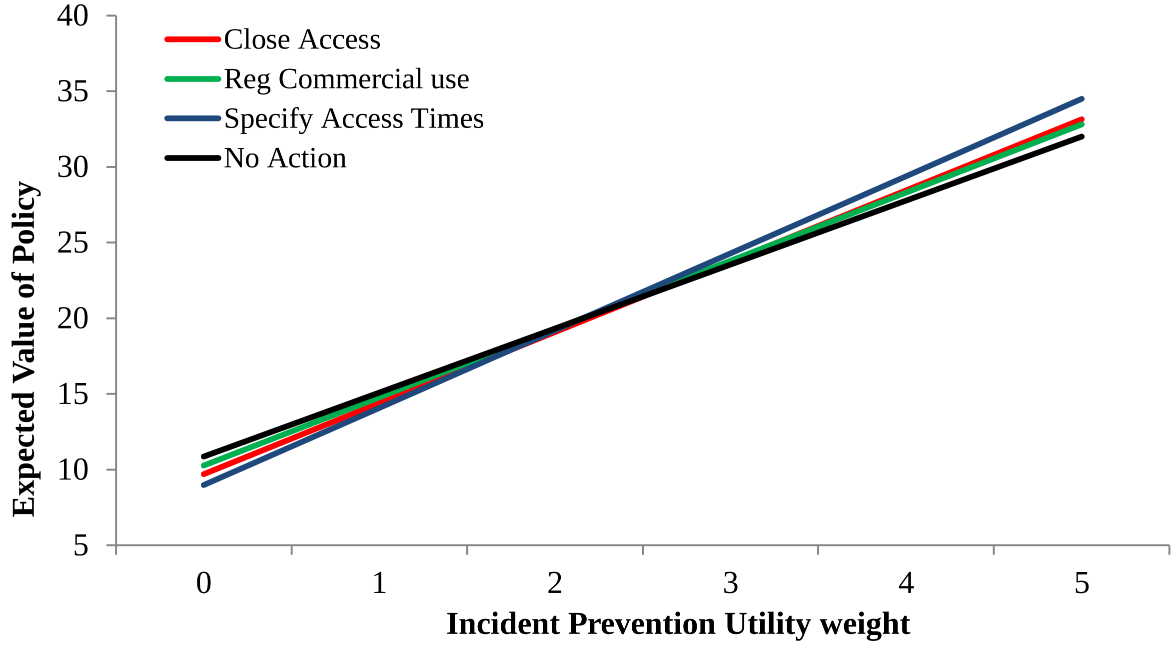

Figure 4.5. Expected value of policies given incident prevention utility weights ranging from 0 to 5. Incident-prevention and access control decisions with the highest expected utility were selected as stable to assess how access control decisions changed over the range of incident-prevention utility weights. A weight of one is equal to the value that the brown bear working group assigned to the utility. Points where lines cross indicate ranks where the decision-maker is indifferent to overlapping decisions. For example, given a weight of 2.25, the decision-maker is indifferent to all actions.

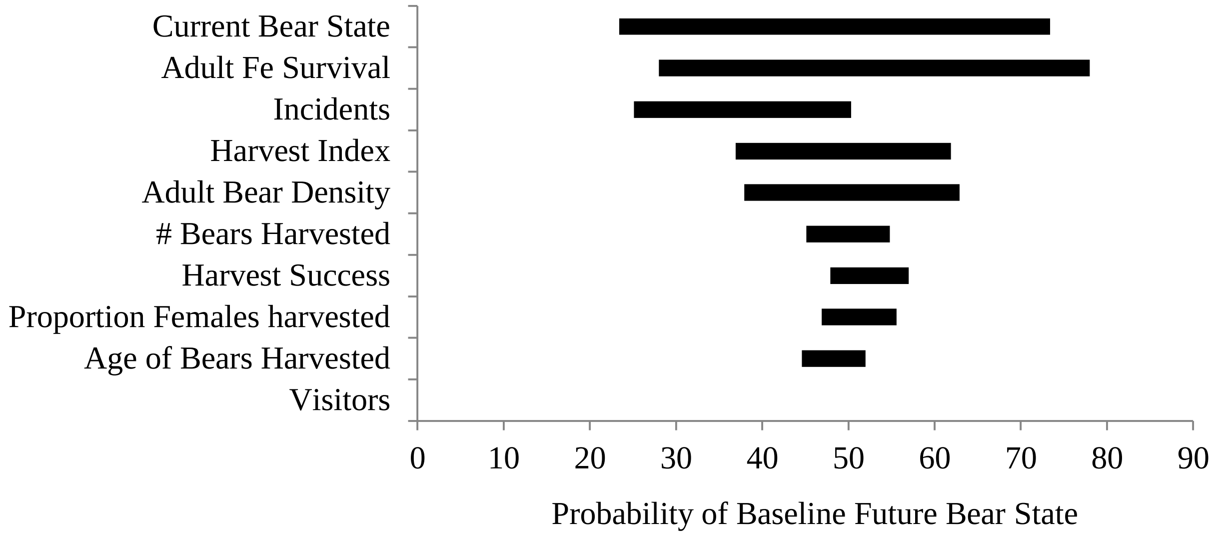

Figure 4.6. One-way sensitivity analysis with Noatak decision model components listed from greatest (top) to least influential to the probability that future bear state will be baseline. For each component, the bar length represents the extent to which the probability of future bear state varies in response to changes in the value of that component, with all other components held at base values.

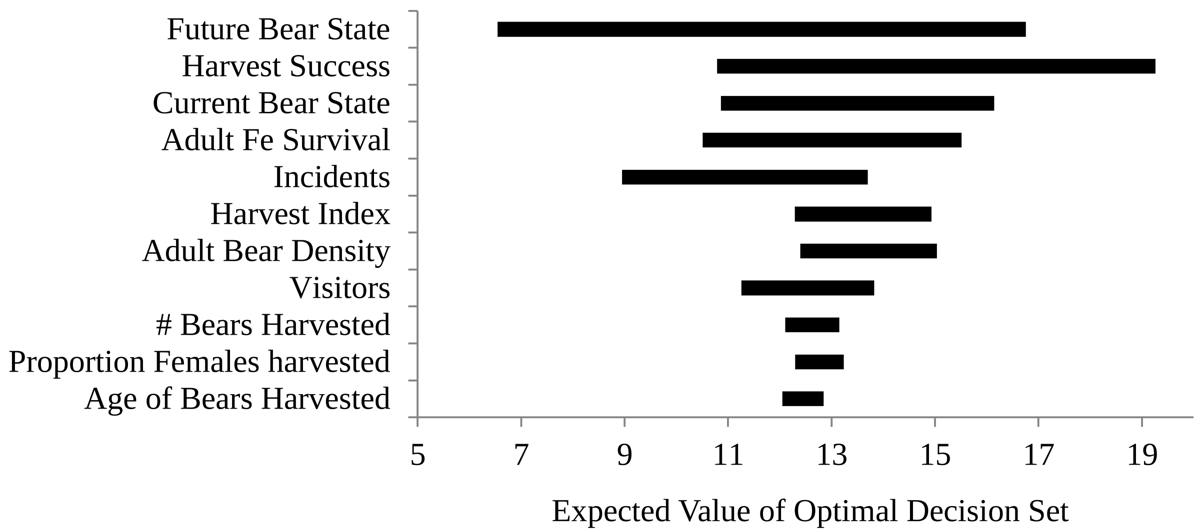

Figure 4.7. One-way sensitivity analysis with Noatak decision model components listed from greatest (top) to least influential to the expected value of the optimal decision. For each component, the bar length represents the extent to which the expected value of the decision varies in response to changes in the value of that component, with all other components held at base values.

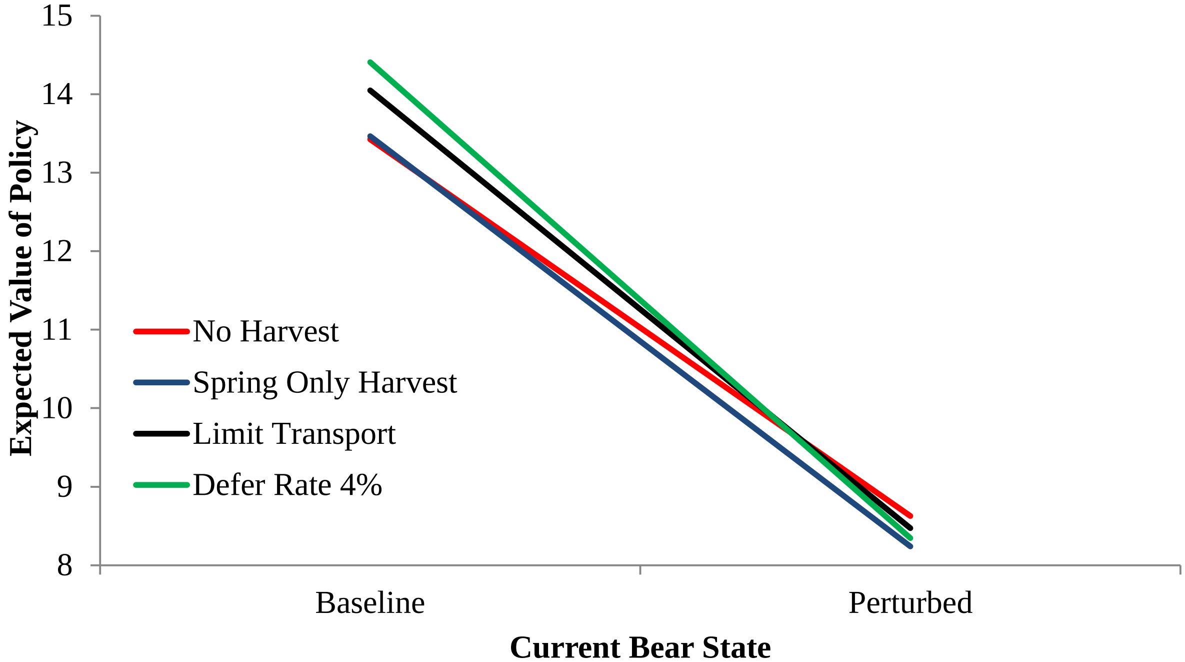

Figure 4.8. Expected value of policy given that the probability of current bear state is perturbed. The optimal harvest decision becomes more restrictive as the probability of current bear state becomes more likely to be perturbed.

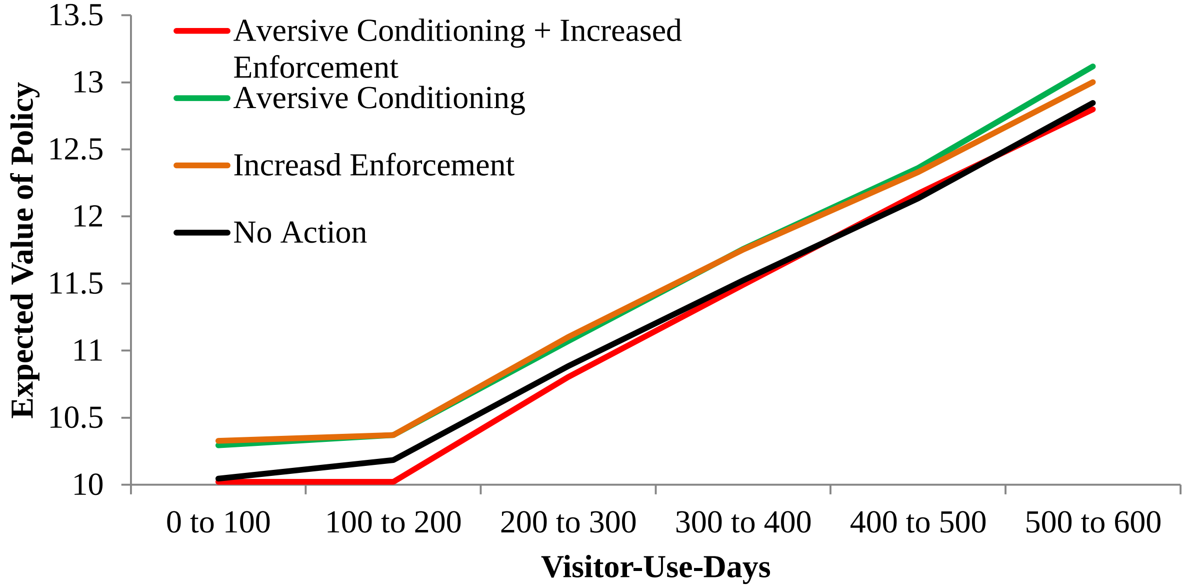

Figure 4.9. Expected value of policy given visitor-use-days ranging from 0 to 600 visitor-use-days per year. The optimal access restriction decision changes from increased enforcement to aversive conditioning as visitation increases.

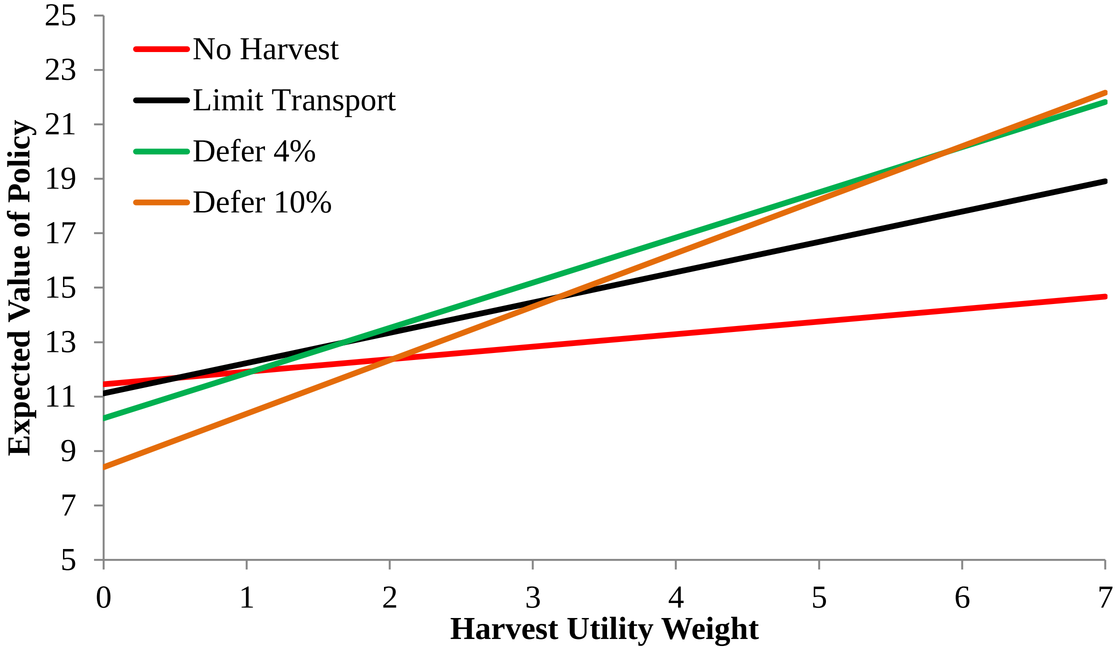

Figure 4.10. Expected value of policy given harvest success utility ranks ranging from 0 to 7. Incident-prevention and access control decisions with the highest expected utility were selected as stable to assess how harvest decisions changed over the range of harvest success utility weights. A weight of one is equal to the value that the brown bear working group assigned to the utility. Points where lines cross indicate ranks where the decision-maker is indifferent to overlapping decisions. For example, given a weight of 0.5, the decision-maker is indifferent to *No Harvest* and *Limit Transport* management actions.

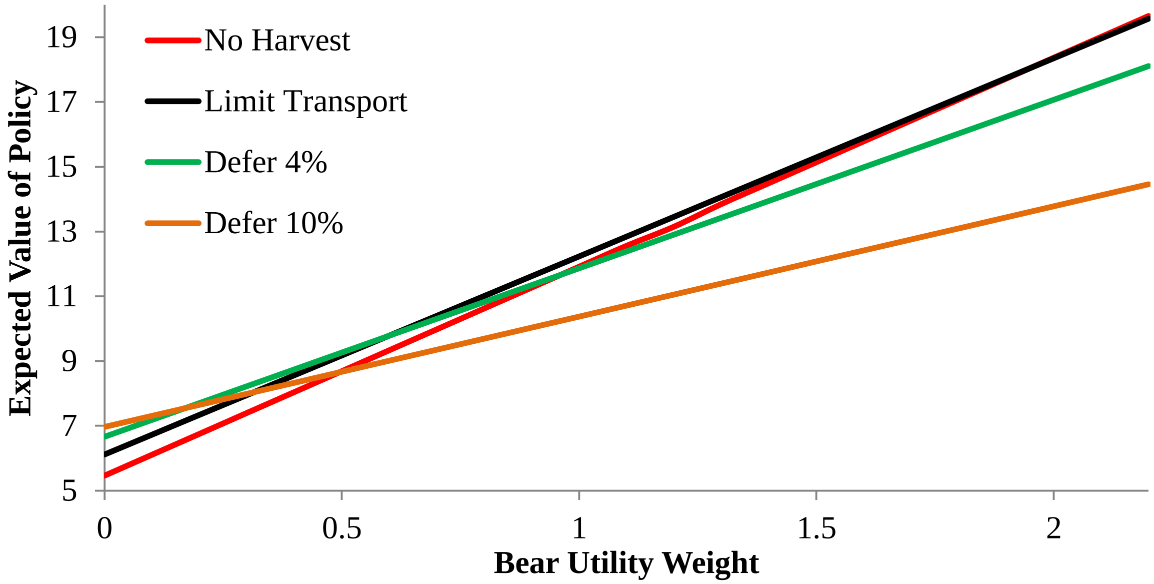

Figure 4.11. Expected value of policy given bear utility ranks ranging from 0 to 2. Incident-prevention and access control decisions with the highest expected utility were selected as stable to assess how harvest decisions changed over the range of bear utility weights. A weight of one is equal to the value that the brown bear working group assigned to the utility. Points where lines cross indicate ranks where the decision-maker is indifferent to overlapping decisions. For example, given a weight of 0.2, the decision-maker is indifferent to *Defer 10%* and *Defer 4%* management actions.

CHAPTER 5 : A BAYESIAN BELIEF NETWORK MODELING APPROACH TO FORECASTING SEA OTTER (*ENHYDRA LUTRIS KENYONI*) POPULATION STATUS IN KATMAI NATIONAL PARK, ALASKA

INTRODUCTION

Sea otters were once contiguously distributed in near shore habitats ranging from Japan to Baja California but were extirpated throughout their range during the 18th and 19th century fur trade (Kenyon 1969). The entire contemporary sea otter population is descended from six small (10s-100s of animals) remnant colonies that remained after the Fur Seal Treaty was passed in 1911. Consequently, all existing populations of sea otters have suffered at least one persistent population bottleneck (Bodkin et al. 1999, Larson et al. 2002a).

While some otter populations naturally recovered to pre-exploitation population sizes by the late 1960s, translocations of otters from remnant populations were conducted in the 1960s and 1970s in an effort to reestablish populations (Jameson et. al 1982, Bodkin et. al. 1999). Translocated otter populations were thus subject to at least two population bottlenecks. Levels of genetic variation measured for sea otters were similar to those measured in other mammals that have experienced prolonged population bottlenecks (e.g. the northern elephant seal) (Larson et al. 2002a); moreover, a low level of variation at major histocompatibility complex genes represents a dramatic reduction in functionally important variability (Aguilar 2008). The patchy distribution and nonmigratory behavior of extant sea otters further limits gene flow (Gorbics and Bodkin 2001, Bowen et al. 2006), all of which has resulted in a contemporary sea otter population characterized by low genetic variability relative to outbred mammalian species (Aguilar 2008).

A recent sea otter population collapse has occurred throughout the Aleutian Archipelago and in portions of the Alaska Peninsula (Doroff et. al. 2003, Burn and Doroff et. al. 2003, Burn et. al. 2003). Aerial surveys conducted in 2000 revealed that widespread and precipitous population declines occurred throughout the Aleutian Islands since a previous survey in 1992. Burn et al. (2003) estimated that sea otter populations in the Aleutians have been reduced to less than 10% of carrying capacity. Additional skiff and aerial surveys conducted in 2003 and 2005 suggested that sea otter abundance continued to deteriorate resulting in an estimated 95.5% overall population decline throughout the Aleutian Archipelago and a current sea otter population that is at 3% of carrying capacity (Burn et al. 2003, Estes et al. 2005). As a result of these declines, the southwest Alaska stock of sea otters is currently listed as federally threatened pursuant to the Endangered Species Act (ESA) and depleted according to the Marine Mammal Protection Act (MMPA).

Population declines in SW Alaska are thought to be due to killer predation (Estes et al. 1998). The prevailing hypothesis is that sequential declines in great whale, cetacean, and pinniped populations triggered a prey-switch that, in turn, resulted in killer whales feeding on sea otters. If higher calorie killer whale prey populations (e.g. cetaceans and pinnipeds) in the North Pacific recover, it is possible that sea otters in southwest Alaska will be released from killer whale predation pressure. However, the remaining otter populations in the Aleutian Islands have become small and isolated such that Allee effects may be limiting recovery and contributing to continued declines (Estes et al. 2005). Moreover, there is considerable uncertainty regarding the cause, duration, and extent of declines. Within the southwest Alaska stock, sea otter populations in the Aleutians and parts of the Alaska Peninsula have undergone significant declines; however, populations within the spatial extent of Southwest Alaska Network (SWAN) Park Units have not experienced this decline and appear to be stable (Coletti et al. 2011). As such, the NPS is concerned about declines affecting sea otters in SWAN Units and would like to be able to detect effects should they occur.

In contrast to the situation in Southwest Alaska, significant conflicts with native residents and commercial shellfisheries have developed as sea otters recolonize parts of their historic range in Southeast Alaska. The intensity and importance of competition between human users and sea otters varies by area, but there has been a relatively widespread, negative change in attitude towards sea otters and managers in Southeast Alaska (Johnson 1982). Policy makers responded to complaints about fishery-otter conflicts by introducing a bill to amend the Marine Mammal Protection Act to allow the sale of intact sea otter pelts overseas (http://www.govtrack.us/congress/bill.xpd?bill=h112-2714). If enacted, this bill has direct and potentially imminent implications for harvest of sea otters in Alaska. Moreover, it does not take into account the economically important recreational activities associated with recovering otter populations, such as viewing and photography.

Drastic declines in the southwest Alaska population stock (Estes et al. 1998; Doroff et al. 2003) combined with new anthropogenic threats and changing attitudes towards sea otters beg for a synthesis of available research. Abundant data exist on sea otter population dynamics (e.g. Monson et al. 2000a; Tinker et al. 2006), energetics (e.g. Yeates et al. 2007), diet (e.g. Watt et al. 2000), predators (Estes et al. 1998; Vos et al. 2006), and much more. In addition, recent and currently planned monitoring of sea otters in national parks as part of the SWAN I&M Program (Bodkin et al. 2001; Bodkin et al. 2007a, Esslinger and Bodkin 2009) can provide quantitative data useful for parameterizing an integrated model. Combining existing data into a single framework – that can also accommodate expert knowledge where data is lacking - can help managers identify important measurable outcomes that can, in turn, inform NPS inventory and monitoring efforts by identifying important uncertainties. The purpose of this work was to provide a framework for evaluating sea otter population viability that also identified important uncertainties regarding sea otter population dynamics in SWAN park units. This approach allowed for the integration of new and existing data so that models and knowledge of ecosystem responses could be improved as NPS I&M data are collected. Towards this end, this project further developed and evaluated quantitative modeling tools and information to assist biologists in the assessment of SW Alaska sea otter populations.

MODEL DEVELOPMENT

Model development was initialized using a prototype system model that was constructed based on a literature review and feedback from sea otter knowledge experts. The prototype model was constructed in the form of an influence diagram to create a graphical representation of ecological system dynamics. We then constructed the Bayesian Belief Network, which is simply a probabilistic form of an influence diagram, to depict causal relations among demographic, environmental, and anthropogenic factors that could potentially influence the future sea otter population status. Model development involved a number of interactive sessions between modelers and knowledge experts. The model went through numerous iterations as sea otter working group participants explored alternative means of describing system variables, defining and discretizing states for each model component, depicting causal relationships, and identifying proxies for hard to measure system components. The final sea otter BBN is an explicit representation of a current system understanding.

BBNs are composed of three types of model components, referred to as nodes, including state of nature, utility, and decision nodes. State of nature nodes represent system parameters and the probabilities of various states associated with those parameters (i.e. in the form of a conditional probability table). At least one state of nature node will represent the population response or outcome node. In the sea otter BBN, we have three population response nodes: future sea otter density, future prey density, and population trend

A BBN modeling approach was chosen for a number of reasons. First, they are particularly useful in efforts that involve combining expert opinion and empirical data to synthesize large amounts of qualitative and quantitative information (Nyberg 2006). Model components parameterized via expert opinion can be updated relatively easily as new empirical data becomes available (Cain et al. 2000). Moreover, BBNs express outcomes as likelihoods which provide a basis for risk analysis and risk management (Marcot 1998, Marcot et. al. 2001).

Despite their advantages, BBNs do have several disadvantages. They do not allow for feedback loops among variables, particularly from the response variable back to the predictor variable (Nyberg 2006). Because of this, it is generally difficult to represent complex temporal dynamics and interactions between model components. Due to their limitations, we combined the BBN modeling approach with a more traditional, empirically-based stochastic analysis of population viability (Boyce 1992) that involved forward simulating otter population demographic using empirically derived demographic estimates.

GENERAL MODEL OVERVIEW

The sea otter Bayesian Belief Network is a stochastic model that tracks sea-otter population density through time in Southwest Alaska Network (SWAN) national parks. It is composed of environmental factors (e.g., habitat availability and prey density), population dynamics, and anthropogenic components. The model operates on an annual time step and estimates sea otter density at three points in time: 1, 3, and 100 years from the present. The spatial extent of the model is currently specified as the size of the near shore coastal zones in Katmai National Park and Preserve (NPP). However, the model was constructed to be portable to similar sea otter management areas throughout their northern range.

The model is graphically represented as an influence diagram that consists of model components, referred to as nodes with each node consisting of environmental states that are mutually exclusive and collectively exhaustive. The directed arcs indicate causal relationships between model components with parent nodes influencing (pointing into) child nodes. For instance, population trend (a child node) is influenced by current sea otter population density (a parent node) and future sea otter population density (also a parent node).

The model was constructed in two main phases – the population dynamic phase and the BBN phase. During the BBN phase, the model was structured and parameterized (for the most part) in the Netica modeling shell. The population dynamic phase involved development of a density-dependent, stochastic, stage-structured simulation model that tracked sea otter density over time. The population dynamic model was developed in the SAS modeling shell, and findings were incorporated into the BBN to parameterize associated conditional dependencies (for demographic model components).

The sea otter BBN model structure can be divided into four major subcomponents: (1) the *baseline population dynamic submodel* consists of nodes that represent demographic population parameters (e.g. current population size, survival, immigration and carrying capacity); (2) the *survival submodel* represents environmental variables or anthropogenic stressors that could potentially influence sea otter survival rates (e.g. disease, contaminants, harvest); (3) *the prey density submodel* models environmental or anthropogenic factors that could potentially influence sea otter prey availability (e.g. nearshore productivity, extreme weather events, oil spill) ; and (4) the *habitat capacity submodel* models factors related to density-dependence (e.g. foraging behavior, habitat size); (Figure 5.1).

Prior probabilities for root nodes and dependencies among parent and child nodes were parameterized (via meta-analysis) using published relationships (models) and empirical data. When data were completely lacking, relationships among model components were parameterized using expert judgment (e.g., Rieman et al. 2001). Output nodes, including *Future Population Density, Future Prey Density and Population Trend,* represent overall responses to the suite of population dynamics, anthropogenic stressors and environmental variables included in the model. Below we identify and describe model components, their associated states, and the sources of information that were used to parameterize each node and associated conditional dependencies.

MODEL PARAMETERIZATION

<u>Disease Prevalence</u>

States: High (100-60%), Moderate (60-30%), Low (30-0%)

Child Nodes: Post-Weaning Survival, Adult Survival

Node Description:

There is limited information on disease and parasite exposure or cause-specific mortality in Alaska sea otter populations. However, in California, where carcass recovery is more common, disease has been identified as the leading cause of mortality and is thought to be an important factor in the limited recovery of southern sea otters (Kreuder et al. 2003). Diseases recently identified in northern sea otters include *Brucella* spp., Morbillivirus, *S. infantarius* and phocine distemper virus (Goldstein et al. 2009, Goldstein et al. 2011). *Brucella* causes reproductive failure in terrestrial mammalian hosts, but pathogen isolates from marine mammals sympatric to sea otters suggest that there may be several different strains of the bacterium that can have varied effects in different hosts (Hanni et al. 2003). Other types of diseases may contribute directly to mortality of sea otters, as in the case of an outbreak of *S. infantarius* at Kachemak Bay in Alaska (Doroff 2008), or may be closely associated with other causes of death, such as heart disease or shark predation (Kreuder et al. 2003).

It is not evident that disease is influential in driving the population status of sea otters in Alaska; though, there is some evidence to suggest that it could be locally relevant (Goldstein et al. 2009, Goldstein et al. 2011). However, disease vulnerability of sympatric marine mammal species (Gulland and Hall 2007) and changes in ocean conditions due to climate change (Burek at al. 2008), suggest that northern sea otter populations may become vulnerable to parasites and disease in a changing ocean climate.

The influence of disease on sea otter survival rates is highly variable and is dependent on the type of infection influencing the sea otter population. For example, the 2002 phocine distemper outbreak in Atlantic harbor seals, which caused > 30,000 deaths, is a highly contagious disease that resulted in large reductions in survival. Conversely, *Toxoplasma gondii*, is quite prevalent in southern sea otter populations but is not contagious and thus has an important but less acute influence on sea otter survival rates.

Parameterization

We described the range of disease influence in the sea otter BBN using 3 states of disease prevalence: high, moderate and low. High and moderate states represent the potential for two levels of disease influence that result in reductions of baseline survival rates. Baseline survival was defined for each age class using a range of empirical estimates for northern sea otters (Table 5.1). In the event of a moderate influence, baseline survival rates are reduced but remain above survival rates produced by high disease prevalence. Low disease prevalence does not reduce survival below baseline levels.

Expert elicitation surveys were used to ask survey respondents to define state cutoff levels for high, moderate and low levels of disease prevalence. States represent the percent of the population that is infected. Average respondent replies resulted in the following definitions for state cutoff values:

- A state of high represents a disease prevalence rate of 60-100%.
- A state of moderate represents a disease prevalence rate of 30-60%.
- A state of low represents a disease prevalence rate of 0-30%.

Survey respondents were also asked how they expected adult (> 3 years of age) and post-weaning (0.5 - 3 years of age) survival rates to vary from baseline conditions when the population was subjected to high and moderate levels of disease prevalence. Because of pup dependency, pre-weaning (< 0.5 years of age) survival was modeled to change as a direct proportional response to changes in adult survival. On average, respondents expected post-weaning survival to be slightly more sensitive to high and moderate disease prevalence than adult survival (Tables 5.2, 5.3).

<u>Contaminant Concentrations</u>

States: High (5x), Moderate (5x-1.5x), Low (1.5x-0x)

Child Nodes: Disease Prevalence

Node Description:

Sublethal concentrations of PCBs, DDTs, BTs, and PFCs have been detected in sea otters throughout their range (Estes et al. 1997, Murata et al. 2008, Hart et al. 2009). There is some evidence from California sea otters to suggest that suppressed immunocompetence is associated with chronic contaminant exposure (Kanaan et al. 1998), but direct effects on survival and reproduction have not been detected. This node represents the potential relationship between contaminant loading and lowered immunocompetence.

Parameterization:

Node cutoff states were defined using a unit less multiplier for high, moderate and low levels of contaminant concentrations. High and moderate states represent the potential for two levels of contaminant influence that result in reductions of baseline survival rates. A level of low contaminant influence does not reduce survival below baseline rates. Expert elicitation surveys were used to ask survey respondents to define state cutoff levels for high, moderate and low levels of contaminant exposure. The mean of respondent replies resulted in the following state cut-off values:

- A state of high represents contaminant concentrations that are greater than 5 times background levels.

- A state of moderate represents contaminant concentrations that range from 1.5 to 5 times background levels.
- A state of low represents contaminant concentrations that range from 0 to 1.5 times background levels.

Survey respondents were also asked how they expected adult (> 3 years of age) and post-weaning (0.5 - 3 years of age) survival rates to vary from baseline conditions when subjected to high and moderate levels of contaminant exposure. Because of pup dependency, pre-weaning (< 0.5 years of age) survival was modeled to change as a direct proportional response to changes in adult survival. Respondents generally expected post-weaning survival and adult survival to be equally sensitive to high and moderate levels of contaminant loading (Tables 5.4).

Predation

States: Average, Moderate, Severe

Child Nodes: Post-Weaning Survival, Adult Survival, Distribution Response

Node Description:

Killer whale predation has been cited as the leading cause of recent declines in the southwest Alaska sea otter population stock ranging from the Western Aleutian Islands to Castle Cape (Estes et al. 1998, Williams et al. 2004). Populations in the central Aleutian Archipelago have experienced precipitous declines, reducing numbers to approximately 3% of carrying capacity (Estes et al. 2005). To date, the declines appear to be limited to portions of the southwest Alaska population stock. Additional predators of sea otters throughout their range include sharks, bald eagles, coyotes and brown bears.

Springer et al. (2003) suggest that killer whale dominated predation on sea otters is ultimately a result of the overharvest of great whales by post-WWII industrial whalers. It is thought that dwindling great whale populations triggered a prey-switch that, in turn, resulted in killer whales feeding on smaller marine mammals. This hypothesis is partially supported by an observed sequential collapse of smaller marine mammals in the north Pacific, including declines in stellar sea lion, harbor seal, northern fur seal and sea otter populations. As higher calorie killer whale prey populations (i.e., cetaceans and pinnipeds) in the North Pacific recover, it is possible that sea otters in southwest Alaska will be released from killer whale predation pressure. Tracking the status of alternate killer whale prey populations in tandem with the status of relevant sea otter populations could result in the reduction of uncertainty associated with this mechanism. In cases where tracking this mechanism is relevant and monitoring alternate killer whale prey populations is feasible, managers could add model components to the BBN that represent abundance or density of alternate killer whale prey populations.

Parameterization

The predation model component and its associated dependencies represent the relations between predation on sea otters, survival rates, and habitat availability. We described the range of predation influence using 3 states: severe, moderate and average. Severe and moderate states represent the potential for two levels of predation that result in reductions of baseline survival rates. In the event of a moderate influence, baseline survival rates are reduced but remain above survival rates produced by severe predation. Low disease prevalence does not reduce survival below baseline rates. States were defined using state numbers that represent the relative severity of predation influence with 3 representing the most severe influence and 1 representing an average influence.

In addition to effects on survival, sea otter populations that experience killer whale dominated predation may become limited in range. Evidence suggests that sea otters experiencing killer whale dominated predation restrict their distribution to protected bays and inlets and relatively shallow bathymetric contours (< 5m bathymetry; Burn et al. 2003; J. Bodkin personal communication). The arc connecting the predation node to the distribution response node reflects the potential for this mechanism. A distribution response is thought to be somewhat latent so it was modeled to occur at the 3 year and 100 year time steps (it is not observable at the 1 year time step).

Expert elicitation surveys were used to ask respondents how they expected adult (> 3 years of age) and post-weaning (0.5 - 3 years of age) survival rates to vary from baseline conditions when subjected to severe and moderate levels of predation. Because of pup dependency, pre-weaning (< 0.5 years of age) survival was modeled to change as a direct proportional response to changes in adult survival. Respondents predicted that both post-weaning survival and adult survival would be greatly reduced by severe and moderate predation (Tables 5.5, 5.6). Respondents indicated that they expected adult survival to be slightly more sensitive to predation effects than post-weaning survival (Tables 5.6, 5.7).

Human Take

States: NoTake (0%), Low (0-2.4%), Medium (2.4%-15%), High (15%-27%)

Child Nodes: Post-Weaning Survival, Adult Survival

Node Description:

This component represents the combined influence of sea otter mortality that results from intentional and incidental take by humans. Indigenous people from Alaska are permitted to harvest sea otters for subsistence purposes. There are no limits to this harvest, and an illegal harvest of unknown magnitude purportedly occurs (Bodkin and Ballachey 2010). Sea otters are also taken incidental to gillnet, seine, and crab-trap fisheries, commercial shipping activities and as a result of vessel traffic (e.g. boat strikes). Fishery by-catch details for sea otters are available for each of the 3 Alaska stocks in USFWS Stock Assessment reports (see http://alaska.fws.gov/fisheries/mmm/seaotters/reports.htm). The USFWS summary of fisheries by-catch for each stock is as follows: (1) fishery mortality and serious injury for the southwest Alaska stock of the northern sea otter is considered insignificant and approaching a zero (less than 10 animals per year out of ~ 50,000 animals); (2) numerous fisheries exist within the range of the south-central Alaska stock of northern sea otters but none have been identified as contributing significantly to mortality or serious injury rate; and (3) numerous fisheries exist within the range of the southeast Alaska stock of northern sea otters but none have been identified as contributing significantly to mortality or serious injury rate. These summaries are based on data compiled from the NOAA Fisheries Observer Program, which monitors a portion of commercial fisheries in Alaska and reports injury and mortality of marine mammals that occur incidental to fishery operations. Additionally, vessel owners are required by NOAA-Fisheries to report the number of sea otters killed or injured incidental to commercial fishery operations.

Data on the number of otters taken for subsistence use is collected by the U.S. Fish and Wildlife Service's marine mammal Marking, Tagging, and Reporting Program. From this program, the average number of animals harvested annually for each population stock was estimated as follows for the years 2001 - 2006: (1) 91 animals for the SW stock, (2) 346 otter for the SC stock, and (3) 322 animals for the SE stock (USFWS 2008a, b, c).

Subsistence harvest is not permitted within national park boundaries, and human take is very limited due to the remote locales of SWAN Park Units. However, this node was included in the BBN to facilitate portability of the model to otter populations outside of national parks. Data from the aforementioned programs (and elsewhere) can be used to parameterize the prior probabilities that are subject to human take.

Parameterization

State cutoff values represent a range of maximum sustainable harvest rates, ranging from 0- 27%, identified by Bodkin and Ballachey (2010). Their study concluded that the compensatory relationship between harvest and survival was largely dependent upon the magnitude of harvest, the population growth rate at the time of harvest, and the extent to which females were included in the harvest. The range of harvest rates included (0 – 27%) encompasses sustainable rates for stable (λ = 1.005), moderately (λ = 1.072), and rapidly growing (λ = 1.145) populations. However, higher rates of additional mortality (8 – 27%) are only sustainable if some females (1/3 of harvest) are taken as part of the harvest. Only very low harvest rates (1.2% male only or 2.4% 1:3 female: male harvest ratio) are sustainable in populations that have reached an equilibrium growth state (λ = 1.005; Bodkin and Ballachey 2010).

<u>Genetic Variability</u>

States: Average (He = > 0.40), Low (He = 0 – 0.4)

Child Nodes: Disease Prevalence, Pre-Weaning Survival

Node Description:

All existing populations of sea otters have suffered at least one persistent population bottleneck as a result of the 18th and 19th century fur trade (Bodkin et al. 1999), while otter populations that were established via translocations were subject to at least two population bottlenecks. The patchy distribution and nonmigratory behavior of extant sea otters further limits gene flow (Gorbics and Bodkin 2001, Bowen et al. 2006), all of which has resulted in a contemporary sea otter population characterized by relatively low genetic variability (Aguilar 2008). As a result, these small populations of sea otters are particularly susceptible to the effects of inbreeding depression, including reduced immunocompetence and slow population growth rates (Kreuder et al. 2003, Aguilar et al. 2008). Genetic variability is therefore influenced by otter population size and may contribute to an increased susceptibility to parasites and disease and/or reduced fecundity. This component and its associated dependencies represent these hypothesized relationships.

Parameterization

We described the range of genetic diversity exhibited by sea otters using two states: average and low. Because genetic variability in sea otters is so low relative to other mammals, there is no “high” state for this node. Microsatellite heterozygosity provides the most general measure of genome wide variation (Larson et al. 2002) and has been used as a measure of genetic diversity in sea otters in a number of published reports. Published values of heterozygosity were used to set the lower and upper limits for state ranges. The average microsatellite heterozygosity from published reports was 0.421, while the lowest and highest measured were 0.180 and 0.509 respectively (Table 5.8). Most measured values of microsatellite heterozygosity were greater than 0.40, so this value was used to set the lower bound on the average state. The low state represents microsatellite heterozygosity ranging from 0 to 0.40.

Expert elicitation questionnaires were used to survey respondents about their beliefs regarding the relation between genetic diversity, population density and fecundity. Respondents indicated that they expected most populations to exhibit average microsatellite heterozygosity (Table 5.9). As population density declines, the expected likelihood of low heterozygosity increases but remains smaller than the expected likelihood of average heterozygosity unless the population becomes extirpated (Table 5.9).

Respondents were also asked how they expected fecundity to vary from baseline levels given a state of low microsatellite heterozygosity. On average, respondents indicated that they expected fecundity to be somewhat reduced by low genetic diversity (Table 5.10).

Oil Spills

States: Catastrophic Spill, No Spill

Child Nodes: Adult Survival, Post-weaning Survival, Future Prey Density

Node Description:

Due to their reliance on the insulative characteristics of their pelage, sea otter populations are particularly susceptible to acute mortality in the event of a large scale oil spill (Garshelis 1997). In addition to an acute mortality event, chronic effects are likely to result from sub-lethal oiling, long-term exposure to residual oil, and spill-related effects on invertebrate prey items (Monson et al. 2000b, Bodkin et al. 2002). In the event of a large scale oil spill, an acute influence is likely to occur at a time scale of days to months, while chronic effects may be influential for > 10 years (Bodkin et al. 2002). This component represents the relation between oiling, sea otter mortality, and prey availability.

Parameterization

States in the oil spill model component represent each of two potential outcomes - a catastrophic oil spill has occurred, or a catastrophic oil spill has not occurred. The Exxon Valdez oil spill resulted in extremely depressed sea otter population growth rates and elevated mortality rates in the years immediately following the spill (Bodkin et al. 2002). Population growth rates and survival rates slowly recovered but were still depressed nearly 20 years after the oil spill. Survival effects were modeled to reflect this observed recovery pattern such that they are most severe immediately following the spill and eventually recover to baseline levels after approximately ~ 25 years.

Expert elicitation surveys were used to ask respondents how they expected adult (> 3 years of age) and post-weaning (0.5 - 3 years of age) survival rates to vary from baseline conditions in the event of a large scale oil spill. Because of pup dependency, pre-weaning (< 0.5 years of age) survival was modeled to change as a direct proportional response to changes in adult survival. Respondents generally expected that both post-weaning survival and adult survival would be extremely reduced in the event of a large scale oil spill (Tables 5.11, 5.12).

Survey respondents were also asked how they expected prey density to vary from baseline conditions in the event of a large scale oil spill. Similar to expected effects on survival, respondents predicted that an oil spill is likely to result in drastic reductions in baseline prey densities (Table 5.13).

Potential Habitat Availability

States: 0-300 km^2, 300-600 km^2, 600-900 km^2, 900-1500 km^2

Child Nodes: Habitat Used

Node Description:

Because of their high energetic requirements and their reliance on benthic invertebrate prey items, sea otters are restricted to relatively shallow bathymetric contours. Burn et al. (2003) used the definition for high density survey strata, waters <40 m deep, waters 400 m from the shoreline, and waters in bays and fjords <6 km across (Bodkin and Udevitz 1999), to delineate sea otter habitat in the Aleutian Islands.

Parameterization:

Using the method of Burn et al. (2003), potential available sea otter habitat in SWAN park units was delineated using GIS bathymetric data from National Ocean Service hydrographic survey data (Bodkin et al. 2007a; Table 5.14). The area delineated in this node does not necessarily reflect the amount of habitat that is actually being used by sea otters. Rather, it represents the amount of habitat potentially available to sea otters solely based on bathymetry and distance from shore.

Distribution Response

States: <5m, Up to 40m

Child Nodes: Habitat Used

Node Description:

Recent observations suggest that strong killer whale predation pressure in Southwest Alaska has restricted the sea otter spatial distribution to contours of less than 5m depth (J.

Bodkin personal communication). In the absence of this type of predation pressure, sea otters commonly forage in depths of up to 40m (Bodkin et al. 2004).

Parameterization:

This node represents the potential for a predation-mediated distribution response and is thus conditional to the predation node. Because a distribution response is expected to occur latently, the effect was modeled to be most pronounced at longer (3 and 100 yr.) time steps. The distribution response node is characterized by 2 states: 1) < 5 meters, and 2) up to 40 meters. The 'up to 40 meter' state represents baseline habitat use and was delineated using the definition for high density survey strata (Burn et al. 2003). This definition was modified by restricting habitat use to waters of < 5 m. depth to delineate habitat used after a predation mediated distribution response.

Human Non-take Interaction

States: No Disturbance, Moderate Disturbance, Severe Disturbance

Child Nodes: Habitat Use

Node Description:

Sea otters have been observed to be deterred from using available habitat if the area is disturbed by frequent vessel traffic (Garshelis and Garshelis 1984). Disturbances in national park boundaries may include fishing boat traffic and tourist activities including float plane arrivals and departures, vessel traffic, and wildlife viewing activities. Permitting entities within national park units are able to minimize this type of disturbance via the use of stipulations placed on commercial use authorizations. Stipulations can be used to place spatial and/or temporal restrictions on commercial activities within park boundaries to prevent this type of interaction.

Outside of parks disturbances that may restrict sea otter habitat include, but are not limited to, construction of new harbors and docks, dumping of fish waste, dredging for gold, burying underground cables, blasting for new runways, and hovercraft operations.

Parameterization

This node represents the potential for a nonlethal, anthropogenic disturbance that results in a reduction in baseline sea otter habitat use. We described the range of nonlethal human disturbance using 3 states: severe, moderate, and no disturbance. Severe and moderate states represent the potential for two levels of disturbance that result in habitat restriction. A state of no disturbance does not result in habitat restriction. States were defined using state numbers that represent the relative severity of disturbance with 3 representing the most severe disturbance and 1 representing no disturbance.

Expert elicitation surveys were used to ask respondents how they expected habitat use to vary from baseline conditions when subjected to severe and moderate levels of nonlethal, anthropogenic disturbance. Change in habitat use was measured as the proportion of habitat that respondents expected a population to lose in the event of relative disturbance levels. Respondents indicated that a severe disturbance would result in habitat restriction roughly twice the size of that incurred by a moderate disturbance (Table 5.15).

<u>Habitat Used</u>

States: 0-300 km^2, 300-600 km^2, 600-900 km^2, 900-1500 km^2

Child Nodes: Habitat Capacity

Node Description & Parameterization:

This node represents the fraction of available habitat that is actually used by sea otters. Delineation of habitat used will be based on both bathymetric requirements (as described above) and potential range limitations (due to disturbance). More specifically, habitat used was modeled to be conditional to potential habitat available (based on bathymetric requirements), nonlethal human disturbance and killer whale predation. In the case of an anthropogenic disturbance, otters may avoid local habitat that would otherwise be available to them (see human non-take interaction for a more detailed description). Otters experiencing killer whale dominated predation may become restricted to very shallow bathymetric contours (< 5m deep) and protected bays and inlets (see distribution response for a more detailed description).

<u>Current/Future Prey Density</u>

States: High (100–200m^{-2}), Medium (40-100m^{-2}), Low (0-40m^{-2})

Child Nodes: Time Spent Foraging

Node Description:

This node represents the density of prey occupying current and future sea otter habitat. The estimated future prey density at the end of a time step will become the current prey density for the next time step. The future density of sea otter prey species is determined by bottom-up influences, including ocean productivity and ocean acidification, and top-down influences, such as current sea otter density, fisheries interactions, invasive species and catastrophic disturbances (e.g. seismic events or oil spills).

In order to meet their high energetic requirements, otters consume an amount of food equivalent to 23%-33% of their body weight each day (Bodkin 2003). As a result, sea otters exhibit considerable influence over the distribution, abundance, and diversity of their prey populations (Estes and Palmisano 1974), and prey availability is largely determined by the length of time otters have occupied a particular habitat (VanBlaricom 1988, Kvitek et al. 1992). For example, Kvitek et al. (1992) found that bivalve densities were much higher in sites unoccupied by sea otters (192 bivalves/m^2) than in sites that had been occupied for < 5 years (49/m^2), 5-15 years (41/m^2), and longer than 25 years (26/m^2). Similarly, densities of clams and urchins were observed to be 3 – 9 times lower in a long-occupied (> 20 years) region of southeast Alaska when compared to recently colonized habitat (Bodkin et al. 2007b). Moreover, Estes (1990) found that sea otters were able to enhance their equilibrium density by acting as a keystone predator in urchin barrens. Otters preying upon sea urchins released kelp from intense grazing by urchins which, in turn, provided new habitat for kelp bed fishes. A diet which included kelp bed fishes elevated otters at to a higher equilibrium density than had been reached on a diet of invertebrates alone.

The diet of sea otters also varies by habitat-type and time of year. For example, sea otters at Sheep Bay in Prince William Sound, a soft-bottomed habitat, consumed mostly clams and mussels, whereas those living in a rocky-bottomed habitat along the California coastline consumed abalone, rock crab, and sea urchins (Estes et al. 1982). In the Aleutian Islands, rock greenling spawn during the summer and sea urchins reach maximum gonadal development in the winter. In response, sea otters shifted their diet to include rock greenling in the summer, which were presumably easier to catch while spawning, and they ate mostly urchin in the winter when the urchins were of greatest nutritional value (Estes et al. 1982).

Parameterization

We described the range of sea otter prey densities using 3 states: high, medium and low. High and low states represent densities that are greater than or less than baseline density respectively. A state of medium represents baseline density. Because of the extreme variability in sea otter prey type and distribution, state cutoff values for this node will be variable and dependent upon habitat type and length of occupation. For example, using the densities provided by Kvitek et al. (1992) for bivalves in soft-bottomed nearshore habitats, one could define the following state cutoff values:

- A state of high is defined by 200 to 50 bivalves per meter squared.
- A state of medium is defined by 50 to 25 bivalves per meter squared.
- A state of low is less than 25 bivalves per meter squared.

However, these same cut-off values would not be appropriate in rocky-bottomed habitats where bivalves are not the dominant prey type. Further, baseline prey density may change over time because of the considerable influence that sea otters have on their prey populations. State cut-off values for this node should be assessed and redefined as needed.

The future prey density node in the sea otter BBN is conditional to the system productivity, fisheries resource response and environmental disturbance event nodes. Future prey density (P_{t+1}) was modeled as a function of current prey density (P_t), system productivity (S_t), fisheries interactions (F_t), environmental disturbance (E_t), oil spill (O_t), and sea otter population size (D_t):

$$P_{t+1} = \beta_0 + \beta_1 * P_t + \beta_2 * (P_t * S_t) + \beta_3 * (P_t * F_t) + \beta_4 * (C_t * E_t) - \beta_5 * (P_t * O_t * 0.5) - \beta_6 * (P_t * D_t * 0.05) + \varepsilon \qquad (1)$$

Time Spent Foraging

States: High (37-55%), Average (30-37%), Low (20-30%)

Child Nodes: Habitat Capacity

Node Description:

A negative relation between length of occupation and sea otter foraging success has been established (Estes et al. 1982, Garshelis et al. 1986), such that sea otters in relatively newly-occupied (< 3 years) habitat obtain more calories per time than those in long-occupied (≥ 30 years) habitat. This is a reflection of the influence that sea otters exhibit over their prey populations - prolonged occupation leads to a decline in the availability of prey making it necessary for sea otters to spend more time foraging than in comparatively recently occupied habitat (Garshelis et al. 1986, Bodkin et al. 2007c). As a result, time budgets are often used to detect food limitation in sea otter populations. As a population reaches carrying capacity, sea otters must spend more time foraging to meet their high caloric needs.

Parameterization:

The time spent foraging node is a proxy for measuring where a population stands relative to carrying capacity. The states for this node represent the observed range of activity time budgets for sea otters in Alaska (J. Bodkin and T. Tinker personal communication) and are defined as the proportion of a 24-hour day that otters spend foraging.

- A state of *high* indicates that otters spend 37-55% of a 24 hr. period foraging. This state suggests food limitation. A population that has a high activity time budget is likely at or near carrying capacity.
- A state of *average* indicates that otters spend 30-37% of a 24 hr. period foraging. This state suggests some food limitation. A population that has an average activity

time budget has likely not reached carrying capacity yet but has occupied its current habitat for some time.

- A state of *low* indicates that otters spend 20-30% of a 24 hr. period foraging. This state suggests that high quality prey items are readily available to sea otters. A population characterized by a low activity time budget is likely well below carrying capacity.

Expert elicitation questionnaires were used to survey respondents about their beliefs regarding the relation between time spent foraging and prey density. Several respondents had over 20 years of experience observing sea otter foraging behavior and were very confident in their responses. Respondents indicated that otters are much more likely to spend less time foraging when prey density is high. Correspondingly, respondents indicated that the likelihood of otters spending a large proportion of their time foraging is very high when prey density is low.

<u>System Productivity</u>

States: Decrease (- 0.25), Stable (0), Increase (+0.25)

Child Nodes: Future Prey Density

Node Description:

This node represents the potential for either an increase or a decrease in nearshore productivity that may result from the interaction of a number of complex processes (e.g., random prey influx, ocean circulation, mixed-layer dynamics, upwelling). Changes in productivity could occur at a large scale, particularly in the face of climate change, or at a local scale as a result of a suite of ecological events that could trigger shifts in the structure of the nearshore community. A decrease in system productivity is likely to have a negative impact on prey density, while a positive change would likely have a beneficial influence on sea otter prey density. Because of the complexity and uncertainty associated with the biological and physical processes (i.e. ocean circulation, mixed-layer dynamics, upwelling, atmospheric dust deposition, the solar cycle) that drive ocean productivity, there is a high degree of uncertainty associated with this node (i.e. the future state of ocean productivity is completely uncertain).

Parameterization:

States representing an increase or decrease in system productivity result in positive or negative changes respectively to baseline prey densities. A state of stable system productivity does not change baseline prey density. Expert elicitation surveys were used to ask survey respondents to define the magnitude of change in system productivity (on a scale of 0 to 1) that would be needed to produce a measurable change in future prey density. These responses were used to define state values and are in units of proportional change. The mean of respondent replies resulted in the following state cut-off values:

- An increase in system productivity represents a +0.25 proportional change.
- Stable system productivity represents zero change.
- A decrease in system productivity represents a -0.25 proportional change.

Survey respondents were also asked how they expected prey density to vary from baseline conditions given an increase or decrease in system productivity. There is a good deal of uncertainty associated with this node, and the range of expected effects reflects this uncertainty. Respondents did not expect the specified magnitude of change in system productivity to result in > 40% increase or decrease in baseline prey density.

Fisheries Resource Response

States: No Extraction (0), Prey Extraction (-0.30)

Child Nodes: Future Prey Density

Node Description:

Most fishery interactions with sea otters occur in the form of incidental take due to the use of fishing equipment that causes sea otter mortality. This component represents the potential for another type of fisheries interaction - the extraction of important sea otter prey items by competing fisheries. Prey extraction could result in a decrease in prey density.

Parameterization

A state of prey extraction was parameterized to result in reductions of baseline prey density, while a state of no extraction does not influence the future prey density outcome. State numbers (-0.30 and 0) represent the expected proportional change in baseline prey density given extraction or no extraction. Expert elicitation surveys were used to define the expected change in baseline prey density given an extraction effect (Table 5.16).

Environmental Disturbance Event

States: Severe, Moderate, None

Child Node: Future Prey Density

Node Description:

This node represents the potential for environmental disturbances that may ultimately influence sea otter prey availability. Potential types of disturbances include, but are not limited to, ocean acidification, the invasion of nonnative species, and catastrophic seismic or weather events (i.e. an earthquake or volcanic eruption). The potential implications of each of these disturbances are discussed in more detail below.

Ocean Acidification

It has been estimated that the oceans have absorbed more than 50% of CO_2 released from fossil fuel burning since the industrial revolution (NOAA 2008). In turn, the global pH of the Earth's oceans has been reduced and a continued decline is anticipated. Ocean acidification reduces the availability of carbonate ions which are important in the formation of shells for a number of marine organisms (Feely 2004). Using predicted CO_2 emissions from the Intergovernmental Panel on Climate Change's IS92a scenario1 for 2000–2100, Caldeira and Wickett (2003) predicted a decrease of 0.1 in pH to occur over the next 100 years. If ocean acidification continues, the availability of sea otter prey items is likely to be influenced via a reduction in the abundance of nearshore invertebrates that rely on $CaCO_3$ for shell formation. For example, Gazeau et al. (2007) demonstrated that calcification rates of shellfish decline linearly with increasing CO_2 and predicted that mussel and oyster calcification may decrease by 25% and 10% respectively by the end of the century.

Invasive Species

Because sea otters are generalist predators, invasive species are most likely to serve as novel prey items beneficially influencing sea otter prey densities. However, the invasion of a nonnative species also may have both direct and indirect negative influences. Invasive species might compete with a preferred sea otter prey species resulting in the reduction of preferred prey densities. Furthermore, the invasion of a novel species could trigger a suite of ecological responses resulting in community-level changes that ultimately influence the types of prey available to sea otters (e.g., Kurle et al. 2008).

Seismic Event

Previous earthquakes and volcanoes in Alaska have been shown to significantly alter the nearshore environment. For example, the second largest earthquake ever recorded had a magnitude of 9.2 and occurred in south-central Alaska in 1964. Clam mortality was observed to be as high as 90% at some Prince William Sound (PWS) field stations (Hanna 1971). Additionally, because the tidal range in PWS is ~ 10ft., uplift that exceeded 10 feet resulted in the complete destruction of this zone and the littoral invertebrates that inhabited it. Acute mortality of intertidal zone invertebrates and algae was also very high, but recolonization was evident within one year following the earthquake. Similarly, the eruption of the Katmai volcano in 1912 resulted in dramatic acute mortality of nearshore flora and fauna, but recovery was evident two years post-eruption (Rigg 1914). Recent evidence suggests that iron-rich volcanic ash may serve as a natural fertilizer in the iron-limited coastal environment of the NE Pacific (Langmann et al. 2010).

Parameterization

The suite of potential environmental stressors represented in this node is highly variable and, in turn, effects are extremely uncertain. In early iterations of the sea otter BBN prototype, this model component was represented by several individual nodes. After much discussion, these nodes were combined into one summary node that represents the potential for some stochastic event that could influence future sea otter prey density. Severe and moderate states result in relative reductions of baseline prey densities, while a state of none does not influence future prey density. Expert elicitation surveys were used to ask survey respondents how they expected baseline prey densities to change in response to a severe or moderate environmental disturbance event. Average respondent replies (Table 5.17) were used to set state numbers used as multipliers in equation 1.

<u>Population Dynamics Model</u>

Nodes: Current/Future Population Density, Adult Survival, Post-weaning Survival, Pre-weaning Survival, Immigration, Habitat Capacity, Relative Size of Nearby Populations, Inter-population Distance

Parameterization of demographic nodes in BBN

A process similar to that described by Lee and Rieman (1997) was used to estimate the conditional probabilities for demographic nodes (Figure 5.2) in the sea otter BBN. During this process, population dynamics were simulated using the stochastic sea otter population dynamic model (Tinker et al. 2006 and USFWS 2010). Population model output was used to parameterize the conditional probability tables of demographic nodes. 100,000 simulations were computed using random combinations of parameters from pre-defined ranges. To ensure adequate representation from the pre-defined range of initial population size and habitat capacity, we randomly selected values for these nodes from uniform distributions.

Population Dynamic Model Overview

We used a simplified version of the Tinker (USFWS 2010) sea otter population model to represent population dynamics of otters in SWAN park units. This model is a density-dependent, stochastic, stage-structured model that tracks sea otter density over time. It has three stages – dependent pups (0-0.5 years), juveniles (0.5-3 years) and adults (> 3 years). Each simulation began with an initial population density and a stable age distribution for each of three stages.

Initial densities were randomly selected from a uniform distribution and included a range of densities reported in the literature (0-15 otters per m^2). The model operated on an annual time step and each simulated year began with pup production. The model assumes a 40%:60% male to female ratio (Bodkin and Ballachey 2010) and the number of pups produced was the product of the average fecundity of female adults (dependent pups and juveniles are assumed to be non-reproductive) and the corresponding density of mature females (i.e., 60% of the adult population). Dependent pup density was estimated as a function of the total number of pups produced and pre-weaning survival of individuals in the first age class. These individuals were added to the population as dependent pups. Individuals in each stage were promoted to the next age class using empirically estimated annual survival rates. Dependent pups from the previous time step were promoted to year 1 juveniles (i.e., age 0.5-1.5 years old). Juveniles who survived to 4 years of age were promoted to adults ($\geq$ 4 years old). Survival of age 13 sea otters was assumed to be zero.

Stage-specific (i.e., Lefkovitch matrix) transition probabilities were estimated using reported age-specific transition probabilities and the technique detailed in Caswell (2001). Vital rate estimates for a low density (LD) population and a high density (HD) population were incorporated into the matrix model. Low-density parameter estimates produced a population growth rate (λ) of slightly less than 1.15, while high density values produced a rate of growth of slightly less than 1.00. Year to year variability in survival estimates was estimated using a theta-logistic density-dependent function as described by Tinker et al. 2006 (Equation 2, 3). A multiplier (v) was used to interpolate between high and low density populations. Specifically, the density of each sub-population, D_x, is described as a ratio of carrying capacity ($D_x=N_x/K_x$), and for a given value of D survival is interpolated as:

$$S(D) = S^{HD} * v(D) + S^{LD} * (1\text{-}v(D)) \qquad [2]$$

where:

$$v(D) = 1.005 * (N/K)^{1.933} \qquad [3]$$

Parameters

We incorporated the uncertainty associated with population parameter estimates (e.g., pre-weaning, post-weaning and adult survival) by assigning probability distributions for each based on empirical estimates from previous studies (Table 5.18). Empirically derived survival rates were used to define “baseline” levels referred to throughout the model description. Empirical estimates of immigration rates were unavailable however. Using the method of T. Tinker (USFWS 2010), the total number of animals immigrating from population *x* to population y in year *t* was drawn as a random integer from a Poisson distribution with parameter $\gamma_{y,x,}$ where $\gamma_{y,x}$ was modeled as a decreasing function of the distance between populations ($\Delta_{y,x}$) and the relative density of nearby sea otter populations (D_x):

$$\gamma_y, x = \beta_1 * D_x^{\beta 2} / [(1 - \beta_3) + \beta_3 * e^{\Delta y, x}] \qquad [4]$$

Reproductive rate is largely invariant both between populations and over time regardless of environmental conditions (Jameson and Johnson 1993, Monson et al. 2000a); thus it was modeled as a constant in the population model (R=0.90, CV=0.10) and was not explicitly included as a node in the Bayesian belief network.

Pre-Weaning Survival

This node represents the survival of pups 0-6 months of age. Reproductive output of sea otters is largely invariant, both between populations and over time, regardless of resource availability (Monson et al. 2000a). Rather than limiting reproductive output, female otters abandon their offspring early in pup dependency if food resources are limited. Thus, pup survival rates can be quite low and are largely dependent upon resource availability. The relation between habitat capacity and pup survival represents this dependency, while the potential for inbreeding depression is modeled as a function of genetic variability and this node. The influences of factors thought to contribute to additional mortality (e.g., disease, predation) were mediated through maternal survival. The states of this component were defined using a discretized range of values based on those reported in previous studies (Table 5.19).

Post-Weaning Survival

This node represents the anticipated response of juvenile sea otter survival (0.5 - 3 years old) to the sum total of factors, anthropogenic and natural, that are expected to influence mortality within the spatial extent of the model. The factors include contaminant and disease exposure, the potential for catastrophic oil spills, human take, predation and density dependent resource limitation. Juvenile survival was modeled to be more sensitive to unfavorable environmental conditions than adult survival, particularly when the population is at a high density state. The states of this component were defined using a discretized range of values from zero to one.

Adult Survival

This node represents the anticipated response of adult sea otter survival (> 3 years old) to the sum total of factors, anthropogenic and natural, that are expected to influence mortality within the spatial extent of the model. The factors include contaminant and disease exposure, the potential for catastrophic oil spills, human take, predation and density dependent resource limitation. The states of this component were defined using a discretized range of values from zero to one.

Immigration

Long distance migrations of sea otters are thought to be limited to 10s of kilometers due to their high energetic requirements and reliance on nearshore benthic invertebrates as prey (Garshelis and Garshelis 1984). The potential for sea otter immigration is thus influenced by the availability of nearby habitat that also contains a less dense population of sea otters. Using the methods described by T. Tinker (USFWS 2010) immigration was modeled as a decreasing function of inter-population distance and an increasing function of the relative density of nearby populations.

Emigration is thought to occur as a density dependent mechanism such that otters leaving the current population would not influence the population's status at equilibrium density. Thus, emigration was not explicitly included in this model, but was implicit in that otter survival was reduced when the population was at or above the carrying capacity (i.e., otters 'left' the population in greater numbers when the population was at or above the carrying capacity).

Relative Size of Nearby Populations

States: More Dense, Same, Less Dense

This node represents the density of nearby populations relative to the density of the population of interest. The probability of immigration is higher if nearby populations are more dense relative to the population of interest.

Inter-Population Distance

States: 0 – 25km, 25 – 50 km

Due to their limited dispersal capabilities, the probability of successful sea otter immigration from adjacent populations is expected to decline as inter-population distance increases. State cutoff values were obtained from USFWS 2010.

Habitat Capacity

States: High, Medium, Low

This node represents carrying capacity and is expected to influence immigration and survival of all three age classes. As the population of interest nears habitat capacity (i.e. equilibrium density) the probability of immigration of new individuals into the population becomes less likely. Similarly, survival is negatively related to habitat capacity when the population exceeds carrying capacity and the effect differs among age classes, with the greatest effect on dependent pup survival and the least on adult survival.

Current/Future Population Density

States: High, Medium, Low, Extirpated

These model components (current and future) represent the numerical density of sea otters within a park. Future population density is an outcome node and is a statement of the relative probability that future otter density will be high, medium, low, or extirpated given the full suite of potential influences included in the model. The estimated future population status at the end of a time step becomes the current population status for the next time-step. State cut-off values for this node were defined using a discretized range of values that encompass those simulated in the US FWS (2010) population models for sea otters in SW Alaska.

MODEL BEHAVIOR AND SENSITIVITY

As an initial coarse assessment of model behavior, we evaluated each model component and associated dependencies to ensure that they produced outcomes that were within the range of what has been observed empirically or for which there are strongly prevailing hypotheses in the biological community. This assessment revealed that the model reasonably approximated northern sea otter population dynamics in SW Alaska. .

Sensitivity analysis examines the relative influence of model components on a particular model outcome (Clemen 1996). We conducted six sensitivity tests using the modeling shell Netica to determine the degree to which model components influenced the outcome of each submodel in the sea otter BBN (Habitat Capacity, Prey Density, and Survival of each 3 age classes) and the overall model outcome (Future Population Density).

Survival Submodel Sensitivity Tests

Pre-weaning survival was most sensitive to adult survival which is a reflection of pup dependency (Figure 5.2a). Response profiles of adult and dependent pup survival were similar because survival effects on young pups (< 6 months) were mediated through adult survival (Figure 5.2a, b). Adult and dependent pup survival was most sensitive to predation, disease and habitat availability model components. Survival of pre-weaned pups was more sensitive to genetic variability than was either adult or juvenile survival (Figure 5.2a, b, c). Because fecundity was not explicitly represented as a node in the BBN model, the potential for inbreeding depression was represented as a reduction in baseline pre-weaning survival (i.e. reduced pre-weaning survival was used as a proxy for reduced fecundity that can result from inbreeding depression). Greater sensitivity of dependent pups to genetic variability is a reflection of this relationship. Habitat availability, human take and prey density were also relatively influential components to adult and pre-weaning survival (Figure 5.2a, b).

Juvenile survival (of pups age 0.5 – 3 years of age) was most sensitive to pre-weaning survival, contaminants, disease and predation (Figure 5.2c). The sensitivity of juvenile survival to pre-weaning survival is intuitive as young pups must survive the dependent life stage to make the transition to become independent juveniles. Predation was an influential model component on all stages of survival (Figure 5.2a, b, c) which reflects experts' belief in the importance of this variable on sea otter population dynamics (i.e. belief in the megafaunal collapse hypothesis). Adult, pre-weaning and juvenile survival nodes in the BBN were least sensitive to the human non-take disturbance model component. This is a reflection of the small effect sizes predicted by experts during the expert elicitation process (Figure 5.2a, b, c; Table 5.20).

Survival of all three stages (pre-weaned pups, juveniles and adults) was also quite sensitive to disease (Figure 5.2a, b, c). There was a good deal of uncertainty and variability associated with questionnaire responses that were used to parameterize the relation between disease and survival. This is, in part, because the effects of different diseases are highly variable. Over time, we have modified the disease model component in a variety of ways in attempts to better reflect the complexity of disease influence in sea otter populations. For example, we know that some diseases are highly contagious (e.g. morbillivirus) while others are not (e.g. toxoplasmosis), so we initially included states that represented varying degrees of disease contagion level (e.g. contagious vs. not contagious) and various types of effects on a population (acute vs. chronic effects). However, because the states in each node must be mutually exclusive and collectively exhaustive, the large number of states required to represent all possible types of contagion and effect size made parameterizing the conditional probabilities associated with this model component unmanageable. The sea otter BBN working group decided that a disease prevalence node was sufficient considering the spatial extent of this modeling exercise (i.e. sea otter populations in SWAN park units). Should the spatial extent of the model shift to habitat where disease is highly influential in sea otter population dynamics (e.g. California), a submodel could be developed to specifically address the complex relationship between disease and sea otter survival. This model component is an influential uncertainty because survival rates are highly variable depending on the state of the disease node.

Juvenile and pre-weaning survival were more sensitive to contaminant exposure than was adult survival (Figure 5.2a, b, c). This is likely a reflection of greater vulnerability of young otters to poor environmental conditions and is reflected empirically in lower estimates of survival for otters under 3 years of age. This is another model component that we identified as an important uncertainty (i.e. the population outcome is highly variable depending on the state of contaminants). While significant attention has been paid to effects of chemical pollutants on individual otters, effects of contamination on otter population dynamics are not well understood. Effects of various contaminants can be highly variable and exposure of sea otters to multiple contaminants in concert may have unpredictable effects on population dynamics. The relationship between contaminant loading and sea otter population dynamics may warrant the development of a submodel that can more explicitly address the complexities associated with this relation. Future monitoring and research efforts directed at reducing this uncertainty would be valuable.

It should be noted that sensitivity tests were conducted with the time step in the model specified at 100 years. This explains why the tornado diagrams in Figure 5.2 indicate that the oil spill model component is less influential on sea otter survival rates than other model components despite very large expected departures from baseline survival rates predicted by experts (Tables 5.10, 5.11, 5.12). The influence of oil spills on future population density is better depicted via population viability analysis. Dependencies in the survival submodel were parameterized by changing baseline survival rates (Table 5.19) in the sea otter Lefkovitch matrix population model to reflect changes predicted by survey respondents. Model simulations using baseline survival rates resulted in future population densities that varied closely around carrying capacity (specified using a mean of 3 otters per square kilometer in this exercise; Figure 5.3). When baseline survival rates were modified to reflect predicted survival in the event of a catastrophic oil spill, population density experienced an initial drastic decline and then slowly recovered over the course of ~ 25 years (Figure 5.3).

Habitat Capacity Submodel Sensitivity Tests

The habitat capacity submodel contains model components that represent the potential for density-dependent changes in sea otter population dynamics. The habitat capacity outcome node was most sensitive to habitat availability, current prey density, and time spent foraging (Figure 5.4), and it was least sensitive to the human nontake interaction model component. The factors that habitat capacity was most sensitive to are all proxies that can be used to help determine where a population stands relative to carrying capacity. For example, as a population nears carrying capacity, prey and habitat availability become reduced and, in turn, sea otters spend a greater proportion of their time foraging to meet their caloric needs. The sensitivity of habitat capacity to these inputs is a reflection of these relationships. Limited sensitivity to the human nontake interaction model component is a result of small effect sizes predicted by experts during the elicitation process (Table 5.15).

The considerable sensitivity of habitat capacity to pre-weaning survival rates (Figure 5.4) is somewhat less intuitive but can be explained by the sea otter's "bet-hedging" life history strategy. Reproductive rates for sea otters are largely invariant and do not depend on resource availability (Monson et al. 2000a). Instead when resources are limited, mothers will abandon pups in early dependency (Monson et al. 2000a). Uniform birth rates and a tendency to come into estrus immediately after losing a pup allow otters to exploit unpredictable environmental conditions favorable to pup survival. Viewed from this perspective, variation in pre-weaning survival may be a facultative life history trait under female control that is directly linked to resource availability. Adult and juvenile survival rates are also important contributing factors in determining where a population stands relative to carrying capacity but are less influential than pre-weaning survival. This is because age transitions of juveniles and adults do not contribute to increases in future population density.

A moderate proportion of the variation in the habitat capacity model component can also be explained by predation and distribution response nodes. These two nodes are linked such that states of *Moderate* to *Severe* predation produce a distribution response that ultimately limits the amount of available habitat that sea otters can occupy (Figure 5.5a, b, c). Recall that average predation represents the baseline level (i.e. does not result in changes to baseline survival or habitat use) and that sea otters primarily forage in habitats of up to 40m bathymetry. This relationship in the model is most easily revealed by specifying a known state of *Average* predation which, in turn, results in a conditional probability of 100% for the state of *up to 40m* in the distribution response node (Figure 5.5a). Notice that in this case the model indicates that it is most likely that otters will use most of the habitat available to them. When a known state of *Moderate* predation is specified, the model predicts that a distribution response is more likely (~ 70% probability) and, in turn, that it is most probable (65%) that sea otters will limit habitat use to a small proportion of suitable habitat (Figure 5.6b). A distribution response becomes even more likely (90% probability) when a state of *Severe* predation is specified (Figure 5.6c). This results in a high probability (83.4%) that otters will limit habitat use to small proportion of habitat available to them.

Prey Density Submodel Sensitivity Tests

Sensitivity of the Future Prey Density model component was well balanced, in that sensitivity was distributed relatively equally amongst prey density submodel components (Figure 5.6). System productivity, oil spill and environmental disturbance were most influential on future prey density and were followed closely by a catastrophic environmental disturbance event, fisheries resource response and sea otter population density.

The prey density submodel was further evaluated by assessing how the outcome node varied in response to state changes in input nodes. There are 432 potential combinations of states in the conditional probability table for future prey density, so we chose a few scenarios to exemplify how the model can be used to predict changes in future prey density (Figure 5.7a, b, c). Scenario A represents the “best case” scenario for future prey density. In this scenario, prior probabilities of input nodes were parameterized to be completely known (no uncertainty). Known states were specified as the following: high current prey density, no catastrophic oil spill, medium sea otter population density, stable system productivity, no extraction of prey by competing fisheries, and no catastrophic environmental disturbance event. Given these states the model predicted that future prey density is very likely to be high (90% chance), unlikely to be medium (10% chance), and that it will not be low (0% chance). It is not realistic, however, that the states of input nodes could be known with complete certainty.

In scenario B, prior probabilities of input nodes were parameterized as completely uncertain (i.e. there is equal probability of each state occurring; Figure 5.7b). Given complete uncertainty regarding input nodes, the model predicted that future prey density was most likely to be low (78.1%) > medium (16.9%) > high (4.94%). This is not all that surprising as a “completely uncertain” scenario dictates relatively high probabilities for nodes that can result in catastrophic declines of sea otter prey densities. For example, we know that oil spill occurrence rates are not high enough to warrant a 50:50 odds ratio for the probability of an oil spill at any one time step. A 33.3% probability of occurrence for a catastrophic weather event at any one time step is also much too high given historic meteorological records.

In scenario C, we attempted to create a more realistic view of system dynamics by using our knowledge of prey density submodel variables in SWAN Park Units to specify prior probabilities for input nodes. For example, we know from SWAN monitoring data that current prey density is most likely high and that sea otter population density is approximately medium (i.e. below carrying capacity but not recently colonized). We also know that catastrophic oil spills and extreme weather events are rare occurrences. Likewise, sea otter prey extraction by a competing fishery is very unlikely – particularly in SW Alaska National Parks. Prior probabilities of the system productivity model component were left completely uncertain. Given these priors, the model predicted that future prey density would be relatively uncertain such that probabilities were spread relatively equally among states. It was most likely that future prey density would be high (37.3%), somewhat less likely that it would be medium (35.4%), and least likely that it would be low (27.3%; Figure 5.7c).

Overall Model Outcome Sensitivity Test

The overall population outcome was most sensitive to changes in survival for each of three age classes (Figure 5.8). Survival nodes in the sea otter BBN were summary nodes through which effects of potential stressors were mediated. The factors that were most influential to survival ranked just below survival in the overall sensitivity analysis (Figure 5.8). Again, the model is quite sensitive to changes in predation and disease making these variables important uncertainties. Demographic model components besides survival, including initial population size, immigration and habitat capacity, were the next most influential factors to the overall population outcome. Future sea otter density (at the 100 year time step) was least sensitive to the oil spill and human non-take interaction model components. However, it should be noted that the model was quite sensitive to the oil spill node at shorter time steps (Figure 5.3). It is also important to take into account that our model assumes that enough sea otters would survive an oil spill to allow for recovery. The likelihood of recovery becomes much less likely when population size is reduced below a viable threshold – a scenario that is quite probable given a small initial population size or a particularly catastrophic spill. Limited sensitivity to the human nontake interaction model component is a result of small effect sizes predicted by experts during the elicitation process (Table 5.14).

MONITORING AND MANAGEMENT DISCONNECT

Monitoring and research agencies often pour vast resources into implementing programs aimed at monitoring resources that are not within their management jurisdiction. Monitoring of sea otters in NPS SWAN Park Units is an example of this disconnect. The agency primarily responsible for funding long-term monitoring of sea otter populations in the region is the NPS, while the U.S. Fish and Wildlife Service is responsible for managing sea otters pursuant to both the Marine Mammal Protection Act and the Endangered Species Act. Thus, there remains the need to develop tools to assist the NPS in formally integrating monitoring data with management decision making. While the framework we have developed above allowed us to identify a number of important uncertainties that the NPS could monitor, to be useful for formulating remedial actions, monitoring data should explicitly relate to the objectives of the management agency (US FWS) and be collected in such a manner as to resolve uncertainties that are important to decision-making (Lee 1993; Williams et al. 2002). In general, learning in the absence of active management is done very poorly, requiring at least 10-20 years of monitoring to reduce uncertainty associated with a particular system component (McCarthy 2006)..

SUMMARY AND CONCLUSIONS

Because the sea otter BBN combines expert knowledge with empirically derived information, it should be revisited and updated as new empirical data becomes available and/or as existing prevailing hypotheses change. The alpha level model that we started with has been reviewed and refined by input from multiple knowledge experts via expert elicitation questionnaires and participation in workshops and webinars. The sea otter BBN presented herein is currently at the “beta” level stage (Marcot et al. 2006).

The sea otter BBN was designed to provide a framework in which to synthesize available data, identify important uncertainties, and provide a repository for future monitoring data. Sensitivity analysis identified a number of important uncertainties including factors that were predicted to directly influence survival. Future population status (at the 100 year time step) was most sensitive to predation and disease, followed closely by initial population status, immigration, and habitat capacity. Oil spills were important to population status at shorter time steps.

Monitoring programs for sea otters in SW Alaska are both labor and cost intensive in terms of field and laboratory days and because of the inherent difficulty of gaining access to the resources being monitored. Thus, it is of particular importance that monitoring programs be explicitly designed to reduce key uncertainties to ensure that scarce resources are not wasted. The results of sensitivity analysis can be used as a means by which to identify the most influential variables in the absence of decision making. However, true “key” uncertainties are not only influential in a BBN, but they also potentially change the optimal decision.

While learning can occur via passive monitoring and updating, monitoring that speaks to decision making requires systematic manipulation of system dynamics (i.e., implementation of management actions) followed by monitoring that is designed to measure the performance of model predictions and management actions. Monitoring in the absence of decision-making, and, in turn, the absence of *a priori* hypotheses about system dynamics than can be predicted and measured, occurs much more slowly than monitoring that is formally linked to decision-making (Yoccoz et. al. 2001). In the case of sea otters, this is particularly challenging because the NPS does not have management jurisdiction over the resource they are monitoring. We therefore advocate for a structured decision approach to formally integrating monitoring data with management decision making by the US FWS as an important next step. The sea otter working group identified a number of sea otter management challenges, including fisheries conflicts in SE Alaska, population declines in SW Alaska, changes to subsistence harvest laws in SC and SE Alaska, and oil spill risk assessment that could all benefit from a SDM approach. The model we developed herein can be used as a base – which should be simplified based on decision scope – and to which decisions and objectives can be linked.

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Table 5.1. Average expected influence of disease prevalence on adult (> 3 years of age) baseline survival rates. Results should be interpreted as respondents' expected change in baseline survival levels. For example, assume adult baseline survival is 0.91. On average, survey respondents expected a state of high disease prevalence to reduce survival to 0.85. Ranges are indicated in parentheses.

Disease Prevalence	Δ Baseline Adult Survival
High	-0.06 (-0.05 to -1.0)
Moderate	-0.024 (-0.02 to -0.05)
Low	0

Table 5.2. Average expected influence of disease prevalence on post-weaning (0.5-3 years of age) baseline survival rates. Results should be interpreted as the respondents' expected change in baseline survival levels. For example, imagine post-weaning baseline survival is 0.88. On average, survey respondents expected a state of high disease prevalence to reduce survival to a level of 0.765. Ranges are indicated in parentheses.

Disease prevalence	Δ Baseline Post-Weaning Survival
High	-0.115 (-0.1 to -0.02)
Moderate	-0.05 (-0.04 to -1.0)
Low	0

Table 5.3. Average expected influence of contaminant concentrations on adult (> 3 years of age) baseline survival rates. Results should be interpreted as respondents' expected change in baseline survival levels. For example, assume adult baseline survival is 0.91. On average, survey respondents expected a state of high contaminant loading to reduce survival to 0.869. Ranges are indicated in parentheses.

Contaminant Concentrations	Δ Baseline Adult Survival
High	-0.041 (-0.02 to -0.10)
Moderate	-0.0115 (-0.005 to -0.05)
Low	0

Table 5.4. Average expected influence of contaminant concentrations on post-weaning (0.5-3 years of age) baseline survival rates. Results should be interpreted as the respondents' expected change in baseline survival levels. For example, assume post-weaning baseline survival is 0.88. On average, survey respondents expected a state of high contaminant loading to reduce survival to a level of 0.839. Ranges are indicated in parentheses.

Contaminant Concentrations	Δ Baseline Post-Weaning Survival
High	-0.041 (-0.02 to -0.10)
Moderate	-0.013 (-0.005 to -0.025)
Low	0

Table 5.5. Average expected influence of predation on adult (> 3 years of age) baseline survival rates. Results should be interpreted as respondents' expected change in baseline survival levels. For example, assume adult baseline survival is 0.91. On average, survey respondents expected a state of severe predation to reduce survival to 0.22. Ranges are indicated in parentheses.

Predation	Δ Baseline Adult Survival
Severe	-0.69 (-0.30 to -0.90)
Moderate	-0.31 (-0.10 to -0.60)
Average	0

Table 5.6. Average expected influence of predation on post-weaning (0.5-3 years of age) baseline survival rates. Results should be interpreted as respondents' expected change in baseline survival levels. For example, assume post-weaning baseline survival is 0.88. On average, survey respondents expected a state of severe predation to reduce survival to 0.31. Ranges are indicated in parentheses.

Predation	Δ Baseline Post-Weaning Survival
Severe	-0.57 (-0.30 to -0.90)
Moderate	-0.26 (-0.10 to -0.50)
Average	0

Table 5.7. Published values of microsatellite heterozygosity used to define state cutoff values for the genetic variability model component in the sea otter BBN.

Source	Sample Site	Microsatellite Heterozygosity
Aguilar et al. (2008)	California	0.444
Aguilar et al. (2008)	Prince William Sound	0.451
Aguilar et al. (2008)	Amchitka Island	0.414
Larson et al. (2002)	Amchitka Island	0.451
Larson et al. (2002)	California	0.414
Larson et al. (2002)	SE Alaska	0.508
Larson et al. (2002)	Prince William Sound	0.180
Larson et al. (2002)	Washington	0.509
	Mean	**0.421**

Table 5.8. Average expected probability that genetic variability in a population will be average or low given four levels of population densities. This is a conditional probability table, so probabilities in each row must add to 100.

Population Density (#/km^2)	Average	Low
Extirpated (0 - 0.1)	37	63
Low (0.1 - 2.0)	53	47
Medium (2.0 - 4.0)	69	31
High (> 4)	80	20

Table 5.9. Average expected influence of genetic variability on fecundity. Results should be interpreted as respondents' expected change in baseline fecundity. For example, if baseline fecundity is 0.90, on average, survey respondents expected low genetic variability to reduce fecundity to 0.78. Ranges are indicated in parentheses.

Genetic Variability	Δ Baseline Fecundity
Average	0
Low	-0.12 (0 to -0.20)

Table 5.10. Average expected influence of a catastrophic oil spill on adult (> 3 years of age) baseline survival rates. Results should be interpreted as respondents' expected change in baseline survival levels. For example, assume post-weaning baseline survival is 0.91. On average, survey respondents expected a state of severe predation to reduce survival to 0.198. Ranges are indicated in parentheses.

Oil Spill	Δ Baseline Adult Survival
No Spill	0
Catastrophic Spill	-0.712 (-0.6 to -1.0)

Table 5.11. Average expected influence of a catastrophic oil spill on post-weaning (0.5-3 years of age) baseline survival rates. Results should be interpreted as respondents' expected change in baseline survival levels. For example, assume post-weaning baseline survival is 0.88. On average, survey respondents expected a state of severe predation to reduce survival to 0.156. Ranges are indicated in parentheses.

Oil Spill	Δ Baseline Post- Weaning Survival
No Spill	0
Catastrophic Spill	-0.724 (-0.70 to -1.0)

Table 5.12. Average expected influence of a catastrophic oil spill on baseline prey density. Results should be interpreted as respondents' expected proportional change in baseline prey density.

Oil Spill	Δ Baseline Prey Density
No Spill	0
Catastrophic Spill	-0.52 (-0.10 to 0.70)

Table 5.13. Area of potential habitat available to sea otters in Kenai Fjords (KEFJ) and Katmai (KATM) National Parks

Park Unit	Baseline (km^2)
KEFJ	832
KATM	999

Table 5.14. Average expected influence of non-lethal, anthropogenic disturbance on sea otter habitat use. Results should be interpreted as respondents' expected proportional change in baseline habitat use. For example, assume available habitat for an otter population is defined as 700 km^2. On average, survey respondents expected that a severe disturbance would result in a loss of 153.3 km^2 of habitat. Ranges are indicated in parentheses.

Non-lethal Human Disturbance	Δ Baseline Habitat Use
Severe	-0.219 (-0.10 to -0.70)
Moderate	-0.105 (0 to -0.50)
Average	0

Table 5.15. Average expected probability that time spent foraging will be low, average, or high given three levels of prey density. This is a conditional probability table, so probabilities in each row must add to 100.

Prey Density	High	Average	Low
High	3	15	82
Medium	16	68	16
Low	81	17	2

Table 5.16. Average expected influence of system productivity on future sea otter prey density. Results should be interpreted as the expected proportional change in baseline prey density given a specified magnitude of increase (+0.25) or decrease (-0.25) in system productivity. Ranges are indicated in parentheses.

System Productivity	Δ Baseline Prey Density
Increase	+ 0.21 (0.07 - 0.40)
Stable	0
Decrease	- 0.18 (-0.07 to - 0.40)

Table 5.17. Average expected influence of fisheries resource response on baseline prey density. Results should be interpreted as the expected proportional change in baseline prey density. Ranges are indicated in parentheses.

System Productivity	Δ Baseline Prey Density
Prey Extraction	0
No Extraction	-0.30 (-0.10 to -0.60)

Table 5.18. Average expected influence of an environmental disturbance event on future sea otter prey density. Results should be interpreted as the expected proportional change in baseline prey density given a specified magnitude of increase (+0.25) or decrease (-0.25) in system productivity.

Environmental Disturbance Event	Δ Baseline Prey Density
Severe	-0.48 (0.17 to 0.60)
Moderate	-0.20 (-0.05 to -0.50)
None	0

Table 5.19. Summary of empirical estimates for adult (> 3 years old), juvenile (0.5-3 years old), and dependent pup (0-6 month) survival rates used to assign probability distributions of parameter estimates.

Source	Adult Survival
Monson et al. (2000a)	0.855
Monson et al. (2000a)	0.915
Udevitz and Ballachey (1998)	0.960
Udevitz and Ballachey (1998)	0.875
Udevitz and Ballachey (1998)	0.935
Eberhardt and Siniff (1988)	0.920
	Post-weaning Survival
Ballachey at al. (2003)	0.863
Ballachey at al. (2003)	0.605
Monson et al. (2000a)	0.855
Monson et al. (2000a)	0.934
	Pre-weaning Survival
Siniff and Ralls (1991)	0.46
Siniff and Ralls (1991)	0.58
Monnett and Rotterman (2000)	0.67

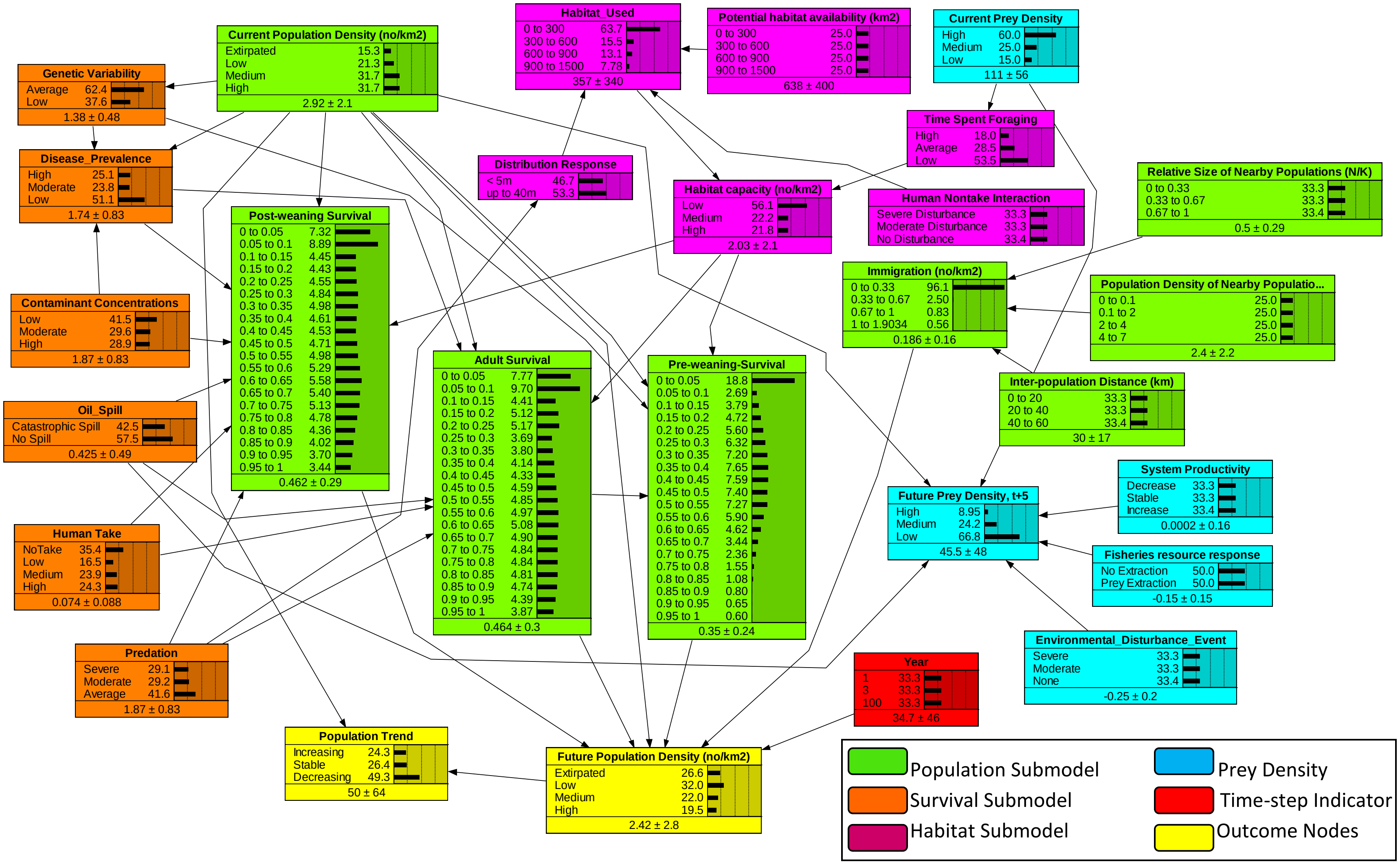

Figure 5.1. Bayesian belief network developed for sea otters in northern Alaska. The model is subdivided into survival, habitat capacity, prey density, and the baseline population dynamic submodels. *Future population density* and *Population trend* nodes are outcome nodes that summarize the entire suite of influences in the network. The *Year* node is used to specify a 1, 3, or 100 year time step. Directed arcs indicate causal relationships with parent nodes influencing (pointing into) child nodes.

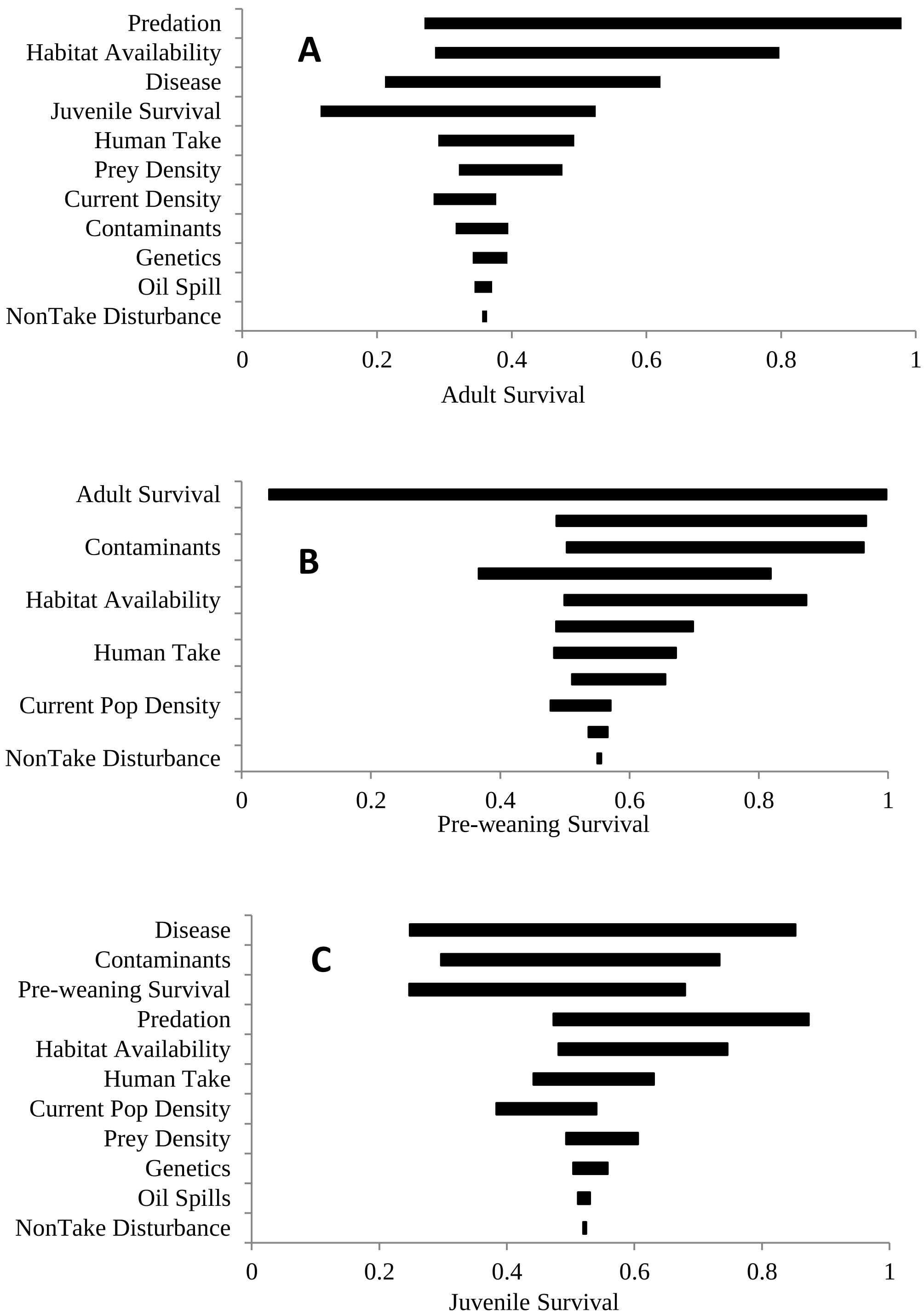

Figure 5.2. One-way sensitivity analysis with model components listed from greatest (top) to least influential for (a) adult (>3 yrs.), (b) pre-weaning (< 0.5 yrs.), and (c) juvenile (0.5 - 3 yrs.) survival model components in the sea otter BBN. For each model component on the y-axis, bar length represents the extent to which survival varies in response to changes in the value of that component with all other model components held at base values.

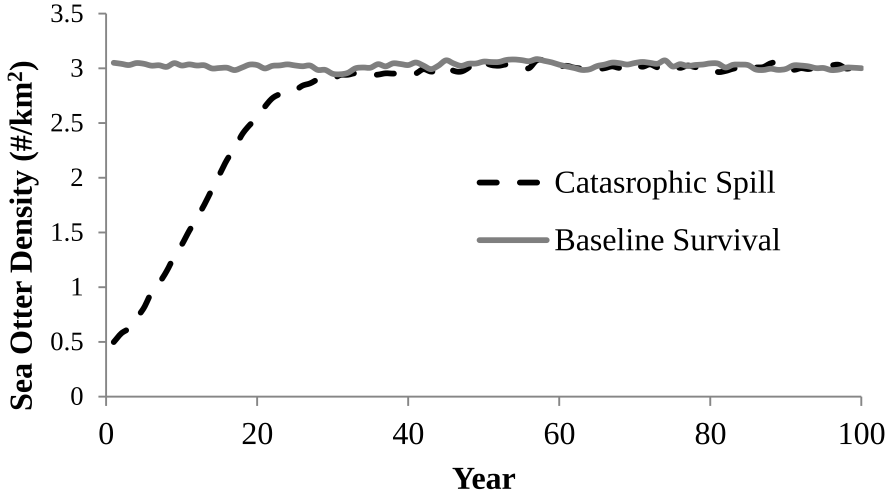

Figure 5.3. Results of Lefkovitch matrix population simulations when survival rates were set to reflect a) baseline conditions (see Table 20), and b) questionnaire respondent predictions about the influence of catastrophic oil spill on survival rates (see Tables 11, 12).

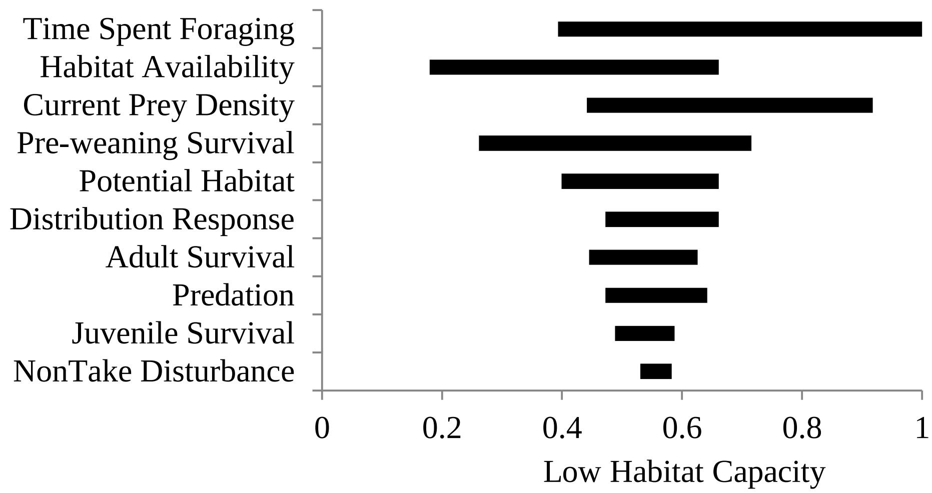

Figure 5.4. One-way sensitivity analysis with model components listed from greatest (top) to least influential for the habitat capacity model component in the sea otter BBN. For each model component on the y-axis, bar length represents the extent to which the state of ‘low’ habitat capacity varies in response to changes in the value of that component with all other model components held at base values.

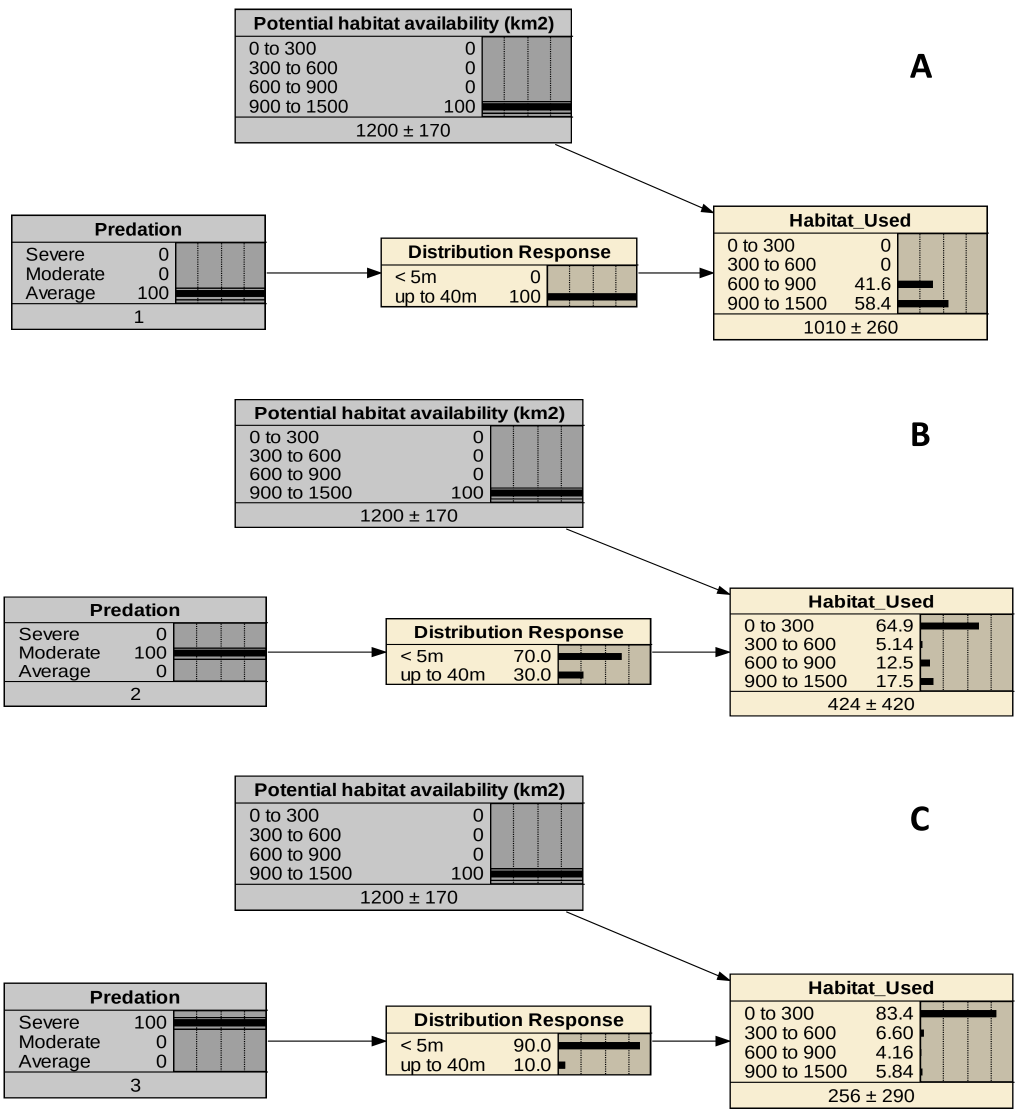

Figure 5.5. Probabilistic network used to illustrate the relationship between killer whale mediated-predation and habitat use by sea otters. All scenarios depict 100% potential habitat availability of 900 to 1500km^2. Three prior probabilities for predation are depicted: A) average 100%, B) moderate 100% and, C) severe 100%. Numbers in the boxes are probabilities of a particular state expressed as a percentage.

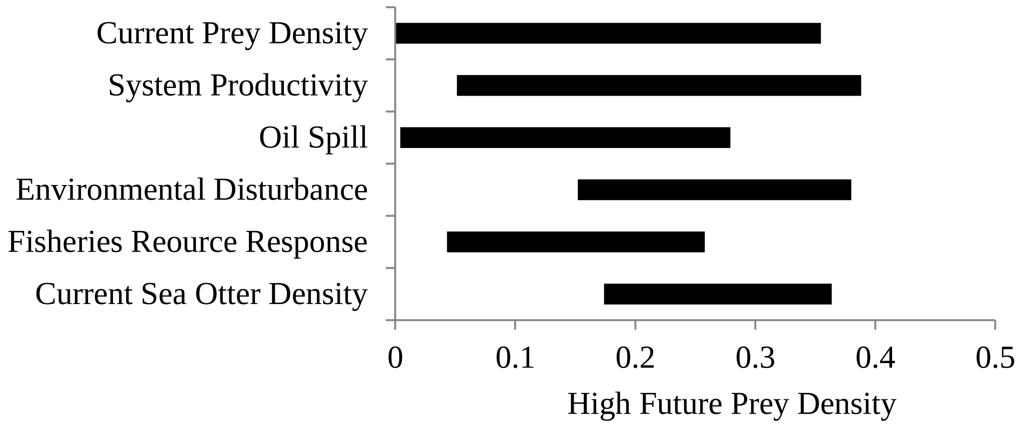

Figure 5.6. One-way sensitivity analysis with model components listed from greatest (top) to least influential for the future prey density model component in the sea otter BBN. For each model component on the y-axis, bar length represents the extent to which the state of ‘high’ future prey density varies in response to changes in the value of that component with all other model components held at base values.

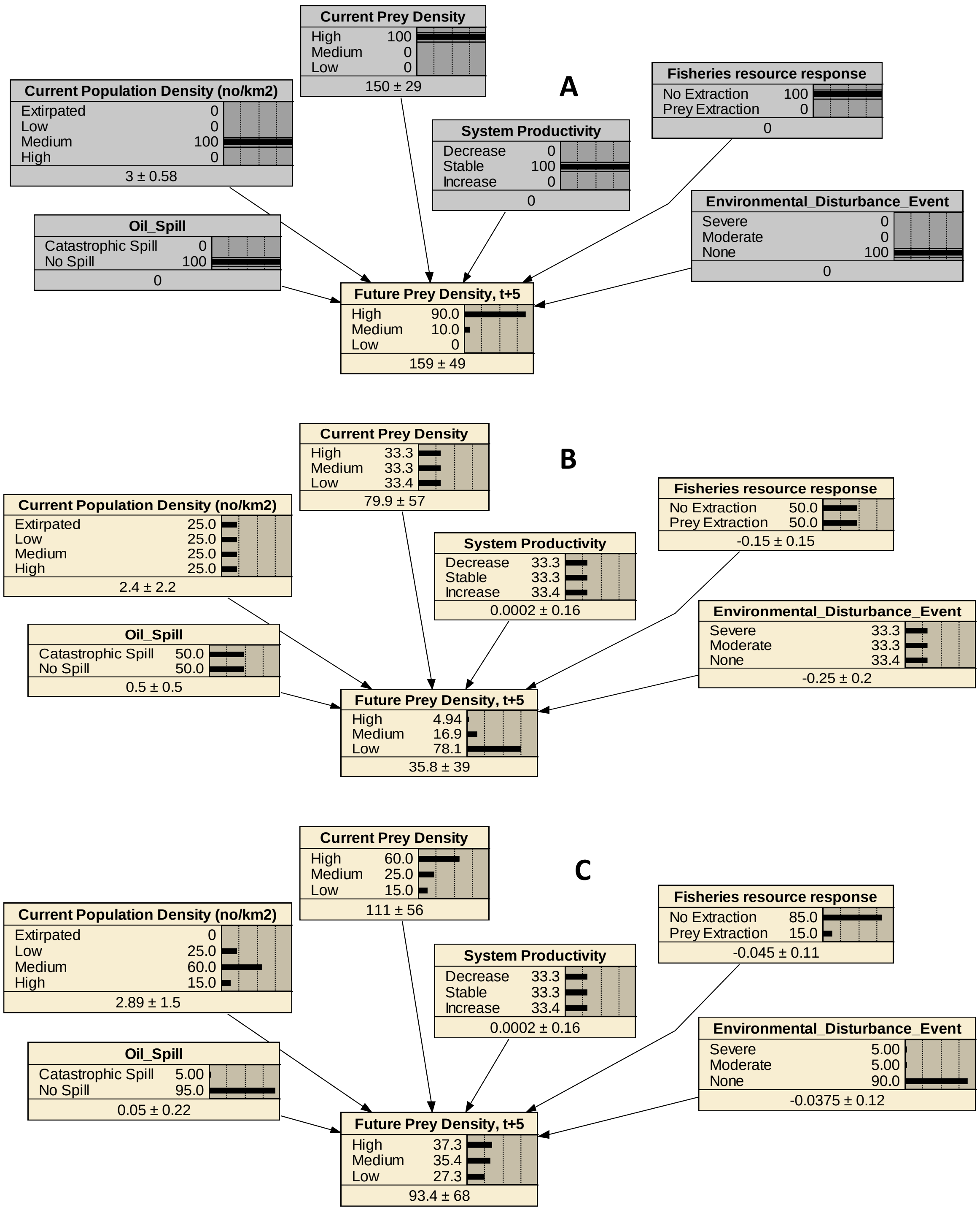

Figure 5.7. Probabilistic network used to illustrate the relationship between future prey density and various prey density submodel components. Numbers in the boxes are probabilities of a particular state expressed as a percentage. Three scenarios are depicted: A) prior probabilities of parent nodes are known with 100% certainty, B) prior probabilities of parent nodes are completely unknown (i.e. probability is distributed equally among states of each component), and C) prior probabilities were specified to reflect system dynamics in SWAN Park Units.

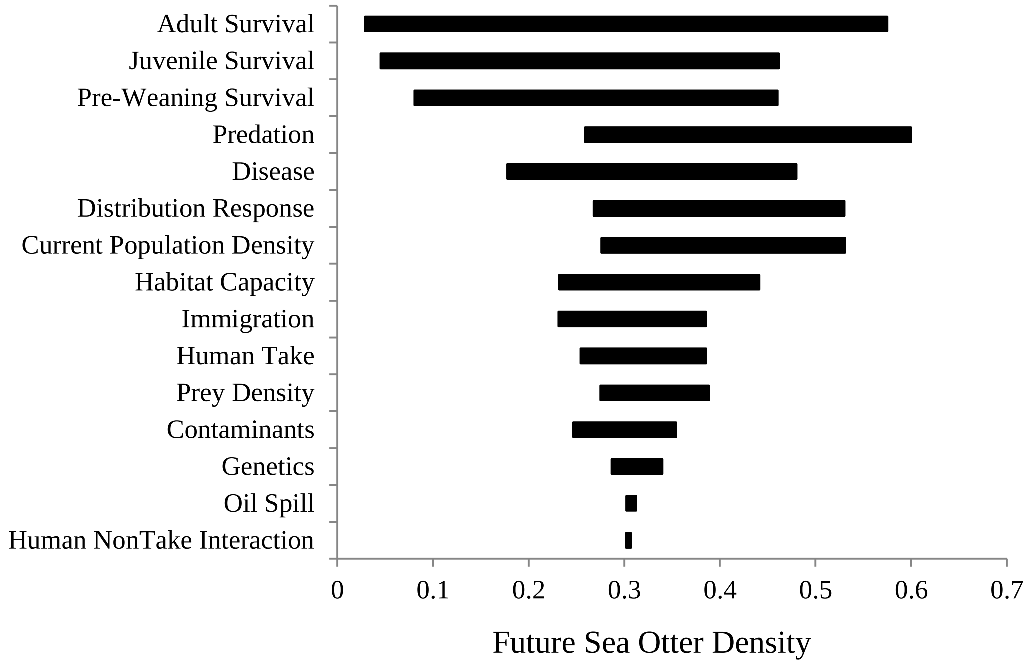

Figure 5.8. One-way sensitivity analysis with model components listed from greatest (top) to least influential for future sea otter density in the sea otter BBN. For each model component on the y-axis, bar length represents the extent to which future sea otter density varies in response to changes in the value of that component with all other model components held at base values.

CHAPTER 6 : SYNTHESIS, CHALLENGES, AND CLOSING THOUGHTS

INTERAGENCY AND TRANS-JURISDICTIONAL CHALLENGES TO SDM

Trans-jurisdictional and interagency management challenges are not uncommon in natural resource management, but they usually arise in one of two contexts: 1) transboundary water management challenges (e.g. ACF water wars in Georgia, Florida and Alabama), or 2) the management of migratory species (e.g. management of American Black Ducks (*Anas rubripres*), Conroy et. al. 2002). Given the relatively small home ranges and non-migratory nature of sea otters and brown bears in Alaska, I did not initially expect such conflicts. Further, in Alaska, management decision-making for sea otters is limited to one agency (the US Fish and Wildlife Service) and for brown bears enabling legislation (namely, the Alaska National Interest Lands Conservation Act) dictates collaborative management between state and federal agencies. In retrospect, not expecting conflict on these management issues may sound naive, but the natural resource management community in Alaska is relatively small and close-knit. The rural nature of Alaskan lands, combined with extreme weather, makes accessibility to resources difficult and expensive (Reynolds et. al. 2011) so managers and biologists across agencies must collaborate to effectively conduct research. For example, access to nearshore sea otter habitat in Katmai National Park requires a several day journey by boat (the gas costs alone are in the tens of thousands of dollars), so biologists from multiple agencies gain access to the park via the same boat and thus share fixed and ongoing costs. Furthermore, Reynolds et. al. (2011) reported that the costs of implementing one line transect aerial survey for brown bears in Togiak National

Wildlife Refuge, Alaska to be $21,460. Historically, ADFG and NPS personnel conducted these surveys in concert (Brad Shults NPS and Harry Reynolds retired ADFG personal communication). This evidence of bottom-up support for collaborative processes (i.e., by biologists and managers), along with some other lines of evidence discussed below, leads me to believe that the jurisdictional and interagency challenges that limited the scope of the brown bear project can be attributed to top-down control and identity conflicts (Buckles 1999, Hamill et. al. 2009). Regarding the seat otter project, underlying conflicts, in addition to administrative challenges, limited the scope of the decision problem.

Sea Otter Challenges

Ideally, the sea otter project would have involved using a SDM approach to explicitly link National Park Service (NPS) monitoring to US Fish and Wildlife Service (FWS) decision-making. Via the USGS Status and Trends Program, NPS Inventory and Monitoring personnel contracted decision analysts to aid in facilitating this process. We initialized the sea otter SDM process by inviting managers from US Fish and Wildlife Service along with personnel from the NPS SWAN Inventory and Monitoring Program to participate in workshops aimed at working through the early design and development phases of SDM (i.e., defining the problem, identifying objectives, and alternatives). Although both monitoring and management agencies were at the table, so to speak, it became clear early on that FWS personnel were reluctant participants. Later, it was revealed that, because NPS contracted the decision analysts while having no jurisdictional authority to manage sea otters, administrators at FWS interpreted the initiation of the process as an admonishment of ineffectual sea otter management practices. This conflict was further complicated by the following two factors: 1) knowledge experts continuously advocated for management actions that FWS managers identified as not feasible (namely regulation of subsistence harvest); and 2) decision analysts constructed a prototype system model (i.e., that did not contain any decisions or values) that was presented at the first workshop with the intent of facilitating discussion. It was later revealed that FWS personnel interpreted this to mean that their involvement in the process was initiated *after* NPS had developed a means for making decisions. In other words, FWS assumed that their presence was requested so they could be told how to properly manage sea otters. FWS personnel did eventually get on-board with the process. I can only speculate as to whether this occurred because of an administrative change (which did occur) or because they realized the efficacy of the tool. Unfortunately, FWS buy-in for the process coincided with the project end-date, at which time we had neither the funds nor resources to continue the sea otter SDM work.

If I could revisit the sea otter problem at the initiation of the process, I would make three major changes that I would also advocate for in all SDM projects. First, I would have conducted a stakeholder analysis (Conroy and Peterson 2013) to identify the relative importance of potential stakeholders. This analysis would have revealed that the Alaska Sea Otter and Stellar Sea Lion Commission, a native group that participates in cooperative subsistence harvest management of otters with US FWS, should have been included as a stakeholder in the decision process. If implemented by the federal government, subsistence harvest regulations would be extremely unpopular, unenforceable, and likely to be overruled politically. There is, however, a precedent of Alaska tribal governments setting their own harvest regulations on subsistence use (i.e. in the case of the endangered Steller sea lion). Secondly, the inclusion of the Alaska Native community as a stakeholder in the SDM process could have facilitated feasibility of subsistence harvest regulations as potential management actions. Minimally, I suspect that their presence would have alleviated some of the conflict between FWS managers who (I speculate) felt like they were being chastised by knowledge experts for not considering subsistence harvest regulations as a feasible alternative. To that end, I would have also educated participants about the different roles of stakeholders (i.e., decision makers and mangers in this case) and knowledge experts at the outset of the process, and I would have established a governance system that assured that each participant did not deviate from their agreed upon roles in the process. Finally, I would have met with an individual stakeholder representative from both NPS, FWS, and relevant native groups to explain the process and hear their concerns in a non-threatening environment (e.g., a community civic space rather than a federal office). This is a practice used in conflict resolution, termed conciliation, which is recognized as an important first-step in identifying and resolving conflicts (Buckles 1999). Had we been able to identify and resolve the underlying conflict that ultimately hindered our process, we would have likely achieved our goal of constructing an integrated process that explicitly linked NPS monitoring to US FWS decision-making.

For example, FWS is now seriously considering translocation as an approach to mitigating declines in abundance and genetic diversity in southwest Alaska. Previous translocations of otters have been successful at recovering historically extirpated otter populations in Southeast Alaska, British Columbia and Washington (Jameson et al. 1982, Bodkin et al. 1999), but this would be the first time otter translocation would take place in currently occupied habitat. Identifying optimal source and destination locations would require an explicit formulation of objectives so that decision making can be directly linked to management objectives. For example, the identification of the optimal source population(s) may vary depending on whether the objective is to: 1) recover degraded populations in SW Alaska; 2) reduce fisheries-otter conflicts in SE Alaska; or 3) address management challenges in both objectives 1 and 2. The fate of translocated otters presents a number of scientific uncertainties as well, such as: 1) will they become killer whale food?; and 2) if that is a likely probability, should they be translocated to protected bays and inlets where they will be safer from predation? Whatever the case, this is a decision problem that is laden with structural uncertainty that certainly could benefit from the application of SDM and ARM. I assert that the comprehensive, quantitative model of sea otter population dynamics developed in this dissertation could be a useful framework for linking decisions to model components in order to represent hypotheses regarding expected effects of translocation. However, I advocate that the extremely complex model we created be simplified to only those components that are relevant to the decision problem.

Brown Bear Challenges

Because I described in detail the deep-rooted conflicts – namely legislative differences and federal versus state sovereignty issues - that limited the scope of the brown bear project in Chapter 2, I will limit this discussion to how the brown bear decision model might be different had the ADFG (and, by proxy, the BOG) been involved in the SDM process. The Board of Game clearly believes that the stakeholders they represent, Alaska resident hunters, value elk and caribou harvest over brown bear consumptive and non-consumptive uses (Van daele et. al. 2003, Boertje et. al. 2009, Miller et. al. 2011). My assumption is that this value would have been presented (i.e., at an SDM workshop) as a scientific uncertainty regarding effects of top predator control on ungulate population size. A SDM approach should have revealed, early on in the process, that the true fundamental objective of BOG is not to implement predator control.

Rather, predator control is a means of achieving their true fundamental objective of maximizing ungulate harvest. Other objectives identified by the NPS via our SDM work, including non-consumptive recreation, subsistence and sport harvest of brown bears, reducing human-bear incidents, and maintaining viable wildlife populations are all reflected in ADFG policy and regulations (ADFG 2013). So, structuring objectives with both the NPS and ADFG should reveal that objectives regarding brown bears are similar but that ADFG values ungulate harvest over bear-related objectives (except, perhaps, incident-reduction). The spatial extent of the decision model could have been expanded to include both lands managed collaboratively by NPS and ADFG and lands managed solely by ADFG. My sense is that the decision-set for lands managed collaboratively by NPS and ADFG would have looked quite similar, while an additional alternative – predator control - may have been included in the ADFG-only decision model. Having two spatial extents for similar bear populations (e.g. 2 neighboring coastal bear populations) would provide for more rapid learning about what level of predator control, if any, would allow ADFG to achieve its objective of maximizing ungulate harvest objective (given a bear sustainability constraint). Because this scenario involves simultaneous implementation of decisions, learning could occur over space by comparing outcomes of alternate policies on neighboring lands. The scientific uncertainty (namely, is predator control effective at maximizing ungulate harvest in X management unit?) could be reduced, and, hopefully, the dialogue would change between resource managers. Ultimately, I don’t expect that this process would resolve deep-rooted conflicts regarding state and federal sovereignty, but it could at least change the discussion so that it is properly framed as a conflict about values rather than a conflict about science.

WHAT IS A NATURAL RESOURCE DECISION ANALYST?

Decision analytic tools include a broad range of methods including, but not limited to, facilitation, elicitation (of stakeholder values and expert knowledge), methods for integrating scientific and other knowledge (e.g. via the use of models), parameter estimation, statistical and optimization techniques. Adaptive management is an extension of structured decision making that uses dynamic optimization (which requires the use of relatively complex mathematical algorithms) to find optimal solutions. A natural resource decision analyst should have strong working knowledge of wildlife management, ecology, conservation biology, and/or some other form of the natural sciences. Moreover, a good understanding of relevant policy is required to properly facilitate the framing of decision problems. In addition to those skills, and the ones I described above, I suggest that natural resource decision analysts add environmental economic and conflict management (or at least identification) tools to their toolbox.

ARM practitioners have effectively borrowed and implemented optimization techniques from the field of economics and have applied them to find optimal solutions to natural resource decision problems. In most cases some biological objective (e.g. species persistence) is optimized, generally under a management cost constraint (or vice versa). Rarely is a rigorous economic analysis of both costs and benefits conducted. This is, at least in part, because natural resource management agencies rarely have the time and resources to perform such an assessment. Instead, costs of management implementation are almost always monetized (as dictated by the National Environmental Policy Act) while benefits are qualitatively described. Monetizing costs while only qualitatively describing benefits may feed the "economy versus the environment" viewpoint by the public (Loomis and White 1996, Bockstael et. al. 2000). Thus, I believe that decision analysts should at least be aware of methods for incorporating economic valuation techniques of environmental commodities into the SDM process (when and if the decision scope dictates that it is appropriate to do so). Applying this critique to my dissertation, I also did not monetize costs of management implementation for the brown bear project. That said, the techniques used to monetize environmental commodities are tools in my decision analyst toolbox, and I hope to use them where feasible and appropriate. I used one of those tools in Chapter 4, benefit transfer, to estimate monetary values for two out of four of the bear fundamental objectives (i.e., harvest and non-consumptive use), but I was unable to monetize the value of bears being "baseline." If I had the benefit of more time, it would have been interesting to use transferred values for harvest and non-consumptive use to evaluate how much bear populations would need to be valued in order to reach the same optimal decisions.

Moreover, this discussion has been laden with details regarding conflict. I have used the terms "underlying" and "deep-rooted" conflicts which are very specific diagnoses in the field of conflict management that refer to levels of conflict (deep-rooted being the most severe; Hammil et. al. 2009). The nature of managing trust resources, which almost always involve multiple user groups, essentially dictates that natural resource decision processes will involve conflict. ARM is designed to resolve conflicts about science, and the SDM process can often resolve conflicts about objectives. For example, during objectives structuring it is often revealed that stakeholders had confused means and fundamental objectives and that true fundamental objectives were not in conflict. Stakeholders may also find that they can satisfy alternate fundamental objectives via the same means, in turn, facilitating identification of common ground and acceptable trade-offs. Finally, multi-attribute utility theory can be used to find an optimal solution that balances conflicting stakeholder values. So, there are certainly tools that SDM and ARM practitioners are armed with when certain conflicts arise; but, in my experience these are not enough. Had I been aware of conciliation at the outset of the sea otter project, perhaps the outcome of that project would have been different. Therefore, I advocate that practitioners at least be able to identify types of conflict, so that they know when to move forward with an SDM/ARM process and when it may be more appropriate to ask for the aid of a conflict management expert.

IN AN IDEAL WORLD

Management programs should involve the creation of collaborative, multi-disciplinary forums that allow specialists to communicate with each other, the public and policy-makers. The long-term protection and management of natural resources is complex as resources span agency jurisdictional lines and stark differences often exist in the rules governing decision-making agencies. These differences can result in a wedge that hinders formation of collaborative relationships that are essential for achieving effective natural resource decision making. If I was president and thus the chief of the executive branch, I would re-organize the current structure of federal agencies within the Department of the Interior to better integrate monitoring, research and management agencies.

Conroy and Peterson (2009) use the analogy of a three-legged stool to describe the relationship between research, management, and decision making. Without one of the legs, the stool would surely collapse. Resource trust agencies in the US federal government are currently structured so that jurisdictional boundaries separate agencies responsible for carrying out management, research, and monitoring. For example, in Chapter 5 I describe the disconnect between NPS monitoring and FWS management. Both agencies have the same objective in regard to sea otters, to minimize extinction risk. However, rather than working together to assure that monitoring data is collected to inform management decision making, both agencies are spending extensive time and money working towards the same goal separately. If I were to re-organize this structure, I would put the research agency (USGS) back into the management agency (USFWS). I would also reorganize jurisdictional boundaries. Lastly, I will close with this rhetorical question: since the NPS has the resources and capacity to conduct monitoring, research, and management of the sea otters within their boundaries, shouldn't they also have the jurisdiction to make management decisions?

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