2014

Decision Support for Natural Resource Management

Jonathan Cummings
University of Vermont

Recommended Citation

Cummings, Jonathan, "Decision Support for Natural Resource Management" (2014). *Graduate College Dissertations and Theses*. 290.
https://scholarworks.uvm.edu/graddis/290

DECISION SUPPORT FOR NATURAL RESOURCE MANAGEMENT

A Dissertation Presented

by

Jonathan Wellesley Cummings

to

The Faculty of the Graduate College

of

The University of Vermont

In Partial Fulfillment of the Requirements
for the Degree of Doctor of Philosophy
Specializing in Natural Resources

October, 2014

Accepted by the Faculty of the Graduate College, The University of Vermont, in partial fulfillment of the requirements for the degree of Doctor of Philosophy, specializing in Natural Resources.

Dissertation Examination Committee:

______________________________________ Advisor
Therese (Terri) Donovan , Ph.D.

____
James (Jed) Murdoch, Ph.D.

____
Jennifer Pontius, Ph.D.

______________________________________ Chairperson
Ruth Mickey, Ph. D.

______________________________________ Dean, Graduate College
Cynthia J. Forehand, Ph.D.

Date: August 21, 2014

ABSTRACT

This research spans a variety of research topics with a common theme, providing decision support through the development and analysis of methods that assist decision making for natural resource and wildlife management. I used components of structured decision making and decision analysis to address natural resources management problems, specifically monitoring and estimating the status of harvested populations, as well as data collection decisions for landscape conservation.

My results have implications for the way populations are monitored and their status is estimated. I find that the inclusion of error in data collection can have a substantial impact of the performance of abundance and growth rate estimates of harvested species and that the selection of estimation methods depends on what management objectives are most important. For example, the Sex-Age-Kill population estimation method best estimates the size of populations, while the Downing population reconstruction method better estimates trends in population growth rates. I provide a framework to support selection of the best estimation method while considering a monitoring program as a whole. Based on this framework the Vermont Fish and Wildlife Department will obtain the most benefits from a monitoring program including necropsy analysis that uses the Downing method to track population status. Finally, I demonstrated the use of value of information analysis as a tool to determine the relative expected benefits of addition spatial data collection for use in landscape mapping and conservation. This type of analysis can provide conservation agencies with a planning tool to direct budgets and mapping efforts.

CITATIONS

Material from this dissertation was submitted for publication to Ecological Applications on December, 18, 2013 in the following form:

Cummings, J.W. and Donovan, T.. The value of maps in natural resource management: an application of Expected Value of Sample Information. Ecological Applications.

ACKNOWLEDGEMENTS

Information critical to the completion of this research was provided by Chris Bernier, Kim Royar, Scott Darling, Kimberly Wallin, and Daniel Herms.

Funding was provided by the United States Geological Survey and the Vermont Fish and Wildlife Department.

Thank you to all those who supported me and the completion of this research! Text here is a poor way to acknowledge your assistance, so I will just list those who helped me and hopefully have the opportunity to thank you in person at some time. Lauren Kordonowy, Anne, James and Daniel Cummings, Stod and Leonore Johnson, Phil and Sharon Cummings, Larry and Lauren Johnson, Robert Johnson, Nancy Gillett, Kim and Paul Kordonowy, David and Gwen and Lydia Kordonowy, Terri Donovan, Jed Murdoch, Jennifer Pontius, Ruth Mickey, Mike Runge, Sarah Converse, Dave Smith, Steve Morey, Brady Mattson, Conor McGowan, Max Post van den Berg, Mitch Eaton, Michelle Haynes, Donna Brewer, Kurt Rinehart, Michelle Brown, Jon Katz, Corrine Brauer, Charlie Bettigole, Scott Schwenk, Flavio Sutti, Michael Macdonald, Jean Lee, Wendy Cole, Hannah Davie, Allison Gulka, Eliese Dykstra, Christine Peterson, Jen Walsh, Sarah Levy, Kara Sarver, Lindsay Havens, Sheldon Hurst IV., Valerie Esposito, Rebecca Carlson, Randall Peterman, Dave Patterson, Merran Hague, Duncan Knowler, John Peterson, Roger Laushman, Dr. Madelina, Mr. Ahern, and Mr. Weiss.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1. INTRODUCTION

1.1 Dissertation Haiku and Big Picture Summary

I recently discovered there is a website that publishes PhD dissertations in haiku form (http://dissertationhaiku.wordpress.com/), so without further ado, here is my PhD in haiku form:

There's a better way
Structured Decision Making
This is how it works

This dissertation spans a variety of research topics with a common theme, decision support for natural resource management. The big picture view of this effort is captured above, with the dissertation itself focusing on developing, demonstrating, and analyzing methods that can assist decision making for natural resource and wildlife management. I describe particular applications of these methods to landscape conservation decisions as well as game species management and monitoring.

Currently the predominant process for making natural resource decisions is structured decision making (SDM), which is the approach to decision support used in this dissertation. SDM is used to identify the components of a problem, namely the objectives to be achieved and the alternatives available to meet them. Once the components of the problem are identified, decision analysis is implemented to determine the alternative that best achieves the objectives.

For this dissertation, I used components of SDM and decision analysis to address natural resources management questions. The questions addressed are wildlife management and landscape conservation related. Specifically, what estimation methods are best for determining the status of game species populations in the presence of error in harvest data collection, which monitoring program best achieves game species management objectives, and how valuable mapping efforts are for landscape conservation.

1.2 Structured Decision Making

Structured Decision Making is a process for deconstructing the pieces of a decision process, examining and developing them one at a time, and finally recombining the pieces to see the full view of a problem and arrive at the best available decision (Gregory et al. 2012, Conroy and Peterson 2013). It is a process that arose from combining elements of economic analysis, management science, conservation planning, and the scientific method (Edwards et al. 2007). From an analytical perspective, the decision analysis techniques used in SDM come from an expansion of cost-benefit analysis to include multiple objectives that are often expressed in units other than dollar values. This form of decision analysis, known as multiple criteria decision analysis (MCDA, Keeney and Raiffa 1976), is the predominant decision analysis method from which SDM is built. Another important expansion of previous decision analysis techniques is that SDM begins by identifying the values decision makers are interested in achieving. These values are specified at the beginning of the process, shape the problem framing that is developed, and therefore aid in determining both the appropriate form of MCDA to conduct and the variables to include (Keeney

1992). The initial focus on the values to be achieved places an emphasis on interaction between decision analysts, decision makers, and the stakeholders whose views are included for consideration in identifying the values to address. Due to the interactive nature of eliciting objectives and identifying alternatives, this portion of the process borrows heavily from techniques in the fields of facilitation, planning, cooperative management, and negotiation.

The steps of the Structured Decision Making approach are referred to using the abbreviation PrOACT (Hammond et al. 1999). The PrOACT steps are: identifying the **Pr**oblem, describing the **O**bjectives, enumerating the **A**lternatives, predicting the **C**onsequences, and evaluating the **T**rade-offs.

The purpose of identifying and documenting the problem for decision analysis is to place all participants (such as the decision analyst, decision maker(s), stakeholders, scientists, public, etc.) on the same page about what is being considered and to aid communication between participants and any other interested parties. The key component of documenting a problem is the decision – the irrevocable allocation of resources. However, other common components include: the trigger that makes the decision a pressing problem, who the decision makers are, when the decision needs to be made, any key objectives, additional actions or uncertainties to consider, and any factors that limit the objectives or alternatives that can be considered.

Objectives are the values or goals the decision maker aims to achieve by making the decision. To make them useful in a decision analysis framework, objectives are specified with a direction and a measureable noun; for example, an objective could be to maximize the number of deer harvested. In this example, the direction is maximizing, and the number of deer harvested gives a measureable attribute to the desire to harvest objective so that outcomes can be compared. Often decisions involve multiple objectives that trade-off with each other. For example, other objectives of a deer management plan likely include maximizing the number of deer in the population, as well as minimizing the number of negative human–deer interactions, objectives that are probably negatively correlated.

Alternatives are the actions or things that the irrevocable allocations of resources are directed towards. A list of alternatives is the list of items that a decision maker is selecting one of when making a decision. A single alternative at times can consist of multiple action elements that are combined into a single selectable entity, (known as a strategy or portfolio alternative).

The problem, objective, and alternatives portions of the process are the areas where facilitation and planning techniques are relevant, because this portion of the process focuses on engaging participants and eliciting information from them. This is also when stakeholders can aid and contribute to the decision making process (Howard 1975, Gregory and Keeney 1994, Redpath et al. 2004, Dankel et al. 2007) by assisting in identifying the attributes (Martin et al. 2000) such as the objectives they deem important, the alternatives they believe could be successful, or the consequences they predict would result from implementing an alternative. The techniques developed in this dissertation will likely be most beneficial when natural resource managers and stakeholders work with a facilitator to guide them through the planning portion of the SDM process.

Once the problem has been framed, i.e., the problem, objectives and alternatives have been identified, the next step is to predict consequences that would result from selecting any one of the alternatives. The consequences are measured in terms of the degree to which they achieve the objectives. The prediction of consequences relies either on elicitation of expert knowledge to produce forecasts (e.g., Ayyub 2001, Martin et al. 2012, McBride et al. 2012, Perera et al. 2012), past observation of outcomes in similar settings (e.g., scientific observation), or some form of predictive statistical modeling (e.g., Starfield and Bleloch 1986, Starfield 1997).

1.3 Decision Analysis

The final step in structured decision making, apart from actually deciding and implementing an alternative, is the analysis of tradeoffs through decision analysis. Decision analysis focuses on determining the best action to take in order to select the best available alternative and address the problem at hand. As noted previously, decision analysis is the key element that SDM was built around. The early development of decision analysis resulted from the efforts of Ronald Howard (Howard 1966, 1975, 1980, 1988). Following Howard's work, there were efforts to expand upon the central decision analysis technique (Keeney and Raiffa 1993), to include the values focused approach to problem framing (Keeney 1992), and to distill the process down to its key components for ease of communication (Hammond et al. 1999). Since its origination, the techniques of decision analysis have been further developed and expanded to match a variety of decision types, and the application to environmental decisions has greatly expanded. Indeed, a review by Ivy Huang et al. (2011) found that the published use of MCDA for environmental problems has increased from the single digits in the 1990s to hundreds of applications by the late 2000s.

Expansion in the use decision analysis, along with the spreading idea that management actions can be tracked over time in the form of scientific observations, has placed a greater emphasis on making transparent, repeatable decisions and on recording the performance of management actions over time, resulting in the expanding use of structured decision making (for example, see: http://nctc.fws.gov/courses/ALC/ALC3159/reports/index.html). The increasing use of adaptive management, a specialized form of SDM for recurrent decisions where learning can improve future outcomes, may also be responsible for the increased interest in SDM. By using SDM in conjunction with adaptive management, decision analysts can provide managers with a monitoring plan as well as a transparent rational for what decisions were made and what actions were taken so that learning can occur over time to improve future decisions (Walters 2001, Walters 2007, Ruhl and Fischman 2010, McFadden et al. 2011).

1.4 Natural Resources and Wildlife Management

This dissertation focuses on applying decision analysis techniques to the management of wildlife and natural resources. Natural resources are the natural capital that supports our human economy (Hawken et al. 1999). Natural resources also benefit us through their general use, through the aesthetic benefits I derive, and through their existence. Wildlife species in particular provide society with a number of benefits, such as filling important roles in an ecosystem, providing recreational, aesthetic, and existence value, and enabling economic and subsistence benefits through harvest

(Decker et al. 1987). The role of wildlife management is to maintain these benefits, which requires ensuring that populations are healthy and sustainable.

1.5 Game Species Management

Successful game species management is an important aspect of effective wildlife management authorities. Game species are those that are harvested in one form or another to provide recreational, subsistence, and economic benefits. Unsuccessful game species management can result in decreased benefits due to individuals being unavailable for harvest both now and in the future and for other non-consumptive uses when over-harvest occurs. Alternatively under-harvest can result in opportunity costs from forgoing current harvest or in damage due to overpopulation, which may lead to excessive human-wildlife conflict. Managing a game species to obtain optimal benefits requires an understanding of its life history, its habitat needs, the way it interacts with its ecosystem, and an assessment of the status of the species (Sinclair et al. 2006). Assessing species status and adjusting management practices and harvest regimes is one of the main tasks game species managers perform.

In order to successfully manage game species and adjust management practices, most managers require an accurate assessment of the population status. Obtaining that assessment requires time and effort to collect and analyze data. Optimal game species management is therefore a combination of collecting data effectively and efficiently and selecting the best method for analysis. Due to the many interactions wildlife managers have with other agencies and the public, collecting data in a way that facilitates interaction with their partners is often another key to effective management (C. Bernier pers. comm., Vermont Fish and Wildlife Department). In the chapters that follow, I evaluate the impacts of data quality on game species status assessment and determine what estimation methods provide the best assessments (chapter 2), and I explore what monitoring program provides the best data for game species assessment while facilitating wildlife management agency outreach efforts and disease detection objectives (chapter 3).

1.6 Estimating Abundance

There are numerous methods available for converting monitoring data into estimates of abundance (Skalski et al. 2005). The particular abundance estimation methods available to a game species manager depends on what is collected (Skalski et al. 2005). The simplest monitoring programs only collect annual counts of the total number of individuals harvested. There are other ways of counting harvest that can provide additional information, such as counting harvest by day, by harvest method, or by season. Counting harvest by age, by age group, or by sex also supports the use of additional estimation methods (e.g., Eberhardt 1960, Downing 1980, Fryxell et al. 1988, Gove et al. 2002, Fieberg et al. 2010).

Monitoring programs can also increase the range of abundance estimation methods available by collecting other information about game species in addition to the numbers harvested, such as hunting effort, life history characteristics, and vital rates (Skalski et al. 2005). Tracking the hunting effort a species was subject to daily or throughout the season allows managers to utilize removal and catch per unit effort abundance estimation methods (e.g., Otis et al. 1978, Huggins 1989, Gould and Pollock 1997). Information about demographic rates of a game species enables use of the more complex abundance estimation methods, such as statistical population reconstruction (e.g., Gove et al. 2002, Skalski et al. 2007, Fieberg et al. 2010). There are a number of methods for collecting information about demographic rates, and studies tracking the fate of marked individuals are used quite frequently.

1.6.1 Harvest Index Method

Harvest indices provide indirect abundance estimates from counts of a portion of a population, such as the number of harvested individuals. The ratios of membership in sub-groups of the population (e.g. the ratio of adult females to adult males that are harvested) are sometimes used as well. For example, both adult sex ratio and juvenile to adult female ratios are common indices of abundance for furbearers (Douglas and Strickland 1987). The number of either harvested individuals or another portion of a total population provides an index of the total population size, but variability in effort and harvest success result in this being an imperfect indicator of the total abundance (Skalski et al. 2005).

1.6.2 Removal Method

The information contained in daily harvest counts enables the use of removal methods to estimate population size (Skalski et al. 2005). Removal methods compute a probability of harvest for each animal in the population for every day of the harvest from daily harvests in order to estimate the total number of animals that do not get harvested during the harvest season (Otis et al. 1978, Huggins 1989). Adding the observed harvest count to the estimated number of individuals that were not harvested produces the pre-season estimate of abundance. However, use of the removal method requires the assumption that the only source of change to the population size is through the removal of harvested individuals (e.g. there are no immigrates or emigrates, no births, and no deaths other than harvest) during the hunting season.

1.6.3 Catch Per Unit Effort Method

With both daily harvest counts and daily effort data, the catch per unit effort methods are options for estimating abundance. Catch per unit effort methods estimate the population size necessary to result in the observed harvest by deriving both the probability of harvest from one unit of effort and the population size necessary to produce the observed harvest given the probability of harvest from one unit of effort and the effort exerted on the population. (DeLury 1947, Otis et al. 1978, Gould and Pollock 1997).

1.6.4 Sex-Age-Kill Method

The Sex-Age-Kill method is based on recreating the total abundance using life history rates for the species being monitored. This method requires estimates of the proportion of the mortality due to harvest, the number of young per adult female, and counts of the number of harvested individuals by age group and sex. Using the proportion of mortality due to harvest, the estimated male harvest is converted into male abundance. Based on the estimated adult sex ratio, the adult female abundance is estimated, and the number of young individuals is estimated from the female abundance using the estimate of young per adult female. Summing the adult male, adult female, and young abundance estimates produces the total abundance estimate (Eberhardt 1960, Roseberry and Woolf 1991, Millspaugh et al. 2009).

1.6.5 Population Reconstruction Methods

Population reconstruction methods are based on data that includes counts of harvested individuals by age, known as age-at-harvest data. These methods back-calculate the initial abundance necessary to produce the year and age specific harvests observed. This provides the minimum abundance necessary to produce the observed harvest. To determine the estimated abundance rather than the minimum abundance necessary to produce the harvest, various virtual population reconstruction methods use different methods of adjusting the minimum abundance (Skalski et al. 2005). These adjustments are based upon calculated demographic rates for the virtual population reconstruction methods or supplied rates from additional data for the statistical population reconstruction methods.

The difference between the various virtual population reconstruction methods is how they account for the survival and exploitation rates. The method utilized by Fry (1949) simply estimates the minimum population size by summing lifetime harvest numbers for each cohort. Because the Fry method does not account for additional sources of mortality, this abundance estimate is only an index of the total population size and not an accurate estimate of the total population size.

The Downing reconstruction method does not estimate vital or harvest rates directly either, but uses a weak proxy of adult mortality to reconstruct the pre-hunt population by backward-addition of known mortality and a minimal assumption of unaccounted-for mortality (Downing 1980). The performance of the Downing method is improved by pooling adults to produce a single adult age class, a practice that is typically followed in the use of this method (Davis et al. 2007).

The Fryxell reconstruction method uses effort data in addition to age at harvest data to inflate harvest counts and to obtain an abundance estimate (Fryxell et al. 1988). This method also requires an estimate of the natural survival rate by age. These additional inputs require more data collection efforts, but can result in less negatively biased abundance estimates than the Fry and Downing methods (Fryxell et al. 1988, Skalski et al. 2005).

The virtual population reconstruction methods listed above have difficulty obtaining estimates from incomplete cohorts (Skalski et al. 2005). Statistical population reconstruction (SPR) methods use auxiliary data to avoid this bias (Gove et al. 2002). SPR methods are flexible to various auxiliary data inputs, so long as they provide information about either a demographic rate of the population or the likelihood of counting an individual. Therefore, there is no single SPR method, but instead a general technique that is adaptable to the information available. The information is used in a joint likelihood framework to determine the population size by finding the abundance with the maximum likelihood for providing the information entered into the SPR analysis.

In chapter 2, I evaluate the performance of the abundance estimators currently available for estimating the abundance of fisher (*Martes pennanti*) in the state of Vermont, USA based on the data the Vermont Fish and Wildlife Department collects from its fisher monitoring program.

1.7 Monitoring Programs

Monitoring programs enable production of the abundance estimates used for wildlife management. While obtaining accurate abundance estimates through monitoring is a key objective of a monitoring program (Lyons et al. 2008), there are additional considerations for selection of a monitoring program. For instance, an agency may have objectives that include minimizing the cost of data collection, maximizing the precision in abundance estimates, minimizing the bias of abundance estimates, maximizing the probability of detecting a disease in the game species, and maximizing the level of citizen, academic institution, and recreational participant engagement in and knowledge of the management process.

The degree to which a monitoring program will achieve these objectives depends upon what activities are included in the monitoring program. For example, to carry out their mission and meet their objectives, the Vermont Fish and Wildlife Department collects three types of data to assess the fisher population status: daily harvest data, daily effort data, and necropsy data, which provides information on the age and sex of harvested individuals, as described below. However, it is possible that collecting only harvest data, or harvest and effort data would better meet the full set of the monitoring program objectives.

I apply structured decision making, and the SMART decision analysis technique to evaluate the tradeoffs between the objectives for the fisher monitoring programs available to the Vermont Fish and Wildlife Department in chapter 3.

1.8 Fisher

I use fisher management in Vermont as the managed game species for analysis in chapters 2 and 3. While fishers were once nearly extirpated in Vermont, they were successfully reintroduced in the 1960s (Powell and Zielinski 1994). Following reintroduction, they have been harvested in Vermont since 1974, other than during a five year trapping reprieve between 1979 and 1983 (Powell and Zielinski 1994).

The fisher is the largest member of the *Martes* genus, with males averaging 3.3 kg and 60 cm in length and females averaging 1.8 kg and 51 cm (Douglas and Strickland 1987). Females produce their first litter at 24 months and proceed to produce one litter per year thereafter, while males become reproductively active at age one (Powell and Zielinski 1994). Breeding females have been found to produce between one and four corpora lutea annually, with averages ranging from 1.8 to 2.7 across ages in studies within the northeastern U.S., but averages are slightly higher for females in their peak reproductive years (Douglas and Strickland 1987, Van Why and Giuliano 2001, Powell et al. 2003). Offspring sex ratio has not been found to differ from 50:50 (Powell 1994). The annual recruitment (birth rate) of offspring into the population has been found to range from 0.63 to 4.14 offspring per female, with means ranging from 1.18 to 2.16 across studies in the northeast (Paragi et al. 1994, Koen et al. 2007, Buskirk et al. 2012).

The estimated life span of a fisher is 10 years (Powell et al. 2003), and the survival rate depends on their age and the trapping rate. The annual without trapping survival rate commonly ranges between 0.7 and 0.8 for juveniles and 0.9 and nearly 1 for adults (Krohn et al. 1994, Powell 1994). In the presence of trapping, adult survival rates as low as 0.61 have been observed, while juvenile survival rates for heavily trapped populations has been recorded to be as low as 0.34 (Krohn et al. 1994, Powell 1994). Fisher density has been found to range from 0.05 to 0.38 fisher per square kilometer, with an average value of 0.18 in habitat similar to Vermont (Powell et al. 2003).

1.9 Mapping

Wildlife and other natural resources exist in landscapes, making both habitat management programs and landscape scale data collection efforts a key component of conservation efforts (Poiani et al. 2000, Hilty and Groves 2008). Many of the most pressing challenges facing wildlife managers include human population growth, landscape development, and climate change, all of which operate predominantly at the landscape scale (Schwartz 1999). Spatial information is used to aid management for these and other landscape scale problems, such as determining the risk of invasive species colonization (Gormley et al. 2011), the design and selection of sites for biodiversity reserves (Csuti et al. 1997, Araujo and Williams 2000, Cabeza and Moilanen 2001), and the prediction of outcomes from wildlife reintroductions (Carden et al. 2010, Cook et al. 2010, Zimmermann et al. 2011). Therefore, the demand for spatially explicit scientific information has increased to address various landscape conservation efforts.

While spatial information can substantially benefit management efforts, these benefits are constrained by the reliability of the spatial information. Reliability is a product of the bias and precision with which landscapes are classified into categories, the size of the area at which classification occurs, any errors accrued during site assessment, and irregularities across combined mapping efforts (Aerts et al. 2003). These factors result in uncertainty that a management action taken based on spatial data will achieve the management goal.

Given the uncertainty present in spatial data collection and the limited resources that land managers have available for landscape scale research, managers may benefit from a means to evaluate alternative management actions and to choose an action that optimizes their management goals (Noon et al. 2012). To address spatial data collection decisions, chapter 4 evaluates the value of spatial data collection to natural resource management using a method known as value of information.

1.10 Value of Information

There are numerous uncertainty types that can affect management decisions and their outcomes. Decisions require predictions of the future. These predictions can be based on a combination of past experience, expert knowledge, or predictive models, all of which can be affected by uncertainty. The uncertainties affecting decisions are: measurement error (i.e., imperfect observation of the past), subjective judgment (i.e., human errors in the elicitation and documentation of expert knowledge), systematic error or bias (i.e., acting in an inherently error prone manner, which can affect all sources of information), the model based parametric uncertainty (i.e., uncertainty about the true value of model inputs), and structural uncertainty (i.e., uncertainty about the form of the model) (Morgan and Henrion 1990). Decision analysts developed decision trees, sensitivity analyses, and other methods in order to account for uncertainty in decision making (Morgan and Henrion 1990).

Decision trees model the possible chain of events between the initial actions a decision maker considers and the possible final outcomes. The intermediate events in a decision tree model the different paths, or branches, that can result from uncertainty about the future. A branching point is added for each factor that can cause multiple possible outcomes given the initial set of available alternatives.

Value of information (VoI) analyses originated as extensions of uncertainty analysis tools, where the initial decisions to be made are: what type of information to use in making a decision, and determining the branching points representing the possible predictions and subsequent decisions that could be made with the various information available (Morgan and Henrion 1990). VoI analyses compare the expected outcome of taking an action or making a decision using only the current knowledge that is available with the expected outcome of collecting additional information prior to making the decision.

The type of VoI analysis I conduct in chapter 4 is referred to as Expected Value of Sample Information (EVSI), where the value of the information contained in a sample (e.g. a survey, map, or field data) is being determined. The EVSI approach is used to provide an estimate of the value of spatial information for natural resource management purposes. By predicting the expected value of obtaining additional spatial information, I provide managers with a means to evaluate the potential benefits of research efforts which can be used to optimize research budgets and better target their management actions.

1.11 References – Introduction

Aerts, J. C. J. H., M. F. Goodchild, and G. B. M. Heuvelink. 2003. Accounting for spatial uncertainty in optimization with spatial decision support systems. Transactions in GIS **7**:211-230.

Araujo, M. B., and P. H. Williams. 2000. Selecting areas for species persistence using occurrence data. Biological Conservation **96**:331-345.

Ayyub, B. M. 2001. Elicitation of expert opinions for uncertainty and risks. CRC Press, Boca Raton, Florida, USA.

Buskirk, S. W., L. Bowman, and J. H. Gilbert. 2012. Population biology and matrix demographic modeling of american martens and fishers. Pages 77-92 *in* K. B. Aubry, W. J. Zielinski, M. G. Raphael, G. Proulx, and S. W. Buskirk, editors. Biology and conservation of martens, sables, and fishers : a new synthesis. Comstock Pub. Associates, Ithaca, New York, USA.

Cabeza, M., and A. Moilanen. 2001. Design of reserve networks and the persistence of biodiversity. Trends in Ecology & Evolution **16**:242-248.

Carden, R. F., C. M. Carlin, F. Marnell, D. McElholm, J. Hetherington, and M. P. Gammell. 2010. Distribution and range expansion of deer in Ireland. Mammal Review **41**:313-325.

Conroy, M. J., and J. T. Peterson. 2013. Decision making in natural resource management: a structured, adaptive approach. Wiley, Hoboken, New Jersey, USA.

Cook, C. N., D. G. Morgan, and D. J. Marshall. 2010. Reevaluating suitable habitat for reintroductions: lessons learnt from the eastern barred bandicoot recovery program. Animal Conservation **13**:184-195.

Csuti, B., S. Polasky, P. H. Williams, R. L. Pressey, J. D. Camm, M. Kershaw, A. R. Kiester, B. Downs, R. Hamilton, M. Huso, and K. Sahr. 1997. A comparison of reserve selection algorithms using data on terrestrial vertebrates in Oregon. Biological Conservation **80**:83-97.

Dankel, D. J., U. Dieckmann, and M. Heino. 2007. Success in fishery management by reconciling stakeholder objectives in Hilborn's "Zone of new consensus". International Council for the Exploration of the Sea Annual Science Conference 2007, Helsinki, Finland.

Davis, M. L., J. Berkson, D. Steffen, and M. K. Tilton. 2007. Evaluation of accuracy and precision of Downing population reconstruction. Journal of Wildlife Management **71**:2297-2303.

Decker, D. J., G. R. Goff, and Wildlife Society. New York Chapter. 1987. Valuing wildlife : economic and social perspectives. Westview Press, Boulder.

DeLury, D. B. 1947. On the Estimation of Biological Populations. Biometrics **3**:145-167.

Douglas, C. W., and M. A. Strickland. 1987. Fisher. Pages 510-529 Wild Furbearer Management and Conservation in North America. Ontario Trappers Association and Ontario Ministry of Natural Resources, Ontario, Canada.

Downing, R. L. 1980. Vital statistics of animal populations. Pages 247-267 *in* S. D. Schemnitz, editor. Wildlife techniques manual. The Wildlife Society, Washington, D.C., USA.

Eberhardt, L. L. 1960. Estimation of vital characteristics of Michigan deer herds. Michigan Department of Conservation Game Division, East Lansing, Michigan, USA.

Edwards, W., R. F. Miles, and D. Von Winterfeldt. 2007. Advances in decision analysis : from foundations to applications. Cambridge University Press, Cambridge, UK and New York, USA.

Fieberg, J. R., K. W. Shertzer, P. B. Conn, K. V. Noyce, and D. L. Garshelis. 2010. Integrated population modeling of black bears in Minnesota: implications for monitoring and management. PLoS One **5**:11.

Fry, F. E. J. 1949. Statistics of a Lake Trout Fishery. Biometrics **5**:27-67.

Fryxell, J. M., W. E. Mercer, and R. B. Gellately. 1988. Population dynamics of Newfoundland moose using cohort analysis. Journal of Wildlife Management **52**:14-21.

Gormley, A. M., D. M. Forsyth, P. Griffioen, M. Lindeman, D. S. L. Ramsey, M. P. Scroggie, and L. Woodford. 2011. Using presence-only and presence-absence data to estimate the current and potential distributions of established invasive species. Journal of Applied Ecology **48**:25-34.

Gould, W. R., and K. H. Pollock. 1997. Catch-effort maximum likelihood estimation of important population parameters. Canadian Journal of Fisheries and Aquatic Sciences **54**:890-897.

Gove, N. E., J. R. Skalski, P. Zager, and R. L. Townsend. 2002. Statistical models for population reconstruction using age-at-harvest data. Journal of Wildlife Management **66**:310-320.

Gregory, R., L. Failing, M. Harstone, G. Long, T. McDaniels, and D. Ohlson. 2012. Structured Decision Making: A Practical Guide to Environmental Management Choices. Wiley-Blackwell, West Sussex, UK.

Gregory, R., and R. L. Keeney. 1994. Creating policy alternatives using stakeholder values. Management Science **40**:1035-1048.

Hammond, J. S., R. L. Keeney, and H. Raiffa. 1999. Smart choices : a practical guide to making better decisions. Harvard Business School Press, Boston, Massachusetts, USA.

Hawken, P., A. B. Lovins, and L. H. Lovins. 1999. Natural capitalism : creating the next industrial revolution. 1st edition. Little, Brown and Co., Boston, Massachusetts, USA.

Hilty, J. A., and C. R. Groves. 2008. Conservation planning: new tools and new approaches.*in* R. L. Knight and C. White, editors. Conservation for a New Generation: Redefining Natural Resources Management. Island Press, Washington, D.C., USA.

Howard, R. A. 1966. Decision analysis: applied decision theory.*in* International Conference on Operational Research. Wiley, New York, USA.

Howard, R. A. 1975. Social decision analysis. Proceedings of the Ieee **63**:359-371.

Howard, R. A. 1980. Assessment of decision-analysis. Operations Research **28**:4-27.

Howard, R. A. 1988. Decision-analysis - practice and promise. Management Science **34**:679-695.

Huang, I. B., J. Keisler, and I. Linkov. 2011. Multi-criteria decision analysis in environmental sciences: Ten years of applications and trends. Science of the Total Environment **409**:3578-3594.

Huggins, R. M. 1989. On the Statistical-Analysis of Capture Experiments. Biometrika **76**:133-140.

Keeney, R. L. 1992. Value-focused thinking : a path to creative decisionmaking. Harvard University Press, Cambridge, Massachusetts, USA.

Keeney, R. L., and H. Raiffa. 1976. Decisions with multiple objectives: preferences and value tradeoffs. Cambridge University Press, New York, USA.

Keeney, R. L., and H. Raiffa. 1993. Decisions with multiple objectives : preferences and value tradeoffs. Cambridge University Press, Cambridge UK and New York, USA.

Koen, E. L., J. Bowman, and C. S. Findlay. 2007. Fisher survival in eastern Ontario. Journal of Wildlife Management **71**:1214-1219.

Krohn, W. B., S. M. Arthur, and T. F. Paragi. 1994. Mortality and vulnerability of a heavily trapped fisher population. Pages 137-145 *in* S. Buskirk, A. S. Harestad, M. G. Raphael, and R. A. Powell, editors. Martens, sables, and fishers : biology and conservation. Comstock Pub. Associates, Ithaca, New York, USA.

Lyons, J. E., M. C. Runge, H. P. Laskowski, and W. L. Kendall. 2008. Monitoring in the context of structured decision-making and adaptive management. Journal of Wildlife Management **72**:1683-1692.

Martin, T. G., M. A. Burgman, F. Fidler, P. M. Kuhnert, S. Low-Choy, M. McBride, and K. Mengersen. 2012. Eliciting expert knowledge in conservation science. Conservation Biology **26**:29-38.

Martin, W. E., H. W. Bender, and D. J. Shields. 2000. Stakeholder objectives for public lands: Rankings of forest management alternatives. Journal of Environmental Management **58**:21-32.

McBride, M. F., S. T. Garnett, J. K. Szabo, A. H. Burbidge, S. H. M. Butchart, L. Christidis, G. Dutson, H. A. Ford, R. H. Loyn, D. M. Watson, and M. A. Burgman. 2012. Structured elicitation of expert judgments for threatened species assessment: a case study on a continental scale using email. Methods in Ecology and Evolution **3**:906-920.

McFadden, J. E., T. L. Hiller, and A. J. Tyre. 2011. Evaluating the efficacy of adaptive management approaches: Is there a formula for success? Journal of Environmental Management **92**:1354-1359.

Millspaugh, J. J., J. R. Skalski, R. L. Townsend, D. R. Diefenbach, M. S. Boyce, L. P. Hansen, and K. Kammermeyer. 2009. An evaluation of sex-age-kill (SAK) model performance. Journal of Wildlife Management **73**:442-451.

Morgan, M. G., and M. Henrion. 1990. Uncertainty: a guide to dealing with uncertainty in quantitative risk and policy analysis. Cambridge University Press, Cambridge, UK.

Noon, B. R., L. L. Bailey, T. D. Sisk, and K. S. McKelvey. 2012. Efficient Species-Level Monitoring at the Landscape Scale. Conservation Biology **26**:432-441.

Otis, D. L., K. P. Burnham, G. C. White, and D. R. Anderson. 1978. Statistical inference from capture data on closed animal populations. Wildlife Monographs:3-135.

Paragi, T. F., S. M. Arthur, and W. B. Krohn. 1994. Seasonal and circadian activity patterns of female fishers, *Martes pennanti*, with kits. Canadian Field-Naturalist **108**:52-57.

Perera, A. H., C. A. Drew, and C. J. Johnson. 2012. Expert knowledge and its application in landscape ecology.

Poiani, K. A., B. D. Richter, M. G. Anderson, and H. E. Richter. 2000. Biodiversity conservation at multiple scales: Functional sites, landscapes, and networks. Bioscience **50**:133-146.

Powell, R. A. 1994. Structure and spacing of *Martes* populations. Pages 101-121 *in* S. Buskirk, A. S. Harestad, M. G. Raphael, and R. A. Powell, editors. Martens, sables, and fishers : biology and conservation. Comstock Pub. Associates, Ithaca, New York, USA.

Powell, R. A., S. W. Buskirk, and W. J. Zielinski. 2003. Fisher and Martin: *Martes pennanti* and *Martes americana* Pages 635-649 *in* G. A. Feldhamer, B. C. Thompson, and J. A. Chapman, editors. Wild mammals of North America : biology, management, and conservation. Johns Hopkins University Press, Baltimore, Maryland, USA.

Powell, R. A., and W. J. Zielinski. 1994. Fisher. Pages 38-73 *in* L. F. Ruggiero, K. B. Aubry, S. W. Buskirk, L. J. Lyon, and W. J. Zielinski, editors. American marten, fisher, lynx, and wolverine in western United States. United States Forest Service, General Technical Report RM-254, Fort Collins, Colorado, USA.

Redpath, S. A., B. E. Arroyo, E. M. Leckie, P. Bacon, N. Bayfield, R. J. Gutierrez, and S. J. Thirgood. 2004. Using decision modeling with stakeholders to reduce human-wildlife conflict: a Raptor-Grouse case study. Conservation Biology **18**:350-359.

Roseberry, J. L., and A. Woolf. 1991. A comparative evaluation of techniques for analyzing white-tailed deer harvest data. Wildlife Monographs:3-59.

Ruhl, J. B., and R. L. Fischman. 2010. Adaptive management in the courts. Minnesota Law Review **95**:424-484.

Sinclair, A. R. E., J. M. Fryxell, and G. Caughley. 2006. Wildlife ecology, conservation, and management. 2nd edition. Blackwell Pub., Oxford, UK and Malden, Massachusetts, USA.

Skalski, J. R., K. E. Ryding, and J. J. Millspaugh. 2005. Wildlife demography: analysis of sex, age, and count data. Elsevier Academic Press, Amsterdam and Boston, Massachusetts, USA.

Skalski, J. R., R. L. Townsend, and B. A. Gilbert. 2007. Calibrating statistical population reconstruction models using catch-effort and index Data. Journal of Wildlife Management **71**:1309-1316.

Starfield, A. M. 1997. A pragmatic approach to modeling for wildlife management. Journal of Wildlife Management **61**:261-270.

Starfield, A. M., and A. L. Bleloch. 1986. Building models for conservation and wildlife management. Macmillan; Collier Macmillan, New York, USA and London, UK.

Van Why, K. R., and W. M. Giuliano. 2001. Fall food habits and reproductive condition of Fishers, *Martes pennanti*, in Vermont. Canadian Field-Naturalist **115**:52-56.

Walters, C. J. 2001. Adaptive management of renewable resources. Blackburn Press, Caldwell, New Jersey, USA.

Walters, C. J. 2007. Is adaptive management helping to solve fisheries problems? Ambio **36**:304-307.

Zimmermann, H., H. Von Wehrden, M. A. Damascos, D. Bran, E. Welk, D. Renison, and I. Hensen. 2011. Habitat invasion risk assessment based on Landsat 5 data, exemplified by the shrub Rosa rubiginosa in southern Argentina. Austral Ecology **36**:870-880.

CHAPTER 2. EFFECTS OF MEASUREMENT ERROR ON POPULATION ESTIMATION OF HARVESTED SPECIES

Jonathan W. Cummings[1]
Vermont Cooperative Fish and Wildlife Research Unit
Rubenstein School of Environment and Natural Resources
University of Vermont
Burlington, VT 05405

Therese M. Donovan[2]
U.S. Geological Survey, Vermont Cooperative Fish and Wildlife Research Unit
Rubenstein School of Environment and Natural Resources
University of Vermont
Burlington, VT 05405

Prepublication Disclaimer:

This draft manuscript is distributed solely for purposes of scientific peer review. Its content is deliberative and predecisional, so it must not be disclosed or released by reviewers. Because the manuscript has not yet been approved for publication by the U.S. Geological Survey (USGS), it does not represent any official USGS finding or policy.

---

[1] jwcummin@uvm.edu
[2] tdonovan@uvm.edu

2.1 Abstract

A large number of alternative methods have been proposed for estimating population size and growth rate (λ) of harvested game species, but the effect of errors in data collection have not been evaluated across estimation methods. Using a simulation setting, I evaluated the effect of data collection errors due to incomplete reporting, incorrect aging, and incorrect sexing of harvested individuals on estimator performance over a range of estimators and population trajectories for a simulated fisher (*Martes pennanti*) population. I evaluated four estimators that require only age-at-harvest data: Fry (Fry 1949), Downing (Downing 1980), Sex-Age-Kill (Eberhardt 1960), and an index method. Using coefficient of error and raw bias as the performance measures, under a stable population and without errors in data collection, the Sex-Age-Kill model had the best performance in terms of estimating abundance, while the Fry and Downing methods were the best performers in terms of estimating population trend. Addition of errors to the data collection process affected performance more than changes in population trend, but did not change the relative ranking of estimators in terms of performance in abundance or trend estimation. Overall, reporting error had a greater effect on performance than the effect of aging and sexing error. The exception to this result was the Sex-Age-Kill estimator, where performance improved with the addition of aging and sexing errors based on the life history of the simulated fisher population and the Sex-Age-Kill estimation algorithm.

Key Words: *Martes pennanti*, abundance estimation, game species management

2.2 Introduction

Game species provide society with a number of benefits, such as filling important roles in a functional ecosystem, providing recreational opportunities, and providing aesthetic and existence value, while enabling economic and subsistent benefits through harvest (Decker et al. 1987). The role of wildlife management is to ensure and maintain these benefits, which requires ensuring healthy and sustainable game populations.

Wildlife management agencies manage game species by assessing the status of populations and adjusting management practices accordingly. In order to successfully manage game species, managers require an accurate assessment of the population status.

A large number of alternative methods have been proposed for estimating population size of harvested game species (Skalski et al. 2005), which can generally be classified into three major methodologies. Virtual population reconstruction methods use the age and sex of harvest individuals through multiple years, and provide an estimate of the population size at the beginning of each cohort by tracing the harvest fate of the cohort through time (Fry 1949, Downing 1980, Fryxell et al. 1988). Populations may also be reconstructed using within-year harvest numbers of adult males, adult females, and juveniles (e.g., the sex-age-kill model; Eberhardt 1960). In addition to reconstruction methods, catch per unit effort models incorporate effort data with the age at harvest data to estimate abundances. Finally, statistical population reconstruction methods combine auxiliary data (e.g., marked animal studies) with age-at-harvest data, enabling statistical estimation of survival, harvest, and abundance parameters (Gove et al. 2002, White and Lubow 2002, Skalski et al. 2005, Conn 2007, Skalski et al. 2007, Conn et al. 2008, Fieberg et al. 2010). Of these, the population reconstruction methods are commonly applied due to the minimal data inputs, requiring only the age-at-harvest data which most agencies collect.

While a number of estimation methods are available, it is not easy for managers to determine which estimation method to select to obtain the best estimate of population status because estimators have rarely been compared directly. Each estimation method embodies a set of assumptions that must be met to obtain a precise and unbiased estimate of the true population size or trend. Although a number of evaluations of these estimation methods have been conducted (e.g., Roseberry and Woolf 1991, Davis et al. 2007, Millspaugh et al. 2009, Skalski et al. 2012), they often vary from one evaluation to the next in terms of the estimators that are evaluated and the species analyzed, often evaluating the performance of only a single estimator by comparing the resultant estimates to a simulated population. For example, Millspaugh et al. (2009) evaluated the performance of the sex-age-kill (SAK) model when the assumptions of a stable-age distribution and stationary population size were violated, and when changes in harvest strategies were introduced, but did not include any other estimation methods in the evaluation.

A key violation of assumptions that has received little attention to date involves data collection and processing. This error includes incomplete reporting of harvest counts, error in aging individuals, and error in sexing individuals (e.g., Atwood 1956, Asmus and Weckerly 2011, Williams et al. 2011b). If analyses are not robust to these violations, the resultant estimates may lead to faulty estimates of the true population abundance and population trend. Because game species management is adjusted based on assessments of population status and trend, accounting for data collection errors in the evaluation of estimator performance is an important consideration for successful game species management.

Here, I build on previous efforts and present a means to evaluate the performance of several common estimators under various scenarios of user-simulated conditions and errors. While I evaluate estimator performance from the perspective of a furbearer biologist in Vermont, USA (VT), and focus on data collection errors under differing levels of population growth, this approach can be used to evaluate estimators for a wide range of species and conditions.

2.2.1 Research Objectives

My objective was to conduct an evaluation of four common abundance estimators available for monitoring furbearers in Vermont: 1) `indexEst` (an index method where population size is estimated based on estimated harvest probability; 2) `fryEst` (a virtual population reconstruction method), 3) `downingEst` (another virtual population reconstruction method), and 4) `sakEst` (the sex-age-kill model). These estimators are widely used and require only the age-at-harvest data (Davis et al. 2007, Millspaugh et al. 2009).

I evaluate these for 13 scenarios representing five models of population trends (strong decrease, weak decrease, stable, weak increase, and strong increase) and 5 models of measurement error: 1) no error in data collection, 2) error in the assignment of age to individuals, 3) error in the assignment of the sex for individuals (males identified as females and vice versa), 4) incomplete reporting rate, and 5) an all error model with all three types of measurement error included (aging and sexing errors as well as incomplete reporting). I evaluated estimators in terms of their ability to estimate abundance and population trend (lambda) using two performance measures: 1) the coefficient of error (see Millspaugh et al. 2009) which combines bias and precision of the estimates into a single measure, and 2) the percent bias in the abundance and lambda estimates.

2.3 Methods

2.3.1 Study Species

To provide insight to estimator selection in VT, my simulated population was designed to approximate the conditions of the fisher population in VT. Following successful reintroduction in the 1960s, fishers have been harvested in Vermont since 1974 with a five year trapping reprieve between 1979-1983 (Powell and Zielinski 1994). Trappers are required to tag all carcasses, submit an accompanying record to the VTFWD within 48 hours of the close of the trapping season, and notify a game warden, who collects and stores carcasses until they can be processed. Age and sex of each harvested individual are collected for each year of the harvest via necropsy, in which aggregated carcasses are matched with submitted records. However, the error rates associated with these data are unknown (C. Bernier pers. comm., Vermont Fish and Wildlife Department). The state also collects annual effort data, measured as the total number of trap-nights (e.g., 2 traps deployed for the full 31 day fisher trapping season would be counted as 62 trap-nights), which are used in simulating annual harvest (see below).

The fisher is the largest member of the Martes genus with males averaging 3.3 kg and 60 cm in length and females averaging 1.8 kg and 51 cm (Douglas and Strickland 1987). Females produce their first litter at 24 months and proceed to produce one litter per year thereafter, with males becoming reproductively active at age one (Powell and Zielinski 1994). Breeding females have been found to produce between 1 and 4 corpora lutea annually, with an average ranging from 1.8 to 2.7 across ages in studies in the northeastern U.S., but slightly higher for females in their prime (Douglas and Strickland 1987, Van Why and Giuliano 2001, Powell et al. 2003). Offspring sex ratio has not been found to differ from 50:50 (Powell 1994). The annual recruitment (birth rate) of offspring into the population averages between 1.18 to 2.16 across studies in the northeast (Paragi et al. 1994, Koen et al. 2007, Buskirk et al. 2012).

The estimated life span of a fisher is 10 years (Powell et al. 2003). The survival rate of fishers depends on their age and the trapping rate. The annual survival rate without trapping ranges between 0.7 and 0.8 for juveniles and is greater than 0.9 adults (Krohn et al. 1994, Powell 1994). With trapping, these rates can decline to as low as 0.34 (Krohn et al. 1994, Powell 1994). Fisher density has been found to range from 0.05 to 0.38 fisher per square kilometer, with an average value of 0.18 in habitat similar to VT (Powell et al. 2003).

2.3.2 Simulated Population Trajectories

I simulated 5 alternative population trajectories of fisher (1 stable, 2 increasing, and 2 decreasing populations) using the `popMod` function in the AMharvest package developed for the Vermont Fish and Wildlife Department. The package combines a mySQL database with a Microsoft Access front-end for data storage, entry and viewing, with R functions for simulating game species population dynamics, harvest data collection (including reporting, aging, and sexing error), and estimating abundance and trend from several, existing population estimators. Using this package I stochastically simulated game species abundance, harvest of that species, and monitoring of that species on an annual basis. The `popMod` function required inputs that control population dynamics across the annual cycle (Figure 2.1). The life cycle is anchored by three major events: the census, in which the true population size is counted immediately before the onset of harvest (and is the goal of population estimation methods to determine), the harvest (the start and duration of the annual harvest season), and the birthday (in which a birth-pulse is assumed). The total number harvested is controlled by a harvest model (`annualHarvestMod` or `dailyHarvestMod` for annual or daily simulation of harvest), which returns the true harvest numbers by age and sex, as well as the error-laden harvest data that would be analyzed by biologists (including reporting rate, age error, and sex error). The numbers of individuals between each event is controlled by vital population rates, such as pre-breeding survival (the probability that animals that have escaped the harvest will survive to breeding) and post-breeding survival (the probability that animals will survive to the census after the birth pulse) and 100% survival between the census and the harvest. By selecting the desired parameterization for the input models `popMod` can mimic a wide range of conditions such that the simulation matches the conditions for a species of interest.

For my estimator comparison, the population modeling function `popMod` is initialized with a population seed (the numbers of individuals in each age and sex class), and is parameterized by selecting 7 "settings" or groupings of inputs which control the numbers and rates through time. These settings include 1) a simulation specification setting, which specifies the number of simulations to run, the start year, end year, and species, 2) a species setting, which specifies the age at first reproduction, maximum age, the birthday, and whether the terminal age class is a composite age class (e.g., 10 year olds and older are all counted as ten year olds) or not (only 10 years old individuals, no survival to age 11), 3) a population setting, which specifies the size of the population seed and vital rates such as survival and birth rates, 4) a stochastic setting, which controls how each life history rate is modeled (stochastic or not), 5) a harvest season setting, which specifies the day the harvest begins and season length, 6) a harvest setting, which specifies the harvest rate (here, controlled by annual harvest effort), the age at first harvest, the percentage of the harvest that is compensatory (mortality that compensates for and therefore reduces the natural mortality rate), and whether the harvest is stochastic, and 7) a harvest-data setting, which introduces reporting, aging, and sexing errors to the true harvest.

Each of the 5 population trajectories required inputs for all 7 settings, 6 of which contained elements that were constant across trajectories. First, for the simulation setting, I simulated conditions similar to the VT fisher population over a 50 year period using a hypothetical start year of 1901 and an end year of 1950. Second, for the species setting, I assumed that the age at first reproduction was 1 and 2 for males and females, respectively. I set the maximum modeled age to 10, where the final age class represented a composite age class of 10+ year olds. Third, while the vital rates varied by trajectory as described below, I used the following population seeds that result in a stable age and sex distribution for males and females for all 5 population trajectories:

Females = [813,380,267,212,178,153,132,114,99,83,65]

Males = [535,267,191,154,129,112,99,88,78,69,59]

This corresponds with the estimated fisher population given available density estimates (Kelly 1977, Powell 1994, Powell et al. 2003) and resulted in an initial population size of 4,277 fishers. Fourth, the life history stochasticity settings were all set to 0, in which none of the vital rates (birth and survival) were modeled with stochasticity. Fifth, for all trajectories, the harvest season setting was assumed to be 31 days beginning on December 1st of each year. And sixth, the age at first harvest was set at age 0 (indicating juveniles are harvested), the compensatory harvest rate was 0 (indicating that harvest is 100% additive to natural mortality), and the stochastic harvest value was set at 1 (indicating that harvest was modeled stochastically). The stochastic harvest was implemented using a binomial distribution with the census abundance at each age as the number of trials and the simulated harvest rate as the probability of success.

I developed several population and harvest models which controlled population rates (Table 2.1), in which the “baseline” models yielded a stable population size through time. The baseline birth rate model included an age and density dependent effect, and resulted in an average of 1.68 offspring per reproductive female (ages 2-10; Table 2.1, Model 1). I assumed a 50-50 offspring sex ratio. The baseline pre-breeding and post-breeding survival rate models were simulated with some small differences by age and sex such that the combined, annual rate was similar to the reported without trapping survival rate, which ranges between 0.7 and 0.8 for juveniles and is greater than 0.9 for adults (Krohn et al. 1994, Powell 1994). The baseline pre-breeding survival rates were 0.73 for male and females juveniles, and increased to a peak survival rate of 0.996 for six year old males and females (Table 2.1, Models 3 and 4). The baseline post breeding survival rates were 0.86 for female and 0.90 for male juveniles, with a peak survival rate of 0.98 for 8 year old females and 0.99 for 9 year old males (Table 2.1, Models 7 and 8). The baseline harvest rate model resulted in average annual harvest rate of 0.154 across ages and sexes, with higher harvest rates for young and old fishers and slightly lower rates for 3 to 7 year old fishers and an annual effort of 15,000 trap-nights (Table 2.1, Models 9 and 10).

The five trajectories varied in their vital rates for the population setting through changes in birth rates and in survival rates, and in their harvest rate through changes in annual effort (Table 2.1), which created stable, increasing, or declining populations through time. An alternative birth, pre-breeding survival, and annual effort were parameterized to simulate changes in population trajectory that result in population growth rates of 1.02, 1.01, 0.99, and 0.98. The birth rate was increased via an increase in the birth rate model’s intercept from 0.32 to 0.37, resulting in an increase to an average of 1.77 offspring per reproductive female (Table 2.1, Model 2). The alternative female and male pre-breeding survival rates were reduced by changing to the female and male pre breeding survival rate intercept values from 1.0 to 0.8757, resulting in a reduction in the average pre breeding survival rate across ages from 0.94

to 0.93 for females and 0.96 to 0.95 for males (Table 2.1, Models 5 and 6). Two alternative harvest probabilities were produced by maintaining the harvest model parameters but varying the effort (the simulated number of trap nights per year in thousands) downward to 11.33 (Table 2.1, Models 11 and 12) and upward to 19.15 (Table 2.1, Models 13 and 14). Without taking the stochasticity into effect, decreasing the simulated effort decreased the average harvest rate across ages by approximately 0.01 and increasing the effort increases the average harvest rate across ages by approximately 0.01.

I then combined the different models to simulate 5 different growth trajectory scenarios (Table 2.2). The five trajectories were a stable population (stable), an increasing population due to the increased birth rate model (increase.birth), a decreasing population due to the decreased survival rate model (decrease.survival), an increasing population due to a decrease in harvest effort (increase.harvest), and a decreasing population due to an increase in harvest effort (decrease.harvset).

Without stochasticity in harvest, the populations ended with 4,277, 6,824, 2,613, 11,260, and 1,593 individuals for the stable, increase.birth, decrease.survival, increase.harvest, and decrease.harvest trajectories which correspond to average annual lambda values of 1.01, 0.99, 1.02, and 0.98, respectively. Including stochasticity in the harvest produced variation in the annual abundance as shown by the ribbons surrounding the median abundance in the plot of trajectories (Figure 2.3).

Each trajectory in Table 2.2 produced a different number of harvested individuals by age, sex, and year. From this harvest data, I then created 6 "error" models that allowed the inclusion of reporting error (the probability that a harvested animal was reported), sexing error (the probability that an animal would be correctly assigned by sex), and aging error (the probability that an animal of a given age would be classified into each alternative age class (Table 2.3). Errors modeled included reporting rate (which included 100% reporting and 90% reporting; Models 1 and 2 respectively) and correct sex classification rates for males and females (100% and 90% correct classification, Models 3 and 4 respectively). In addition, age-error could be applied and was modeled with a distance-to-and-from age class formula:

$$A_t = \sum_{f=1}^{F} A_f * \frac{\mathrm{e}^{f+(f-t)^2*E}}{\sum_{i=1}^{T} \mathrm{e}^{f+(f-\mathrm{i})^2*E}}$$

Where A_t, “age-to” is the number of individuals in the resulting data count for age t, A_f is the number of truly harvested individuals for age f, and E is the age error parameter (see Table 2.3, Models 5 and 6). I use age error parameter values of -25 to produce no age error and -3.54 to produce 5% error in aging, which generally assigned ages to a neighboring age-class (Figure 2.2).

I combined the different error models into five error scenarios that represented alternative rigor in the data collection process. The five scenarios of error were a null scenario with no error in data collection, an age scenario with measurement error in the age assigned to individuals (95% of individuals of age x correctly identified as age x and 5% misidentified as another age), a sex scenario with measurement error in the assignment of the sex for individuals (10% of males identified as females and vice versa), a reporting scenario with a 90% reporting rate, such that the true number of harvested animals was under reported by 10%, and an all-error scenario with all three types of measurement error included (aging and sexing errors as well as incomplete reporting). These represent “slight” errors in the data collection process, but are thought to be representative of the fisher data collection in Vermont (C. Bernier, pers. comm., Vermont Fish and Wildlife Department).

Due to the greater numbers of females in the population, and therefore in the harvest, sex error resulted in harvest datasets with an increased male count and decreased female count (Figure 2.4, Sex Error). Age error had a minor effect on the counts as individuals swapped from one age to another are partially compensated for by the swap in the opposite direction. Zero year olds had the greatest differential in count from any other age, so the main difference caused by aging error was a small reduction in the number of zero year olds as the number of zero year olds reclassified to 1 year olds exceeded the number of 1 year olds reclassified as zero year olds (Figure 2.4, Age Error). Reporting errors reduced the overall count in each category (Figure 2.4, Reporting Error). Combining all the errors causes a further reduction in the count of females because of the shift from females to males caused by the sexing error (Figure 2.4, All Error).

Combining the five error scenarios generated by the error models (Table 2.3) with the five population trajectory scenarios (Table 2.2) would result in 25 combined scenarios. In order to focus the set of evaluations to the key sources of potential influence, I selected a subset (n = 13) of the 25 for evaluation. The differential effects of the sources of measurement error were evaluated only for a stable population trajectory. For the other four trajectories I limited the evaluation to the null error and all error models (Table 2.4).

2.3.3 Estimation Methods

Given the 13 simulated harvest datasets, I estimated population abundance and growth rate (λ) with four different estimation methods. There are a number of methods available for converting the monitoring data into estimates of abundance (Skalski et al. 2005), but a limited selection given only age-at-harvest data as collected for fish monitoring in Vermont, and for many other furbearer monitoring programs. In Vermont, the exact date of harvest is sometimes unknown, and the data are analyzed by compiling the total harvest by age, sex, and year rather than by day. A suite of commonly used estimators in the package, AMharvest, can be evaluated using this aggregated annual data, which are: the index method (`indexEst`), some virtual population reconstruction methods (`fryEst` and `downingEst`), and sex-age-kill method (`sakEst`).

2.3.3.1 Harvest Index Method

Harvest indices provide an indirect estimate of abundance using counts of sub-groups of the total population (e.g. harvested individuals or only adult males) or the ratio of membership in sub-groups (e.g. the ratio of adult females to adult males that are harvested). The number of harvested individuals provides an index of the total population size, but variability in effort and harvest success result in this being an imperfect indicator of the total abundance. Adult sex ratio and juvenile to adult female ratios are also common indices of abundance, but like the harvest index, changes in hunting success for each subgroup, or changes in survival for each subgroup can confound the interpretation of changes to these indices relative to changes in the total population.

The harvest index method in AMharvest uses the function `indexEst`, which takes the annual harvest data and an estimated harvest rate model as inputs. Due to the lack of telemetry or other studies which have estimated the harvest rate of fishers in VT, there is no available estimate of the harvest rate. I use a constant value of 0.15385 (the average harvest rate across age and sex for the stable population trajectory simulation) as the harvest rate input to the indexEst method in all of my evaluations. By using this harvest rate, I am giving the `indexEst` method the best possible chance of providing an accurate estimate of the abundance without adjusting the harvest rate based on changes to the population trajectory, effort, or age and sex effects. A manager would normally not have this information at their disposal, and would use expert opinion or output from another estimator to provide the approximate annual harvest rate required by `indexEst`.

2.3.3.2 Virtual Population Reconstruction Methods

Population reconstruction methods are based on age-at-harvest data. These methods use back-calculation of harvest data to produce year-, age-, and sex-specific abundances. By summing over the age classes, annual abundance levels are estimated by including survival rates that are adjusted to reflect other sources of mortality in addition to the harvest (Skalski et al. 2005). The difference between the different population reconstruction methods is how they account for the survival and harvest rates. The method utilized by Fry (1949) estimates the minimum population size by summing lifetime harvest numbers of each cohort, but does not account for additional sources of mortality, producing only the minimum population size as an index of the absolute abundance. In contrast, the Downing reconstruction method (Downing 1980) does not estimate vital or harvest rates directly, but uses a weak proxy of adult mortality to reconstruct the pre-hunt population by backward-addition of known mortality and a minimal assumption of unaccounted-for mortality (Downing 1980).

The Fry and Downing population reconstruction methods in AMharvest use the functions `fryEst` and `downingEst`, respectively. Both the `fryEst` function and `downingEst` function take annual age at harvest data as input, with the `downingEst` function requiring a grouping age (the age above which all individuals are summed into a single count) input as well. I pooled data into 5 classes, 4 for animals of ages 0 through 3 and a fifth class for animals of age 4 or greater for the Downing estimation method.

2.3.3.3 Sex-Age-Kill Method

The Sex-Age-Kill method is a life-history based method that uses harvest information and sex and age ratios to estimate the abundance of the population (Eberhardt 1960, Roseberry and Woolf 1991, Millspaugh et al. 2009). The Sex-Age-Kill method in AMharvest uses the function `sakEst`, which takes annual harvest data by age group (young, subadults, recruits, and vets), as well as estimates of the proportion of mortality due to harvest, and the young per adult female as inputs. Young are less than one year old, subadults are 1 plus years old but have not yet reached breeding age, recruits first-year breeders that have been recruiting into the breeding population, and vets include experienced breeders (individuals above the age of recruitment).

The method estimates the adult male harvest rate, and the total adult male population is estimated from the adult male harvest rate and the proportion of the total mortality that is due to harvest. The total adult female population is derived from the SAK output of adult sex ratio, and the total juvenile population is derived from the total female adult estimate and the assumed birth rate. Summing the adult male, adult female, and young abundance estimates produces the total abundance estimate.

As with the harvest index method, I used the true values on average from the stable population trajectory simulation as my inputs to the `sakEst` function (proportion of mortality due to harvest and the young per adult female). In this way I are reporting the best possible expected performance from the `sakEst` method. The average total mortality due to harvest in my simulation was 0.4702 and the young per adult females was 1.128, which were used as the `sakEst` inputs for total mortality due to harvest and young per adult females, respectively.

2.3.4 Performance Evaluation

I used the function, `performanceEst` in AMharvest to evaluate the estimators in terms of their Coefficient of Error (CE) in abundance and lambda and in terms of their bias and precision in estimating population size and lambda. I report the estimator performance for year 1 to 40 of the simulations to avoid known biases in the virtual population reconstruction methods (Fry and Downing) that result from estimating the abundance from incomplete cohorts in the most recent years.

The precision of the abundance estimates and the lambda estimates were assessed with the Coefficient of Error (CE) introduced by Millspaugh et al. (2009) that combines bias and precision into a single measure. The CE in abundance is expressed as a percentage calculated as:

$$CE = \frac{\sqrt{\widehat{MSE}}}{\left(\frac{\sum_{i=j}^{n}\sum_{j=1}^{y} N_{ij}}{ny}\right)} * 100, \text{ where}$$

$$\widehat{MSE} = \frac{1}{n}\sum_{i=1}^{n}\left[\frac{\sum_{j=1}^{y}\left(\widehat{N}_{ij} - N_{ij}\right)^2}{(y-1)}\right],$$

Here, y is the number of years being compared ($y = 40$), n is the number of simulations ($n = 100$), N_{ij} is the simulated abundance for simulation i and year j, and $\widehat{N}_{ij}$ is the associated abundance estimate. The CE in lambda is calculated the same way, but substituting $\hat{\lambda}_{ij}$ and λ_{ij} for $\widehat{N}_{ij}$ and N_{ij}:

The CE calculation takes the squared difference between the true metric and the estimated metric, and thus obscures the direction of bias. Because of this, I also evaluated percent bias of each estimator in terms of population estimates and lambda. I measured the percent bias in abundance estimates by taking individual annual abundance estimates, subtracting the true abundance and then dividing by the true abundance, ($\frac{[\widehat{N} - N]}{N} * 100$), and then finding the median value from the 40 years of the simulation. Similarly, I calculated percent bias for lambda estimates in a similar manner to the bias in abundance. First I calculated the annual change in the population size, lambda ($\lambda_t = N_{t+1} / N_t$) for true and estimated abundances starting in year two. The annual bias in lambda was calculated by subtracting the true lambda from the estimated lambda and dividing by the true lambda, ($\frac{[\hat{\lambda} - \lambda]}{\lambda} * 100$).

2.4 Results

2.4.1 Coefficient of error

I evaluated performance using the Coefficient of Error (CE) that summarizes bias and precision in a single value (Millspaugh et al. 2009). A perfect estimator would have a coefficient of error equal to 0. The estimators generally performed better in regards to estimating population trend (Figure 2.5, bottom panels) than they did in regards to estimating abundance (Figure 2.5, top panels). Overall, there was a trade-off in the ranking of the estimators for abundance estimation performance and lambda estimation performance. For the (informed) parameterization provided, the `indexEst` method was best for CE in abundance across all scenarios, and third best for lambda, while `sakEst` was second best for abundance and worst for lambda. The `fryEst` and `downingEst` methods had the lowest and second lowest CE in lambda across all scenarios, but highest and second highest CE in abundance respectively.

For a stable population with no error in data collection, the CE in abundance estimation was lowest for the `indexEst` method with a CE in abundance of 7.35% followed by the `sakEst`, `downingEst` and `fryEst` methods with CE in abundance scores of 21.24%, 47.30%, and 51.59% (Figure 2.5, top panel, λ = 1,null). This is associated with a significant difference in the bias of the abundance estimates by estimation method (Appendix C). Changes in trajectory, without error, resulted in a general decline in performance when estimating abundance (Figure 2.6, top, panels 2-5). For the `sakEst` method, the CE was the highest when lambda was 0.98; under the same lambda the `fryEst` and `downingEst` methods improved in performance

(Figure 2.6, top, λ = 0.98, null). However, these improvements did not change the overall ranking of estimators in terms of the CE in abundance. The median bias of the estimators helps explain this pattern. The `sakEst` method was negatively biased when the population was stable or increasing and positively biased when the population was strongly decreasing for the null error scenarios (Figure 2.7, top, λ = 0.98-1.02, null). Note that this result had high uncertainty, as reflected by the large range in results from trial to trial (Figure 2.7, top panels, `sakEst` whiskers). The `fryEst` and `downingEst methods`, which were the worst performers for abundance, had highly negatively biased estimates of abundance regardless of trajectory (Figure 2.7, top panels).

As a consequence of these biases, the median estimate of population size varied by both estimator and trajectory (Figure 2.8, top panels). For example in Figure 2.8, panel 1, given their biases at λ = 1, null, on average `indexEst` was off by 3 individuals, `fryEst` by -2160, `downingEst` by -1979, and `sakEst` by -124 individuals. Changing trajectory slightly by 0.01 increased these biases slightly (Figure 2.8, top, panels 2 and 4), but as lambda deviated more from 1 the changes were more substantial. For example, when λ = 1.02 with no error, the `indexEst` went from overestimating by 3 individuals to underestimating by -380 individuals, a change in estimate of -383 individuals (the value shown in Figure 2.8 top panel 3). For the same trajectory (λ = 1.02, null), `sakEst` started with a bias of -124 individuals, and this negative bias increased by -402 (value in figure), which resulted in a bias of -526 individuals. In the case of declining trajectories (λ= 0.98), all four estimators produced higher population estimates (Figure 2.8, top, panel 5). For `downingEst` and `fryEst`, this resulted in an improved CE but still significantly worse than the other two estimators. For `indexEst` and `sakEst`, the declining trajectory resulted in an overestimate of population size. Thus the change in bias was most dramatic as lambda deviated from 1.

While `indexEst` and `sakEst` performed best in terms of abundance, `fryEst` and `downingEst` performed best in terms of lambda when there were no errors in data collection (Figure 2.5, bottom, panels 1-5). The `fryEst`, `downingEst` and `indexEst` method all had significantly different mean bias in lambda values than the `sakEst` method, but were not significantly different from each other (Appendix C). For a stable population with no error, the CE in lambda was lowest for the `fryEst` and `downingEst` methods with values of 1.75% and 2.04%, while the `indexEst` value was 5.81% and the `sakEst` value was 22.96% (Figure 2.5, bottom left panel, $\lambda = 1$, null). The estimator performance improved with slight deviations from $\lambda=1$, i.e., $\lambda=1.01$ and 0.99 (Figure 2.6, bottom, panels 2 & 4), but decreased with stronger deviations from 1.0, i.e., $\lambda=1.02$ and 0.98 (Figure 2.6, bottom, panels 3 & 5) relative to the $\lambda = 1$, null scenario, with `sakEst` showing the largest change. The estimators all performed best when $\lambda = 0.99$ (Figure 2.6, bottom panel 4) however, changes in trajectory did not change the relative ranking of estimators in terms of CE in lambda.

2.4.2 Effect of error

The effects of error on CE in abundance values depended on the type of error (reporting, age, or sexing error) and the estimation method. Each error type produce significantly different mean bias in abundance values (with the exception of the difference between reporting and all error as well as sex and age error), but insignificantly different mean bias in lambda values (Appendix C). When λ = 1, reporting error played the biggest role in affecting CE in abundance, increasing CE to 12.14%, 56.37%, and 52.45%, for `indexEst`, `fryEst`, and `downingEst`, respectively (Figure 2.5, λ = 1, reporting). For these estimators, CE increased by roughly 5 units (Figure 2.6, top, panel 1 and 6). This change in CE in abundance for reporting error translated into increases in the negative bias of all estimators (Figure 2.8, top, panel 6). For example, given the `indexEst` was off by 3 individuals, `fryEst` by -2160, `downingEst` by -1979, and `sakEst` by -124 individuals when λ = 1, the bias from reporting error was -407, -2363, -2196 , and -526. These represented a change in bias of -410, -203, -217, and -402 individuals for `indexEst`, `fryEst`, `downingEst` and `sakEst` respectively (Figure 2.8, top, panel 6). This change in performance was larger than the effect of most of the trajectory effects without error (Figure 2.6, λ = 1, reporting).

The introduction of aging and sexing mistakes resulted in a small reduction in CE for `indexEst`, `fryEst`, and `downingEst`, but a small increase for `sakEst` (Figure 2.6, top, panels 7 & 8). For the `sakEst` method, the addition of sex error positively increased the percent bias, which would force the estimator to overestimate abundance (Figure 2.7, top, panel 7). In contrast, without aging and sex effects, the `sakEst` method was negatively biased (Figure 2.7, top, panel 1). The result of this bias would increase the abundance estimate by 330 individuals (Figure 2.8, top, panel

7). When including all sources of error for λ = 1, the performance of `sakEst` improved with the addition of minor error rates in data collection (Figure 2.6, top, panels 1 vs. 11). This improvement diminished as lambda deviated from 1.0. In contrast, errors in the data collection process degraded the performance of `indexEst`, `fryEst`, and `downingEst`.

Inclusion of errors into the estimation of population growth (λ) had a relatively minor effect on CE compared to abundance. When lambda was 1, including reporting, aging, and sexing error did not change the relative ranking of the estimators. Error had small effects on the `indexEst`, `fryEst`, and `downingEst` CE in lambda values, but improved the `sakEst` CE in lambda (Figure 2.6, bottom panels, λ = 1, reporting, sex, age, all). Sexing error caused the largest improvement in `sakEst` performance. Despite this improvement, the `sakEst` remained the worst estimator for CE in lambda by some margin (Figure 2.5, bottom panels, λ = 1, reporting, sex, age, all).

2.5 Discussion

2.5.1 Estimator Performance

I evaluated four commonly used estimators that require only age-at-harvest data across time to produce an estimate of population size and trend. Across estimation methods, I found that obtaining accurate estimates of abundance is a challenge, while estimates of lambda were more accurate. When populations are not stable, particularly for larger changes in growth rate (λ = 0.98 or 1.02), caused by the simulated changes in effort and thereby the harvest rates, accuracy in abundance estimates suffer. This result is in line with those of Davis et al. (2007) and Millspaugh et al. (2009), who found changes in population trends decreased performance of the Downing method and sex-age-kill method respectively. My results allow a comparison of these two widely used methods, and showed that the comparative degree of impact on the virtual population reconstruction methods (Fry and Downing methods) was smaller than the effect on the index and sex-age-kill methods. I further demonstrated that slight error in data collection (5-10%) effected the performance of the estimation methods as much, or more, than a 2% deviation in the population trend from λ = 1.0 with no errors in data collection.

While the `indexEst` method performed best in terms of estimating abundance, this was a direct result of the unrealistically accurate inputs to this estimation method that are not typically available to wildlife managers. Without auxiliary data collection, such as a marking study or other means, to accurately determine the harvest rate for use in the index method, it is unlikely to produce such accurate estimates in practice. As such, the inclusion of the index method here served as a benchmark for the Fry, Downing and SAK estimators, which will be the focus of our discussion.

Based on abundance estimation, the sex-age-kill method was far less biased than the Fry and Downing estimation methods. The performance of all estimators was diminished by changes in population trend, where, estimators were most biased in their abundance estimates for strongly declining populations (λ = 0.98), with Downing and Fry underestimating abundance and Sex-Age-Kill overestimating abundance. This increases the difficulty of management because tracking changing populations is essential, and managers are often precautionary and act to avoid population decline. If a manager used the best performer to track abundance, the sex-age-kill method, while the bias is smallest, the direction of the bias tends to be negatively correlated with the population growth rate. Therefore, managers could be under the false impression that the population is more abundant than it actually is (or vice versa), leading to potential delays in management responses and immoderate harvest allowances (or unnecessary or disproportionate reductions in harvest), which can substantially affect the outcome of management (Artelle et al. 2013). The repercussions of overharvesting a declining population can be difficult to recover from, particularly if species are managed with quotas intended to achieve maximum sustainable yield because once a population is unable to compensate for harvest removals the size of quota reductions must be increasingly more drastic to enable recovery. The risk of failed recovery from overharvest may be slightly smaller for fisher than in other species, as they were able to successfully establish themselves enough to support trapping in the 1970s, and at current rates in 1983 following reintroductions in the mid 1960s. However, fishers are not highly fecund species, with first reproduction in females at age two, and limited until age three at which time greater than two offspring per female is still unusual.

I found that the Downing method was more biased in its estimation of population change than the Fry method for unstable populations and with the inclusion of error. This result is due to the grouping of adult age classes in the Downing method. With this grouping the observed variation from year to year is dampened, resulting in increased bias when the population lambda strays further from 1.00.

Interestingly, the addition of age, sex, and reporting error improved the performance of the sex-age-kill method. This is likely due to the sex-age-kill estimation algorithm, which relies first on an estimate of male harvest rate to estimate the male adult population. The adult female population is then estimated based on the sex ratio of adult males to adult females. In turn, the number of young in the population is estimated by the per capita birth rate times the number of adult females. Thus, if the estimate of adult males is biased, this bias trickles through the estimates of adult females and young. Therefore, an increase in the count of adult males will cause an increase in the sex-age-kill abundance estimate because a count of more males leads to an estimate of more females and more juveniles. With sex and age structured populations sometimes containing greater numbers of females and juveniles, the effect of sex error is to shift individuals from relatively more prevalent female and juvenile classes to the relatively less prevalent adult male class. This inflation in the number of classified males inflates the male abundance estimate and subsequent total estimate. Because the sex-age-kill method initially tended towards a negatively biased estimate, these errors increase estimates, improving the performance as long as the error rate does not overcompensate for the initial negative bias. This is an effect that managers should be cognizant of because many game species have age and sex distributions that favor young and females. This is particularly common when males are selectively harvested, as often occurs in game species due to greater size of males as a food source and for trophy hunting (e.g., Marealle et al. 2010).

The error rates that I applied are believed to mimic the range of error in the current fisher data collection methods in Vermont, but may be low relative to error rates of other game species monitoring programs. In Vermont, trappers are required to submit “cards” containing the age and sex of trapped animals, and to match the card with a carcass. The carcasses are then collected by a warden, and aggregated carcasses are aged and sexed via necropsy. With necropsies, the error is small because the sex of fisher carcasses can be readily assessed as long as they are not too decrepit, and age is accurately assessed from cementum annuli analysis. However, there is the possibility of human error in storage and transfer of carcasses, teeth, and records. Without necropsies, the sex and aging errors would be expected to be greater than what I simulated. Relative to other species, it is possible these error rates are low, particularly for species with less structured management and monitoring such as some other furbearing species monitoring without necropsies as is more typically the case, or those without carcass collection (e.g., muskrat, beaver, fox, opossum, mink, raccoon, skunk, weasel, coyote). Repeating the analysis with a range of error rates representing the spread of data collection errors for other species and monitoring programs would aid the understanding of estimator performance for games species with more or less robust data collection methods. Additionally, altering the error rate by age and sex would likely change the impact of the error because individuals could transfer between groups at different rates depending on age, sex and species.

2.5.2 Estimator Selection

I found that estimating abundance is more difficult than population changes, as the bias in abundance was much greater than the bias in lambda. There also was not a single estimation method that was best for both estimating abundance and population change. While the sex-age-kill method was least biased for abundance estimates, the Fry and Downing methods performed best at estimating lambda, and they were also least sensitive to errors and changes in trajectory for their lambda estimates. Based on this trade-off in performance, there is not a single method that is consistently the best estimation method. The model that will best meet the objectives of tracking population state depends on the perceived importance of the possible objectives, as evidence by the trade-off between performance for abundance and lambda and the differences in robustness to changes in lambda and error.

One approach to selecting an estimation method is to identify a single characteristic for evaluating performance, such as the ability to estimate abundance, in which case the sex-age-kill method would be selected, or the ability to track population change, in which case the Fry or Downing method would be selected.

Alternatively, managers can account for performance across multiple criteria. For example, additional criteria that managers may wish to consider outside of estimator performance itself are: a monitoring program's ability to collect and process different data sources, the cost of collecting data, other analyses a particular set of data allows, or other criteria. Once relevant objectives have been selected, they are weighted according to their relative importance. Thus, managers can incorporate multiple objectives to produce a single score for a population monitoring program that combines the weighted performance of the objectives using a decision analysis framework (Keeney and Raiffa 1993, Cummings and Donovan in preparation-a).

Short of an evaluation of the multiple objectives likely present in the selection of estimation methods and monitoring programs managers may benefit most from a combination of estimation methods, or an adjustment to one of the estimation methods evaluated. For example, using sex-age-kill for abundance estimation, while also using

Fry or Downing for trend, or only using Fry and Downing, but adding a positive adjustment to minimize the bias in abundance.

2.6 Acknowledgements

I thank J. Pontius, J. Murdoch, and R. Mickey for their assistance reviewing this chapter. S. Hafner and K. Rinehart assisted with R coding of the simulation and analysis functions in the AMharvest package. Input on fisher management in Vermont was provided by Chris Bernier, Kim Royar and Scott Darling. Funding was provided by the Vermont Fish and Wildlife Department and the United States Geological Survey.

2.7 References – Chapter 2

Artelle, K. A., S. C. Anderson, A. B. Cooper, P. C. Paquet, J. D. Reynolds, and C. T. Darimont. 2013. Confronting uncertainty in wildlife management: performance of grizzly bear management. PLoS One **8**:9.

Asmus, J., and F. W. Weckerly. 2011. Evaluating precision of cementum annuli analysis for aging mule deer from Southern California. Journal of Wildlife Management **75**:1194-1199.

Atwood, E. L. 1956. Validity of mail survey data on bagged waterfowl. Journal of Wildlife Management **20**:1-16.

Buskirk, S. W., L. Bowman, and J. H. Gilbert. 2012. Population biology and matrix demographic modeling of american martens and fishers. Pages 77-92 *in* K. B. Aubry, W. J. Zielinski, M. G. Raphael, G. Proulx, and S. W. Buskirk, editors.

Biology and conservation of martens, sables, and fishers : a new synthesis. Comstock Pub. Associates, Ithaca, New York, USA.

Conn, P. B. 2007. Bayesian analysis of age-at-harvest data with focus on wildlife monitoring programs. Colorado State University, Fort Collins, Colorado, USA.

Conn, P. B., D. R. Diefenbach, J. L. Laake, M. A. Ternant, and G. C. White. 2008. Bayesian analysis of wildlife age-at-harvest data. Biometrics **64**:1170-1177.

Cummings, J. W., and T. Donovan. in preparation. A decison analysis approach to selecting a program for monitoring population size of game species.

Davis, M. L., J. Berkson, D. Steffen, and M. K. Tilton. 2007. Evaluation of accuracy and precision of downing population reconstruction. Journal of Wildlife Management **71**:2297-2303.

Decker, D. J., G. R. Goff, and Wildlife Society. New York Chapter. 1987. Valuing wildlife : economic and social perspectives. Westview Press, Boulder.

Douglas, C. W., and M. A. Strickland. 1987. Fisher. Pages 510-529 Wild Furbearer Management and Conservation in North America. Ontario Trappers Association and Ontario Ministry of Natural Resources, Ontario, Canada.

Downing, R. L. 1980. Vital statistics of animal populations. Pages 247-267 *in* S. D. Schemnitz, editor. Wildlife techniques manual. The Wildlife Society, Washington, D.C., USA.

Eberhardt, L. L. 1960. Estimation of vital characteristics of Michigan deer herds. Michigan Department of Conservation Game Division, East Lansing, Michigan, USA.

Fieberg, J. R., K. W. Shertzer, P. B. Conn, K. V. Noyce, and D. L. Garshelis. 2010. Integrated population modeling of black bears in Minnesota: Implications for monitoring and management. Plos One **5**:e12114.

Fry, F. E. J. 1949. Statistics of a lake trout fishery. Biometrics **5**:27-67.

Fryxell, J. M., W. E. Mercer, and R. B. Gellately. 1988. Population dynamics of Newfoundland moose using cohort analysis. Journal of Wildlife Management **52**:14-21.

Gove, N. E., J. R. Skalski, P. Zager, and R. L. Townsend. 2002. Statistical models for population reconstruction using age-at-harvest data. Journal of Wildlife Management **66**:310-320.

Keeney, R. L., and H. Raiffa. 1993. Decisions with multiple objectives : preferences and value tradeoffs. Cambridge University Press, Cambridge UK and New York, USA.

Kelly, G. M. 1977. Fisher (Martes pennanti) biology in the White Mountain National Forest and adjacent areas. University of Massachusetts, Amherst.

Koen, E. L., J. Bowman, and C. S. Findlay. 2007. Fisher survival in eastern Ontario. Journal of Wildlife Management **71**:1214-1219.

Krohn, W. B., S. M. Arthur, and T. F. Paragi. 1994. Mortality and vulnerability of a heavily trapped fisher population. Pages 137-145 *in* S. Buskirk, A. S. Harestad, M. G. Raphael, and R. A. Powell, editors. Martens, sables, and fishers : biology and conservation. Comstock Pub. Associates, Ithaca, New York, USA.

Marealle, W. N., F. Fossoy, T. Holmern, B. G. Stokke, and E. Roskaft. 2010. Does illegal hunting skew Serengeti wildlife sex ratios? Wildlife Biology **16**:419-429.

Millspaugh, J. J., J. R. Skalski, R. L. Townsend, D. R. Diefenbach, M. S. Boyce, L. P. Hansen, and K. Kammermeyer. 2009. An evaluation of sex-age-kill (SAK) model performance. Journal of Wildlife Management **73**:442-451.

Paragi, T. F., S. M. Arthur, and W. B. Krohn. 1994. Seasonal and circadian activity patterns of female fishers, *Martes pennanti*, with kits. Canadian Field-Naturalist **108**:52-57.

Powell, R. A. 1994. Structure and spacing of *Martes* populations. Pages 101-121 *in* S. Buskirk, A. S. Harestad, M. G. Raphael, and R. A. Powell, editors. Martens, sables, and fishers : biology and conservation. Comstock Pub. Associates, Ithaca, New York, USA.

Powell, R. A., S. W. Buskirk, and W. J. Zielinski. 2003. Fisher and Martin: *Martes pennanti* and *Martes americana* Pages 635-649 *in* G. A. Feldhamer, B. C. Thompson, and J. A. Chapman, editors. Wild mammals of North America : biology, management, and conservation. Johns Hopkins University Press, Baltimore, Maryland, USA.

Powell, R. A., and W. J. Zielinski. 1994. Fisher. Pages 38-73 *in* L. F. Ruggiero, K. B. Aubry, S. W. Buskirk, L. J. Lyon, and W. J. Zielinski, editors. American marten, fisher, lynx, and wolverine in western United States. United States Forest Service, General Technical Report RM-254, Fort Collins, Colorado, USA.

Roseberry, J. L., and A. Woolf. 1991. A comparative evaluation of techniques for analyzing white-tailed deer harvest data. Wildlife Monographs:3-59.

Skalski, J. R., M. V. Clawson, and J. J. Millspaugh. 2012. Model evaluation in statistical population reconstruction. Wildlife Biology **18**:225-234.

Skalski, J. R., K. E. Ryding, and J. J. Millspaugh. 2005. Wildlife demography: analysis of sex, age, and count data. Elsevier Academic Press, Amsterdam and Boston, Massachusetts, USA.

Skalski, J. R., R. L. Townsend, and B. A. Gilbert. 2007. Calibrating statistical population reconstruction models using catch-effort and index Data. Journal of Wildlife Management **71**:1309-1316.

Van Why, K. R., and W. M. Giuliano. 2001. Fall food habits and reproductive condition of Fishers, *Martes pennanti*, in Vermont. Canadian Field-Naturalist **115**:52-56.

White, G. C., and B. C. Lubow. 2002. Fitting population models to multiple sources of observed data. Journal of Wildlife Management **66**:300-309.

Williams, B. W., D. R. Etter, P. D. DeWitt, K. T. Scribner, and P. D. Friedrich. 2011. Uncertainty in Determination of Sex From Harvested Bobcats. Journal of Wildlife Management **75**:1508-1512.

Table 2.1 List of models used for simulating the fisher population.

Population Model Number	Model Name	Model Type	Transformation	Stochastic	Parameters
1	Baseline Birth Rate	Birth rate	Log	No	intercept = 0.32 AGE = 0.09 AGE2 = -0.008
2	Increased Birth Rate	Birth rate	Log	No	intercept = 0.37
3	Baseline Pre-BS Females	Pre-breeding survival females	Logit	No	intercept = 1.0 AGE = 1.65 AGE2 = -0.16
4	Baseline Pre-BS Males	Pre-breeding survival males	Logit	No	intercept = 1.0 AGE = 1.5 AGE2 = -0.125
5	Decreased Pre-BS Females	Pre-breeding survival females	Logit	No	intercept = 0.8757
6	Decreased Pre-BS Males	Pre-breeding survival males	Logit	No	intercept = 0.8757
7	Baseline Post-BS Females	Pre-breeding survival females	Logit	No	intercept = 1.85 AGE = 0.45 AGE2 = -0.028
8	Baseline Post-BS Males	Pre-breeding survival males	Logit	No	intercept = 2.25 AGE = 0.4 AGE2 = -0.02
9	Baseline Harvest Rate Females	Annual harvest rate females	Logit	Yes	intercept = -1.777 simeffort*=0.0325 AGE = -0.325 AGE2 = 0.03

*simeffort is multiplied by the effort covariate value – 15.00 for the baseline harvest rate models

▪simeffort is multiplied by the effort covariate value – 11.33 for the decreased harvest rate models

°simeffort is multiplied by the effort covariate value – 19.15 for the increased harvest rate models

Table 2.1 continued

Population Model Number	Model Name	Model Type	Transformation	Stochastic	Parameters
10	Baseline Harvest Rate Males	Annual harvest rate males	Logit	Yes	intercept = -1.9 simeffort*=0.0325 AGE = -0.25 AGE2 = 0.02
11	Decreased Harvest Rate Females	Annual harvest rate females	Logit	Yes	intercept = -1.777 simeffort▪=0.0325 AGE = -0.325 AGE2 = 0.03
12	Decreased Harvest Rate Males	Annual harvest rate males	Logit	Yes	intercept = -1.9 simeffort▪=0.0325 AGE = -0.25 AGE2 = 0.02
13	Increased Harvest Rate Females	Annual harvest rate females	Logit	Yes	intercept = -1.777 simeffort°=0.0325 AGE = -0.325 AGE2 = 0.03
14	Increased Harvest Rate Males	Annual harvest rate males	Logit	Yes	intercept = -1.9 simeffort°=0.0325 AGE = -0.25 AGE2 = 0.02

*simeffort is multiplied by the effort covariate value – 15.00 for the baseline harvest rate models

▪simeffort is multiplied by the effort covariate value – 11.33 for the decreased harvest rate models

°simeffort is multiplied by the effort covariate value – 19.15 for the increased harvest rate models

Table 2.2 Simulation trajectories produced from population models. All trajectories use the baseline models unless otherwise specified.

Trajectory Number	Trajectory Name	Trajectory	Birth Rate Model	Survival Rate Model	Simulated Effort Covariate	Average annual lambda
1	stable	stable	1 - Baseline Birth Rate	3 - Baseline Pre-BS Females & Baseline Pre-BS Males	6 - Baseline Effort	1.0
2	increase.birth	increase	2 - Increased Birth Rate	3 - Baseline Pre-BS Females & Baseline Pre-BS Males	6 - Baseline Effort	1.01
3	decrease.survival	decrease	1 - Baseline Birth Rate	4 - Decreased Pre-BS Females & Decreased Pre-BS Males	6 - Baseline Effort	0.99
4	increase.harvest	increase	1 - Baseline Birth Rate	3 - Baseline Pre-BS Females & Baseline Pre-BS Males	7 - Decreased Effort	1.02
5	decrease.harvest	decrease	1 - Baseline Birth Rate	3 - Baseline Pre-BS Females & Baseline Pre-BS Males	8 - Increased Effort	0.98

Table 2.3 List of models used in simulating the data collection process.

Error Model Number	Model Name	Model Type	Transformation	Stochastic	Parameters
1	100% Reporting Rate Females	reporting rate females	None	No	intercept = 1
	100% Reporting Rate Males	reporting rate males	None	No	intercept = 1
2	90 % Reporting Rate Females	reporting rate females	None	No	intercept = 0.9
	90% Reporting Rate Males	reporting rate males	None	No	intercept = 0.9
3	No Error – Females	gender classification females	None	No	intercept = 1
	No Error – Males	gender classification males	None	No	intercept = 1
4	10% Error – Females	gender classification females	None	No	intercept = 0.9
	10% Error – Males	gender classification males	None	No	intercept = 0.9
5	No Age Error	age error	polynomial	No	-25
6	5% Age Error	age error	polynomial	No	-3.54

Table 2.4 List of scenarios and their associated population trajectories and error models used in simulating the data collection process for that trajectory.

Scenario Number	Scenario Name	Error Name	Error Model Numbers	Population Trajectory Name	Population Trajectory Number
1	stable.null	Null	1,3,5	stable	1, $\lambda = 1.00$
2	increase.birth.null	Null	1,3,5	increase.birth	2, $\lambda = 1.01$
3	increase.harvest.null	Null	1,3,5	increase.harvest	4, $\lambda = 1.02$
4	decrease.survival.null	Null	1,3,5	decrease.survival	3, $\lambda = 0.99$
5	decrease.harvest.null	Null	1,3,5	decrease.harvest	5, $\lambda = 0.98$
6	stable.reporting	Reporting	2,3,5	stable	1, $\lambda = 1.00$
7	stable.sex	Sex	1,4,5	stable	1, $\lambda = 1.00$
8	stable.age	Age	1,3,6	stable	1, $\lambda = 1.00$
9	decrease.harvest.all	All	2,4,6	decrease.harvest	5, $\lambda = 0.98$
10	decrease.survival.all	All	2,4,6	decrease.survival	3, $\lambda = 0.99$
11	stable.all	All	2,4,6	stable	1, $\lambda = 1.00$
12	increase.birth.all	All	2,4,6	increase.birth	2, $\lambda = 1.01$
13	increase.harvest.all	All	2,4,6	increase.harvest	4, $\lambda = 1.02$

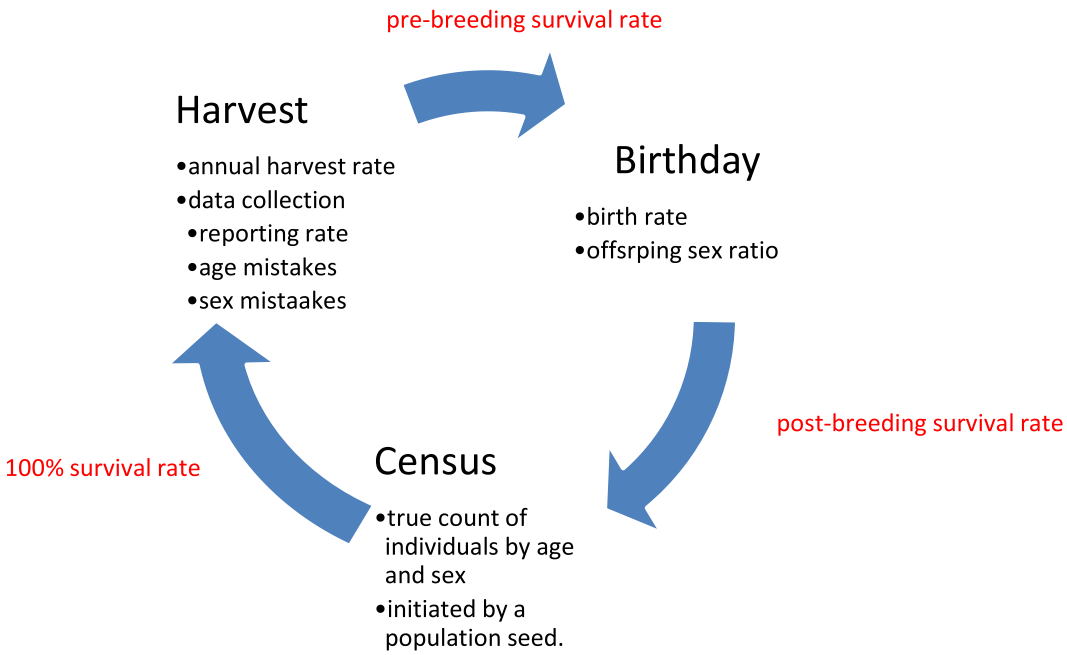


Figure 2.1 Simulated Life Cycle. An annual census occurs at which time the true count of the number of individuals is determined. 100% of individuals survive from the time of the census until the harvest occurs, at which time all mortality is assumed to be due to harvest. Harvest is determined by the simulated harvest rate, with errors resulting in the count of the harvest depending on the error model used. Following the harvest individuals may survive until their birthdays based on the pre-breeding survival rate, at which time they advance in age by one year and reproduce based on the birth rate. Following the birthday individuals advance to the next census depending on the post-breeding survival rate.

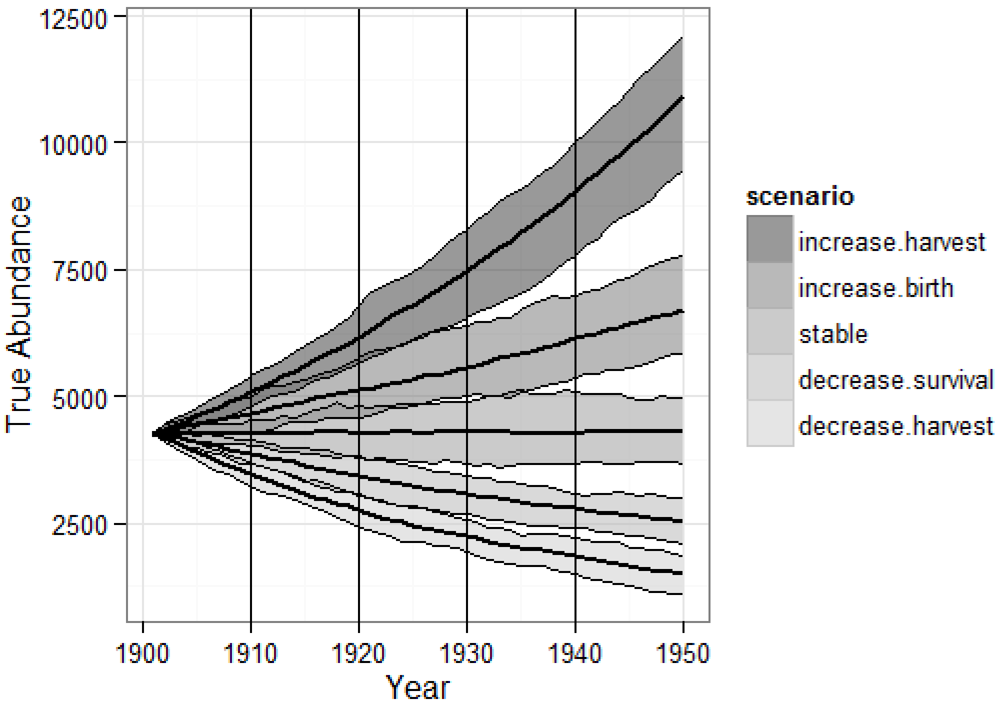


Figure 2.2 Simulated population trajectories. Each line represents the median abundance over the 100 simulations, with the shaded region surrounding each line showing the range from the minimum to maximum simulated abundance in each year. The scenarios are the increase.harvest, increase.birth, stable, decrease.survival, and decrease.harvest from top to bottom.

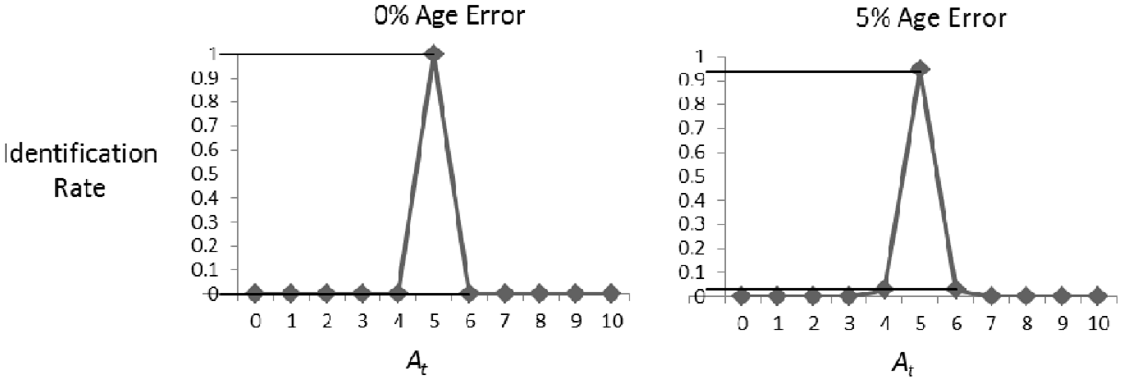
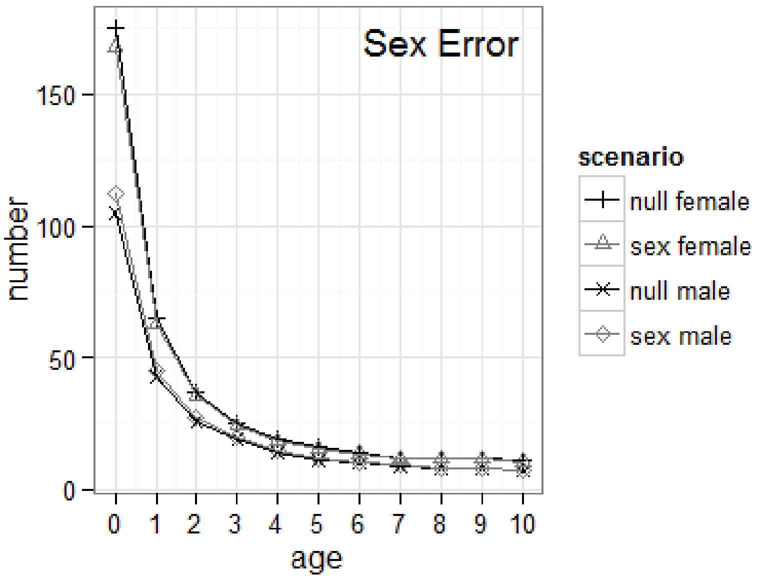
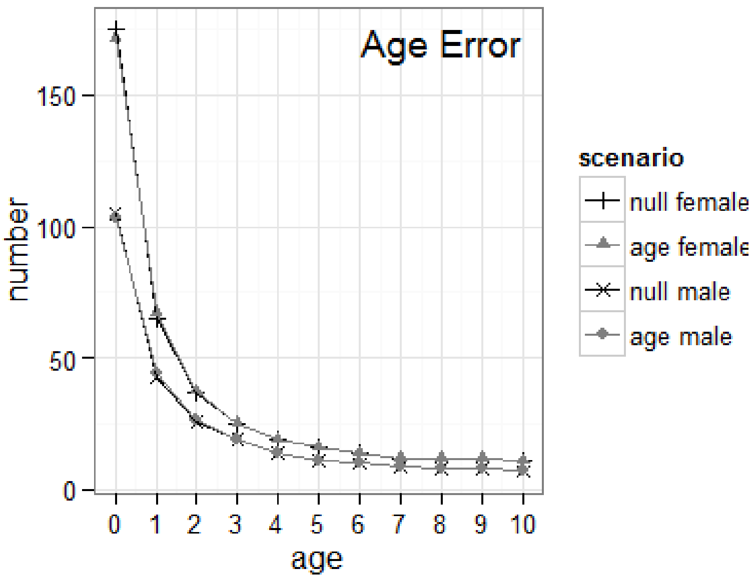
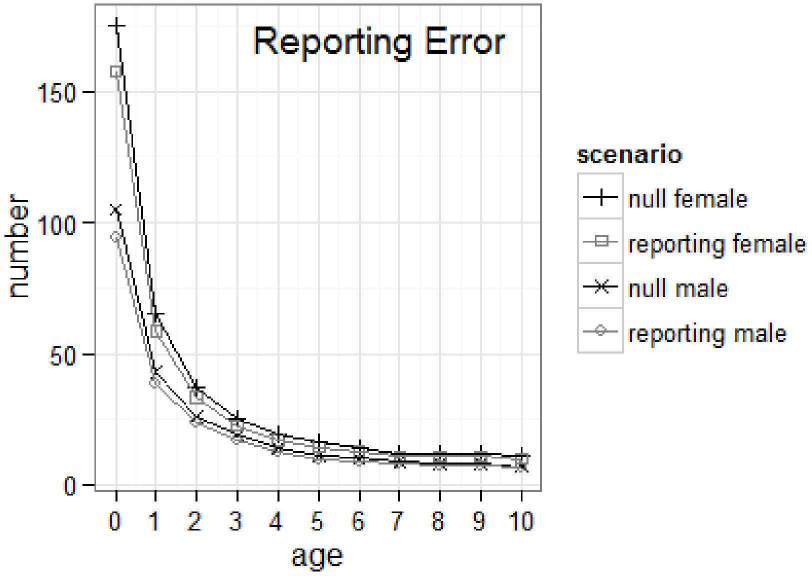


Figure 2.3 Example age classification rate for individuals that are truly 5 years old. The y-axis show the rate at which 5 year olds are classified into each of the ages shown on the x-axis. The left panel shows the rates for no error in age (0% age error. The right panel shows the rates with age error included (5% age error).


Sex Error
number
0
50
100
150
age
0 1 2 3 4 5 6 7 8 9 10
scenario
null female
sex female
null male
sex male


Age Error
number
0
50
100
150
age
0 1 2 3 4 5 6 7 8 9 10
scenario
null female
age female
null male
age male


Reporting Error
number
0
50
100
150
age
0 1 2 3 4 5 6 7 8 9 10
scenario
null female
reporting female
null male
reporting male

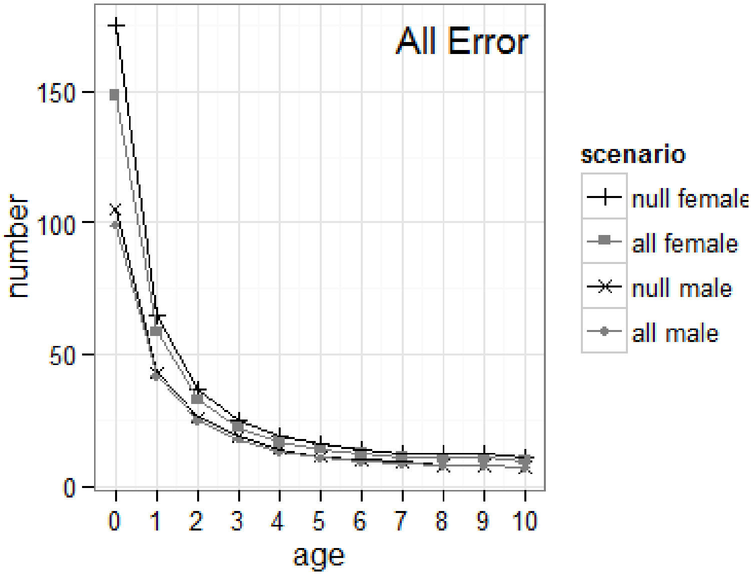

All Error
number
0
50
100
150
age
0 1 2 3 4 5 6 7 8 9 10
scenario
null female
all female
null male
all male

Figure 2.4 Median observed annual harvest counts by age and sex for the different error models. Each panel shows the median null error harvest count for females (null females) and males (null males) in black with the counts including error shown in grey. The top left panel shows the effects of sex error in the counts, the top right of age error, the bottom left of incomplete reporting, and the bottom right shows the combined effect of all three error models.

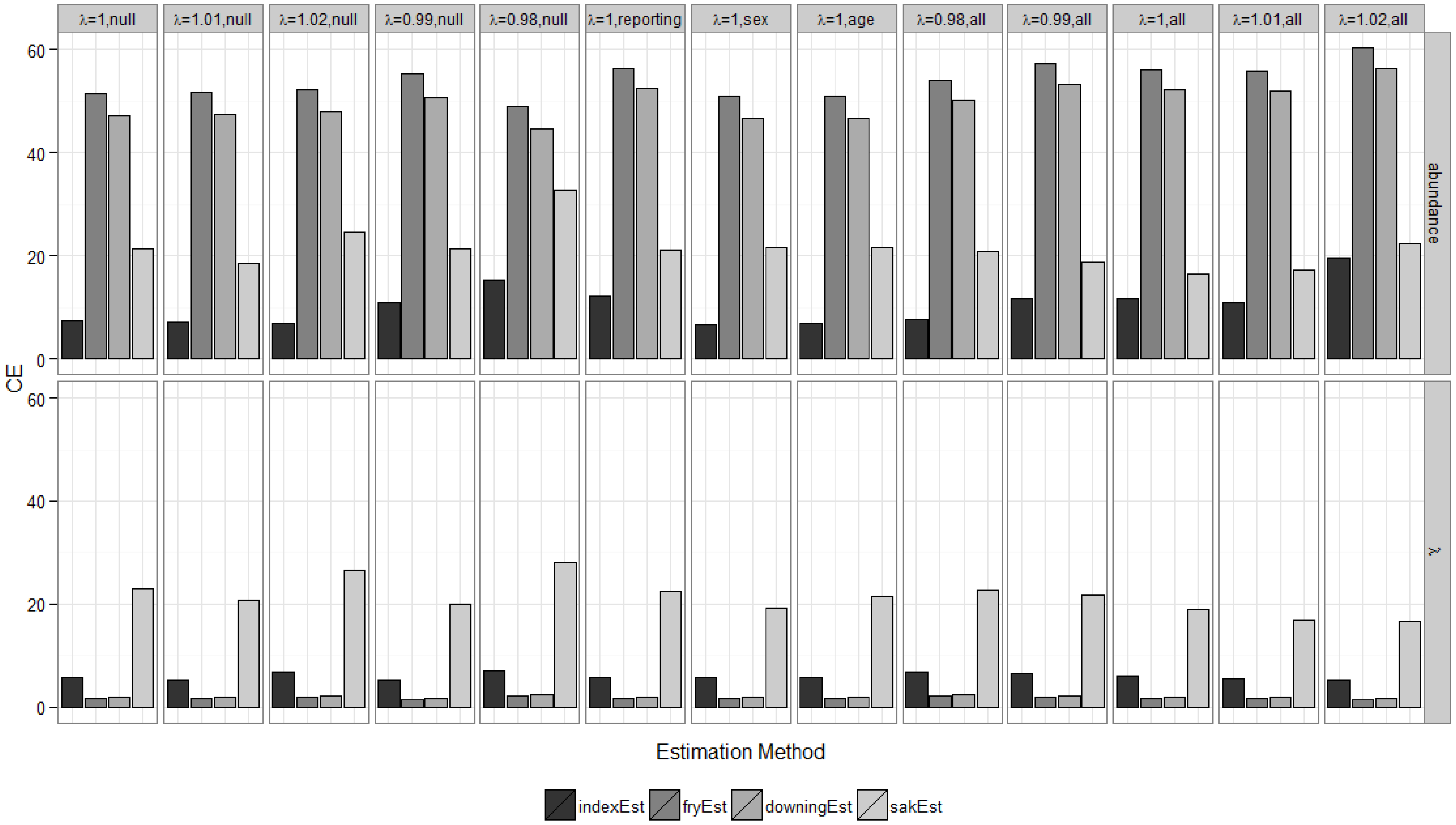


Figure 2.5 Estimator coefficient of error (CE) in abundance and lambda. The CE in abundance is shown in the top panels and CE in lambda is shown in the bottom panels. Each panel contains a bar for each of the four estimation methods (`indexEst`, `fryEst`, `downingEst`, and `sakEst` from left to right). The panels from left to right are the thirteen simulation scenarios, denoted by the scenario lambda value and error model. For example, the left most panel is scenario number 1, which is a stable population (λ = 1) with no error, which is produced by the null error model.

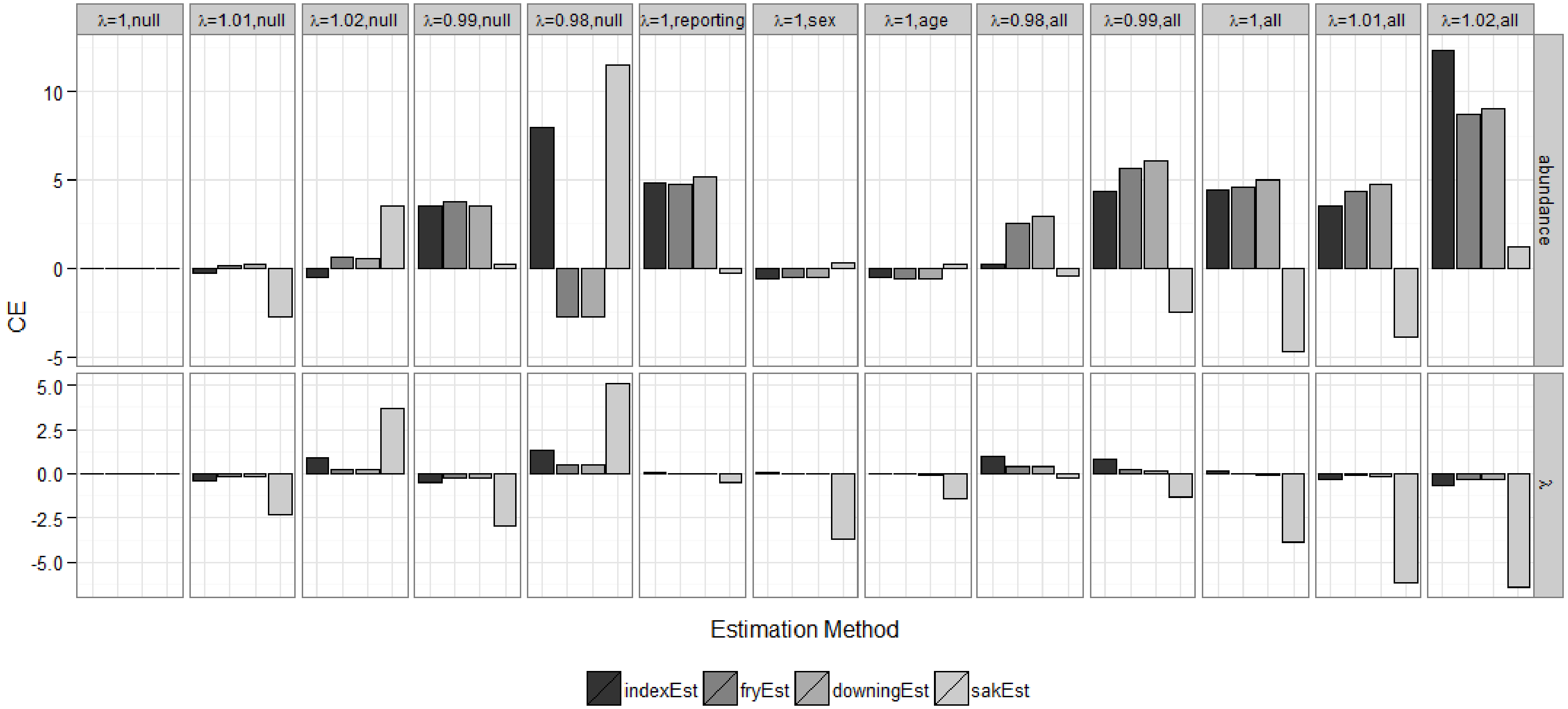


Figure 2.6 Difference from baseline coefficient of error (CE) performance. The change in the CE in abundance (top panels) and change in CE in lambda (bottom panels) by estimator relative to the CE in abundance and lambda in the "stable.null" scenario. Each panel contains a bar for each of the four estimation methods (`indexEst`, `fryEst`, `downingEst`, and `sakEst` from left to right). The panels from left to right are the thirteen simulation scenarios, denoted by the scenario lambda value and error model. The value of each bar is the change in CE from scenario one to the current scenario, by estimator, with negative values indicating a decrease (improvement) in the CE value and a positive value indicating an increase (worsening) in the CE value. For example, the CE for downingEst increase by 5 from scenario one to scenario 11 (λ=1.00, null to λ=1.00, all).

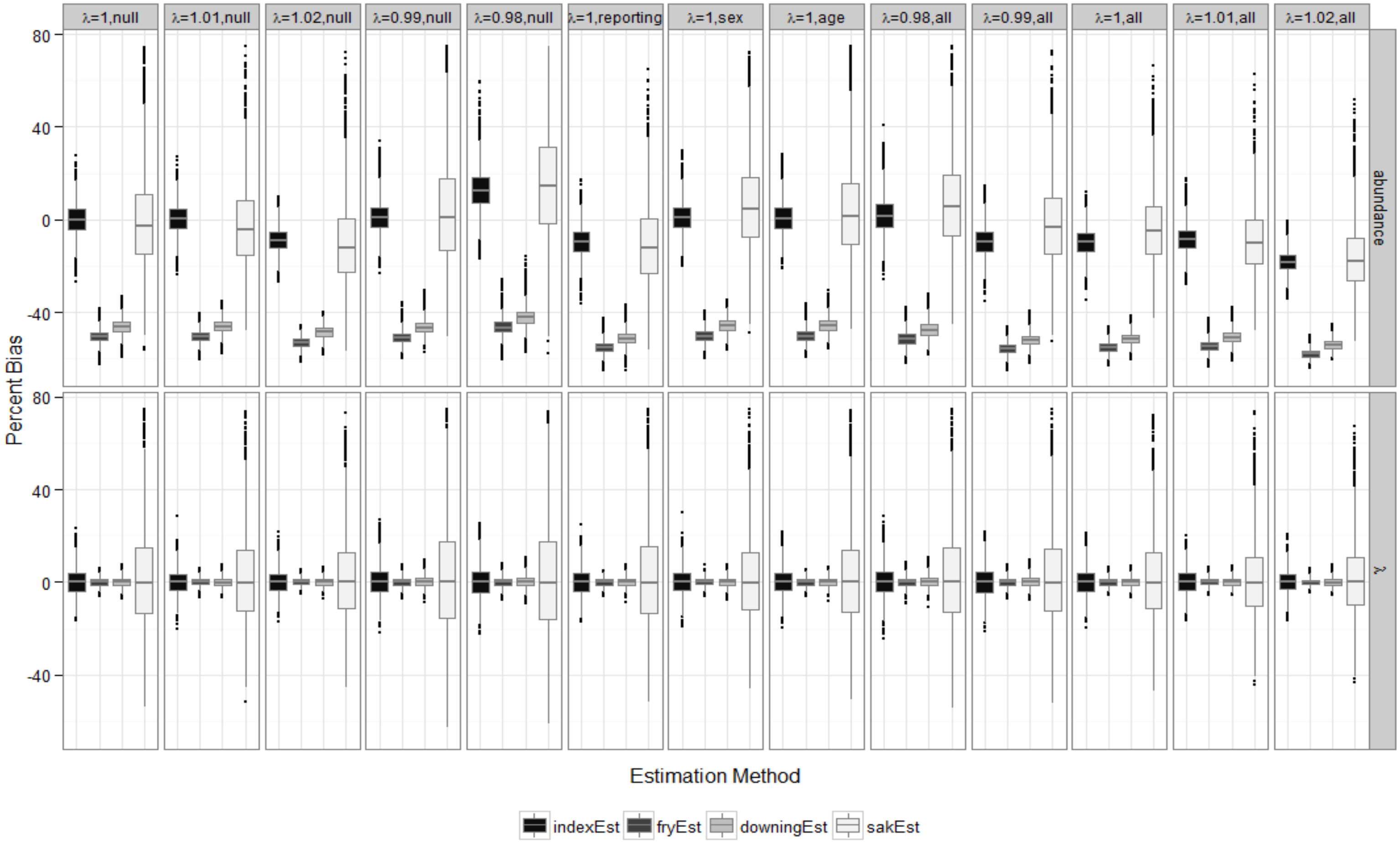


Figure 2.7 Boxplots of raw bias in abundance and lambda. Boxplots of the performance in terms of percent bias in abundance (top panels) and percent bias in lambda (bottom panels) on the y-axes. Each panel contains a box plot of the values across simulations from years 1 to 40 for each of the four estimation methods (`indexEst`, `fryEst`, `downingEst`, and `sakEst` from left to right). The panels from left to right are the thirteen simulation scenarios, denoted by the scenario lambda value and error model.

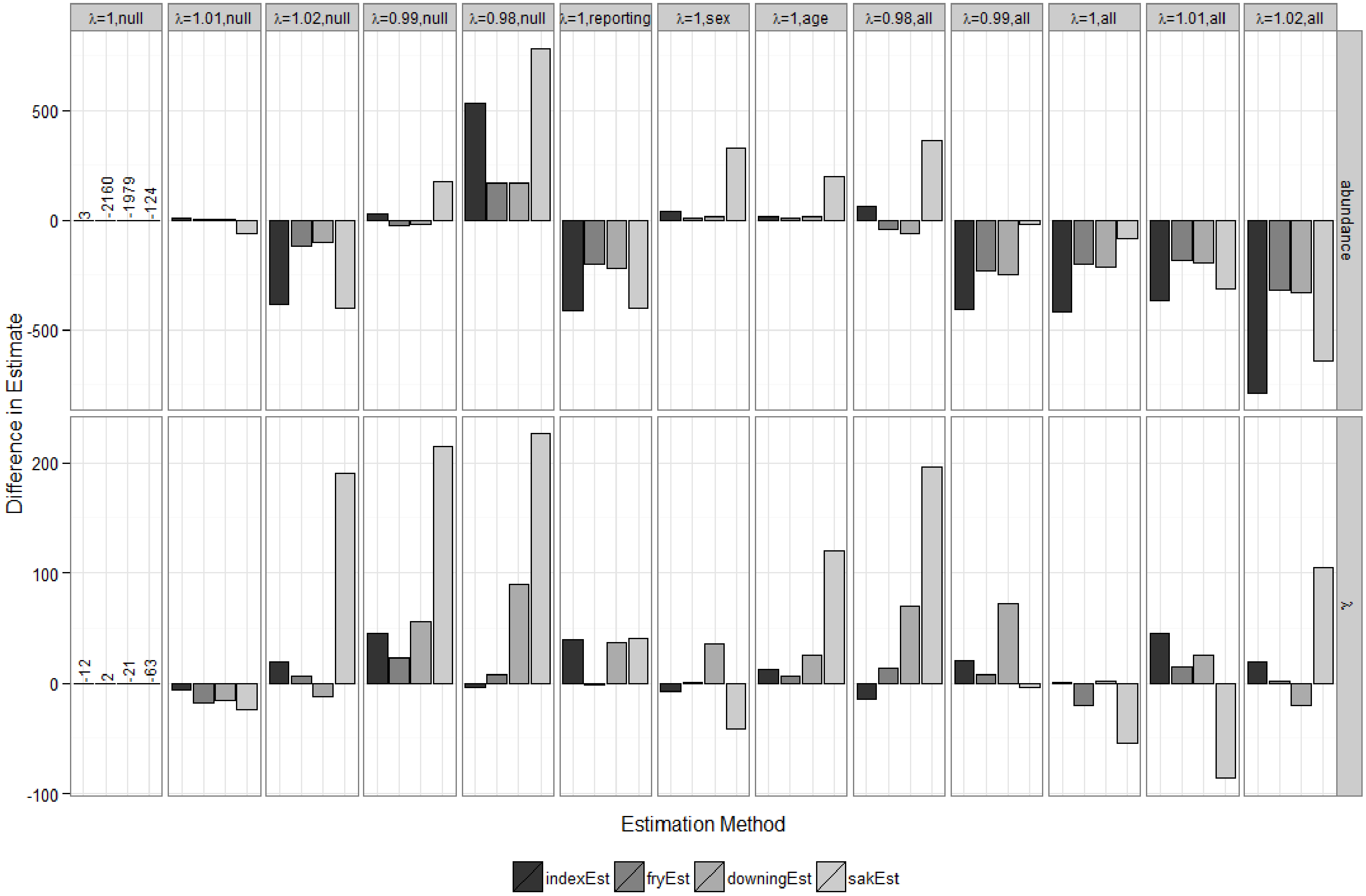

λ=1,null
λ=1.01,null
λ=1.02,null
λ=0.99,null
λ=0.98,null
λ=1,reporting
λ=1,sex
λ=1,age
λ=0.98,all
λ=0.99,all
λ=1,all
λ=1.01,all
λ=1.02,all
abundance
λ
500
0
-500
200
100
0
-100
3
-2160
-1979
-124
-12
2
-21
-63
Difference in Estimate
Estimation Method
indexEst
fryEst
downingEst
sakEst

Figure 2.8 Difference from baseline performance. This figure displays the change in the median estimate of abundance (top panels) and lambda (bottom panels) relative to the median estimate in scenario one (λ=1.00, null) for each estimator. The labels in the left most panels denote the median bias in abundance and the median bias in lambda relative to the initial stable null population size (4277 individuals). For example, the median sakEst abundance estimate was negatively biased by -124 individuals. Each panel contain a bar for each of the four estimation methods (`indexEst`, `fryEst`, `downingEst`, and `sakEst` from left to right). The panels from left to right are the thirteen simulation scenarios, denoted by the scenario lambda value and error model. The value of each bar is the change in the median estimate from scenario one to the current scenario, by estimator, with negative values indicating a change toward negative bias and a positive vale indicating a change toward positive bias. For example, the sakEst median bias for scenario two (e bias. For example, the `sakEst` median bias for scenario 2 (λ=1.01, null) is 61 individuals more negatively bias, and 172 individuals more positively biased for scenario 4 (λ=0.99, null).

CHAPTER 3. A DECISION ANALYSIS APPROACH TO SELECTING A PROGRAM FOR MONITORING POPULATON SIZE OF GAME SPECIES

Jonathan W. Cummings
Vermont Cooperative Fish and Wildlife Research Unit
Rubenstein School of Environment and Natural Resources
University of Vermont
Burlington, VT 05405

Therese M. Donovan
U.S. Geological Survey, Vermont Cooperative Fish and Wildlife Research Unit
Rubenstein School of Environment and Natural Resources
University of Vermont
Burlington, VT 05405

Prepublication Disclaimer:

This draft manuscript is distributed solely for purposes of scientific peer review. Its content is deliberative and predecisional, so it must not be disclosed or released by reviewers. Because the manuscript has not yet been approved for publication by the U.S. Geological Survey (USGS), it does not represent any official USGS finding or policy.

3.1 Abstract

Population monitoring programs aim to meet many objectives. Some common objectives include accurately estimating population size and trend, effectively detecting disease in a population, minimizing management costs, and improving citizen engagement in the management and monitoring process. I present a decision analysis framework that supports monitoring program selection. The framework includes a simulation package that evaluates monitoring programs for their ability to accurately track wildlife populations. The framework also translates this evaluation into a relative performance score for a set of possible monitoring programs. Therefore, unlike the coefficient of error performance measure, this framework enables explicit trade-offs between management objectives and links estimator performance directly to management objectives. Here I demonstrate this approach to evaluate monitoring programs that combine the option to conduct or not conduct necropsies for fisher (*Martes pennanti*) data collection in the state of Vermont, USA with 4 estimation methods: an index method, Fry, Downing, and Sex-Age-Kill. Only index and Sex-Age-Kill are available without necropsy data, because Fry and Downing methods require age at harvest data. I found that the necropsy monitoring program using the Downing estimation method best achieves the fisher monitoring program objectives for the Vermont Fish and Wildlife Department, a conclusion that may not have been reached from the coefficient of error measure alone.

Key Words: population monitoring, abundance estimation, wildlife management, game species, *martes pennanti*, decision analysis, structured decision making

3.2 Introduction

Successful game management is an important aspect of effective wildlife management authorities. Game species provide a wide range of benefits, such as economic and subsistence benefits, personal fulfillment and recreational opportunities, aesthetic and existence value, as well as the benefit of supporting ecological processes (Decker et al. 1987). While stakeholders are interested in successful management outcomes, the objectives must be met within budgetary constraints of management organizations. For game species, sub-optimal management can result in a) a population size that exceeds the target size (resulting in lost opportunity costs of foregone current harvest), or b) a population size below the target size (resulting in lost future harvest and future non-consumptive use while the population recovers). Given the risk, is not easy for managers to determine what monitoring program (defined here as the combination of data collection activities and the estimation method used to estimate the population state) to select to best manage a game species.

A hallmark objective of many monitoring programs is to estimate the state of a population (Lyons et al. 2008) while minimizing cost. State variables of interest can range from occupancy to abundance to population trend, among others. A monitoring program includes all of the activities, data collection, and estimation methods used to assess and track state variable over time. Managers select various combinations of data sources and an accompanying estimation technique to obtain an estimate of the population status to make management decisions. The combination of data sources can range from monitoring total yearly harvest to more involved data collection, including harvest reports by day, necropsies or other techniques to determine age, sex and nutrition of each harvested individual, surveys to assess daily effort and harvest rates, surveys of marked individuals to determine demographic rates, and direct observations of individuals. All of these activities contribute to the cost of operating a monitoring program.

The second objective of many monitoring programs is to maximize the performance of the method used for converting the data into an estimate of the state of the population; that is, select a method which minimizes bias and maximizes precision. I define an estimation method as the mathematical model that converts monitoring data and or expert opinion into an estimate of population state. There are a number of estimation methods available for converting the monitoring data into estimates of abundance, ranging from harvest indices that only need an annual count of the number of individuals harvested to statistical population reconstruction methods that use counts of harvested animals by age and by sex as well as auxiliary observations of individual's fate in order to enter population vital rates as model inputs. Several evaluations have been conducted on the performance of these estimators, often using the Coefficient of Error (CE) method introduced by Millspaugh et al. (2009), which effectively combines bias and precision into a single metric. The evaluations that have been conducted (e.g., Roseberry and Woolf 1991, Davis et al. 2007, Millspaugh et al. 2009, Skalski et al. 2012, Cummings and Donovan in preparation-b, Rinehart and Donovan in preparation) often vary from one evaluation to the next in terms of the estimators evaluated and the species analyzed, making it difficult to compare among alternatives.

To complicate matters, managers may have objectives beyond cost and estimator performance when selecting monitoring programs. For instance, in selecting a monitoring program, an agency may have objectives such as minimizing bias and maximizing precision in the estimation of the state variable(s), minimizing costs in data collection, maximizing participation rate across partner agencies, or others. Accounting for all of these objectives simultaneously requires going beyond the previously developed metrics of estimator performance. In addition, a complicating factor is that objectives vary from agency to agency, and the importance that they place on each objective can vary also.

As an example of this challenge, the primary objectives for management of fisher (*Martes pennanti*) in the state of Vermont (VT), USA are to maintain a sustainable population through an unbiased and precise measurement of the population status and to maximize the opportunity for citizen engagement and participation in data collection. To carry out their mission and meet these objectives, the Vermont Fish and Wildlife Department (VFWD) collects daily harvest data (the number of animals harvested per day during the season) and necropsy data (which provide information on the age and sex of harvested individuals, described below). They additionally conduct a survey of trappers on an annual basis to engage trappers and estimate trapper effort. With these data sources, each with an associated cost, there are several estimation approaches that can be used for long-term monitoring of a state variable. With the harvest totals alone, the index method is the only option. If trappers can accurately identify the sex of the animal and classify animals into age groups (first-year breeders, older breeders, or other), the Sex-Age-Kill method can be employed without the benefit of necropsy. With necropsy data collection, some of the population reconstruction methods such as Fry (Fry 1949) and Downing (Downing 1980), along with the index and Sex-Age-Kill estimator (Eberhardt 1960) are available for use.

In a previous paper (Chapter 2), I evaluated the performance of these four estimators with respect to bias and precision (CE), and how robust they were to errors in the data collection process. I found the Sex-Age-Kill model had the best performance in terms of estimating abundance, while the Fry and Downing methods were the best performers in terms of estimating population trend. However, this evaluation may be insufficient for selecting a monitoring program because the state has additional objectives, including cost and participation with trappers and research that is external to the Department. Selecting the best set of data and estimation method (monitoring program) is difficult. What is needed is an approach that scores the alternatives with respect to the VFWD's multiple monitoring objectives.

In this paper (Chapter 3), I demonstrate the utility of decision analysis as a means to address this monitoring program dilemma. By including demonstrating the analysis of the consequences and trade-offs of selecting one monitoring program over another in terms of the multiple objectives often present for game species monitoring an informed and justifiable decision can be determined. In particular I use the structured decision making approach (Gregory et al. 2012, Conroy and Peterson 2013) to decision framing and evaluation, which follows steps know by the abbreviation PrOACT (Hammond et al. 1999), included in the R package `AMharvest` (Cummings and Donovan in preparation-b, Donovan et al. in preparation). PrOACT refers to the process of breaking a decision into its component parts by identifying the **Pr**oblem, describing the **O**bjectives, enumerating the **A**lternatives, predicting the **C**onsequences, and evaluating the **T**rade-offs in order to identify the best available decision. I use a SMART analysis (simple multi attribute ranking technique) as a decision analysis tool for trade-off evaluation (Von Winterfeldt and Edwards 1986), and demonstrate this approach with a decision problem focused on the selection of a monitoring program for fishers in Vermont.

My objectives are to 1) Describe the decision problem of monitoring program selection for VT furbearer management, 2) Describe my simulation of that problem and its analysis using the R package `AMharvest`, 3) Determine the monitoring program that will best meet the objectives for VT fisher management, and 4) Compare the result with the selection of a monitoring program based solely on a Coefficient of Error (CE) selection method.

3.3 Methods

3.3.1 Fisher

The fisher is the largest member of the *Martes* genus with males averaging 3.3 kg and 60 cm in length and females averaging 1.8 kg and 51 cm (Douglas and Strickland 1987). Females produce their first litter at 24 months and proceed to produce one litter per year thereafter, with males becoming reproductively active at age one (Powell and Zielinski 1994). Breeding females have been found to produce between 1 and 4 corpora lutea annually, with an average ranging from 1.8 to 2.7 across ages in studies in the northeastern U.S., but slightly higher for females in their prime (Douglas and Strickland 1987, Van Why and Giuliano 2001, Powell et al. 2003). Offspring sex ratio has not been found to differ from 50:50 (Powell 1994). The annual recruitment (birth rate) of offspring into the population averages between 1.18 to 2.16 across studies in the northeast (Paragi et al. 1994, Koen et al. 2007, Buskirk et al. 2012).

Following successful reintroduction in the 1960s, fishers have been harvested in Vermont since 1974 with a five year trapping reprieve between 1979-1983 (Powell and Zielinski 1994). The survival rate of fishers depends on their age and the trapping rate. The annual survival rate without trapping ranges between 0.7 and 0.8 for juveniles and is greater than 0.9 adults (Krohn et al. 1994, Powell 1994). The estimated life span of a fisher is 10 years (Powell et al. 2003). With trapping, these rates can diminish to as low as 0.34 (Krohn et al. 1994, Powell 1994). Fisher density has been found to range from 0.05 to 0.38 fisher per square kilometer, with an average value of 0.18 in habitat similar to VT (Powell et al. 2003).

3.3.2 Decision Problem

Currently there are two main elements to the data collection of harvested fisher in VT. First, trappers are required to tag all carcasses and submit an accompanying record to the VTFWD within 48 hours of the close of the trapping season, and notify a game warden, who collects and stores carcasses until they can be processed. These records provide information on the number of harvested animals per trapping season. Second, necropsies are conducted on every harvested fisher collected by wardens. The necropsy process enables managers to obtain data on the age and sex of the fishers that are harvested, as well as providing external researchers the opportunity to collect samples for toxicity, disease, nutritional or other research studies. In addition to the harvest data, the Department conducts an annual survey of trappers to solicit their knowledge and to collect data on annual trapping effort. The Department places value on these external studies for increasing general knowledge about fisher and providing possible alerts that may trigger fisher population change.

However, conducting necropsies and trapper surveys requires a monetary commitment by the VFWD to maintain equipment and support staff, in addition to additional time investments from trappers who provide the carcasses, wardens who collect harvest reports and transport the carcasses to a central data processing area, and volunteers who assist with the necropsy process itself. Because of the time and money that goes into the necropsy process in particular, there is some question for Vermont game species managers as to whether the benefits of using necropsies as part of the fisher monitoring program justify the costs, or if a simpler monitoring program that only collects harvest data (in the form of total number harvested) is sufficient to meet the management objectives. Based on this, the problem to address is: How to monitor the fisher population in Vermont in order to best achieve the objectives of the monitoring program?

3.3.3 Decision Objectives

The objectives I include for evaluating the alternative fisher monitoring programs fall into three categories: 1) maintain a sustainable fisher population, 2) minimize the cost of monitoring the species, and 3) maximize the public knowledge and engagement (Table 1). Within each category, specific decision objectives were defined, resulting in 8 total decision objectives for selecting a monitoring program. To quantify the assessment of these objectives, measureable attributes were identified and importance scores were given to each of the objectives (Table 1).

The objectives and their importance scores (weights) are elicited from the decision maker or decision makers. The furbearer monitoring program is designed and administered by Chris Bernier, the VT Fish and Wildlife Department furbearer managers, with input from the Big Game lead and committee. Therefore, I interviewed the objectives and measureable attributes were developed via interviews with Chris Bernier to represent the interests the VT Fish and Wildlife Department wish to achieve through fisher monitoring and the relative importance of achieving each of them.

The interview process was completed in three steps. In the first interview session I explained the structured decision making process, the role objectives play in the analysis, and how objectives are structured. During the second interview I elicited the objectives, their measureable attributes, and the with and with-out necropsy consequences for the objectives unrelated to estimator performance. Following this interview Chris discussed the interview results with the VTFWD big game committee and the objectives and their consequences were re-evaluated and the objectives weights were elicited in a third interview.

Within the "maintain sustainable population" category, there were five objectives that the monitoring program selection can affect, based on the type of data collection that occurs, that are means to achieving the sustainable fisher population objective. They are: minimizing the bias in lambda estimates, maximizing the precision in lambda estimates, minimizing the bias in abundance estimates, maximizing the precision of abundance estimates, and maximizing the probability of detecting disease in the population. The bias objectives are measured by the bias in the estimates, and the precision estimates are measured by the 5th to 95th percentile range of the estimates (see Decision Consequences). The disease detection objective was measured by the probability that the monitoring program selected will detect a disease if one is present. These probabilities were elicited from Chris Bernier, the Vermont Fish and Wildlife Department furbearer manager.

Under the cost category (decision objective 6), the cost of the monitoring program derives from staff time, travel costs, equipment, and data processing necessary to track the status of the population and obtain information from trappers, the public, and academic institutions, which is affected by the type of data collection that occurs.

The goal of the public knowledge and engagement category (decision objectives 7 and 8) is to have an informed citizenry that is aware of the management and monitoring efforts undertaken for game species management and the status of the population. There are two groups of individuals that managers are concerned with, the trappers who directly participate in the harvest of fishers, and secondly academic institutions and the general public that help inform management and communicate the status of management and the species.

The weights for the objectives representing the relative importance of the objectives were placed on a 100 point scale. The most important objective identified was the maximize precision of lambda objective with an importance score of 20, followed by precision of the abundance estimate with a score of 18, bias in the lambda estimate with a score of 16, bias in the abundance estimate with a score of 14, and disease detection with a score of 12. The cost objective was assigned an importance score of 12. The trapper engagement objective received an importance score of 5 and the academic and public engagement objective received an importance score of 3. A combined final score of 100 would indicate that an alternative was best for all objectives, a score of zero that it was worst, and a score of 50 that an alternative's average outcome was half-way between the best and worst alternatives' outcomes.

3.3.4 Decision Alternatives

3.3.4.1 Estimation Methods

There are a number of methods available for converting the fisher monitoring data into estimates of abundance that I evaluate here, namely: the index method (`indexEst`), two virtual population reconstruction methods (`fryEst` and `downingEst`), and the sex-age-kill method (`sakEst`). Each of these estimators has unique data input requirements, along with different costs.

The harvest index method in `AMharvest` uses the function `indexEst`, which takes the annual harvest data (total or by age and sex) and an estimated harvest rate model as inputs. This rate is normally based on expert opinion. Harvest indices provide an indirect estimate of abundance using counts of sub-groups of the total population (e.g. harvested individuals or only adult males) or the ratio of membership in sub-groups (e.g. the ratio of adult females to adult males that are harvested). The number of harvested individuals provides an index of the total population size, but variability in effort and harvest success result in this being an imperfect indicator of the total abundance.

The estimators introduced by Fry (1949) and Downing (1980) are known as population reconstruction methods. These methods use back-calculation of harvest data to produce year-, age-, and sex-specific abundances. By summing over the age classes, annual abundance levels are estimated by including survival rates that are adjusted to reflect other sources of mortality in addition to the harvest (Skalski et al. 2005). The difference between the different population reconstruction methods is how they account for the survival and harvest rates. The method utilized by Fry (1949) estimates the minimum population size by summing lifetime harvest numbers of each cohort, but does not account for additional sources of mortality, producing only the minimum population size as an index of the absolute abundance. In contrast, the Downing reconstruction method (Downing 1980) does not estimate vital or harvest rates directly, but uses a weak proxy of adult mortality to reconstruct the pre-hunt population by backward-addition of known mortality and a minimal assumption of unaccounted-for mortality (Downing 1980). The Fry and Downing population reconstruction methods in `AMharvest` use the functions `fryEst` and `downingEst`, respectively.

The Sex-Age-Kill method is a life-history based method that uses harvest information and sex and age ratios to estimate the abundance of the population (Eberhardt 1960, Roseberry and Woolf 1991, Millspaugh et al. 2009). The Sex-Age-Kill method in `AMharvest` uses the function `sakEst`, which takes annual harvest data by age group (young, subadults, recruits, and vets), as well as estimates of the proportion of mortality due to harvest, and the young per adult female as inputs. Young are less than one year old, subadults are 1 plus years old but have not yet reached breeding age, recruits first-year breeders that have been recruiting into the breeding population, and vets include experienced breeders (individuals above the age of recruitment). The `sakEst` method estimates the adult male harvest rate, and the total adult male population is estimated from the adult male harvest rate and the proportion of the total mortality that is due to harvest. The total adult female population is derived from the SAK output of adult sex ratio, and the total juvenile population is derived from the total female adult estimate and the assumed birth rate. Summing the adult male, adult female, and young abundance estimates produces the total abundance estimate.

3.3.4.2 Monitoring Programs

I considered 6 alternative monitoring programs, consisting of an estimation method and the data collection process (Table 2). Namely, I evaluated the consequences and trade-offs of a monitoring program that includes necropsy analysis and trapper surveys (with necropsy) against the consequences of a monitoring program that does not include conducting necropsies (without necropsy). When necropsies are conducted, all of the above estimation methods are available for use, resulting in 4 alternatives with necropsy (N-Index, N-Fry, N-Downing, and N-SAK). I assumed that the necropsy data would be supplemented with an annual trapper survey. Without necropsy, age data is not available and sex data is likely to be more error prone, which eliminates the population reconstruction methods (Fry and Downing) from consideration, leaving the index method (WO-Index) and the sex-age-kill method (WO-SAK), which must now rely on trapper or warden age-group and sex classifications that are less reliable because they are unconfirmed by necropsy. In both without-necropsy alternatives, I assumed that annual trapper surveys would continue as the cost of conducting them is compensated for by the benefits of maintaining trapper engagement in fisher management.

3.3.5 Decision Consequences

The consequences of a decision analysis link the 8 decision objectives and 6 alternative monitoring programs through predictions of the outcomes of each alternative for each objective. The methods used to determine the consequence of an alternative varied from objective to objective.

3.3.5.1 Performance Evaluation (Decision Objectives 1-4)

Decision objectives 1-4 focus on evaluating each of the 6 monitoring program alternatives with respect to bias (minimize) and precision (maximize) of abundance and lambda estimates. To determine the consequences of these objectives with respect to the 6 alternative monitoring programs, I simulated a fisher population, its harvest, and data collection that produce a population that mimics the VT fisher population, its harvest, and the fisher monitoring program (both with and without necropsy). I determined the bias and precision that results from each monitoring program using population simulation and estimator evaluation functions in `AMharvest` (Cummings and Donovan in preparation-b). The primary functions for simulating the true population through time and its associated harvest datasets were `popMod` (which simulates annual population dynamics with discrete, one year time steps), `annualHarvestMod` (which simulates the harvest of individuals from `popMod`), and `harvestDataMod` (which incorporates error into the harvest data from `annualHarvestMod`). For a full description of the simulation structure see Cummings and Donovan (in preparation-b).

Briefly, `popMod` is parameterized with an initial population size (seed) by age and sex for the first year census period, with subsequent harvest, pre-breeding mortality, birth, and post-breeding mortality determining the age and sex based count at the next years census (Figure 1). I simulated conditions similar to the VT fisher population over a 30 year period using a hypothetical start year of 1901 and an end year of 1930. I assumed that the age at first reproduction was 1 and 2 for males and females, respectively and the final age class represented a composite age class of 10+ year olds. The initial population (the seed) was:

Males = [535,267,191,154,129,112,99,88,78,69,59]

Females = [813,380,267,212,178,153,132,114,99,83,65]

in all simulations, for a total of 4,277 individuals. The harvest season setting was assumed to be 31 days beginning on December 1st of each year, with all ages susceptible to additive harvest (harvest is 100% additive to natural mortality).

The baseline birth rate model included an age and density dependent effect, and resulted in an average of 1.68 offspring per reproductive female (ages 2-10; Table 3, Model 1) which conforms with published rates for the northeast (Krohn et al. 1994, Van Why and Giuliano 2001, Buskirk et al. 2012). I assumed a 50-50 offspring sex ratio. The baseline pre-breeding and post-breeding survival rate models were simulated with some small differences by age and sex such that the combined, annual rate was similar to the reported without trapping survival rate, which ranged between 0.7 and 0.8 for juveniles and is greater than 0.9 for adults (Krohn et al. 1994, Powell 1994). My baseline pre-breeding survival rates were 0.73 for male and females juveniles, and increased to a peak survival rate of 0.996 for six year old males and females (Table 3, Models 2 and 3). The baseline post breeding survival rates were 0.86 for female and 0.90 for male juveniles, with a peak survival rate of 0.98 for 8 year old females and

0.99 for 9 year old males (Table 3, Models 4 and 5). The baseline harvest rate model (used by `annualHarvestMod`) was a function of simulated annual harvest effort, which ranged between 11.3 and 19.2 thousand trap nights per year. This resulted in average annual harvest rate of 0.154 across ages and sexes, with higher harvest rates for young and old fishers and slightly lower rates for 3 to 7 year old fishers (Table 3, Models 6 and 7).

With the exception of the post-breeding survival rate, all rates (birth rate, pre-breeding survival, and harvest effort) include stochasticity in the model intercept term, with values drawn from uniform distributions between two values (Table 3.3). In addition, annual harvest was implemented using the binomial distribution with the census abundance at each age as the number of trials and the simulated harvest rate as the probability of success. These inputs produced the 250 simulated population trends (Figure 2), with resultant lambda values that ranged from 0.96 to 1.04 (Figure 3).

Each simulation produced a different number of harvested individuals by age, sex, and year (a true value), to which I applied a harvest data “error” via the function, `harvestDataMod`, which introduces reporting error (the probability that a harvested animal is reported), sexing error (the probability that a harvested male or female are correctly classified by sex), and aging error (the probability that a harvested animal of age X is classified into each age group). I used `harvestDataMod` to simulate the harvest datasets with and without necropsies. With necropsies, trappers must submit carcasses to the state, so I assumed that all trapped fishers are reported, sexed, and age correctly for the necropsy data set. Without necropsies, the likelihood of reporting likely remains high as pelts would still require tagging. However, aging of individuals to year would not occur and would be restricted to age group (young, adult) with some error. Without carcasses, sexing would occur in the field by trappers or wardens, which increases the likelihood of error. I modeled a 95% reporting rate, 10% aging error, and 10% sexing error rate for the without necropsy monitoring alternative (Table 4). Age errors were modeled with a distance-to-and-from age class formula:

$$A_t = \sum_{f=1}^{F} A_f * \frac{\mathrm{e}^{f+(f-t)^2 * E}}{\sum_{i=1}^{T} \mathrm{e}^{f+(f-\mathrm{i})^2 * E}}$$

where A_t, “age-to” is the number of individuals in the resulting data count for age t, A_f is the number of truly harvested individuals for age f, and E is the age error parameter (see Table 4). I used age error parameter values of -25 to produce no age error and -2.791 to produce 10% error in aging (Figure 4). These represent the expected errors in the data collection process from the two monitoring programs (C. Bernier, pers. comm., Vermont Fish and Wildlife Department).

For each harvested dataset, I estimated the true abundance and lambda with four alternative estimators, all of which input the annual harvest dataset. The harvest index method in `AMharvest` uses the function `indexEst`, which takes the annual harvest data and an estimated harvest rate model as inputs. I used a constant value of 0.15385 (the average harvest rate across age and sex for the stable population trajectory simulation) as the harvest rate input to the `indexEst` method in all of my evaluations. By using this harvest rate, I gave the `indexEst` method the best possible chance of providing an accurate estimate of the abundance without adjusting the harvest rate based on changes to the population trajectory, effort, or age and sex effects. A manager would normally not have this information at their disposal, and would use expert opinion or output from another estimator to provide the approximate annual harvest rate required by `indexEst`. As with the harvest index method, I used a constant value from (the true values on average from the stable population trajectory) simulation as my inputs to the `sakEst` function. In this way I reported the best possible expected performance from the `sakEst` method. The average total mortality due to harvest in my simulation was 0.4702 and the young per adult females was 1.128, which were used as the `sakEst` inputs for total mortality due to harvest and young per adult females, respectively. Both the `fryEst` function and `downingEst` function take annual age at harvest data as input, with the `downingEst` function requiring a grouping age (the age above which all individuals are summed into a single count) input as well. I pooled my data into 5 classes, 4 for animals of ages 0 through 3 and a fifth class for animals of age 4 or greater for the Downing estimation method. The combinations of datasets and analysis method represented the 6 alternative monitoring programs that are the basis for the decision analysis problem (Table 5).

For decision objectives 1-4, I measured the bias in abundance estimates under each monitoring program by taking individual annual abundance estimates, subtracting the true abundance and then dividing by the true abundance ($[\widehat{N} - N]/N$) for each simulation. The measurable attribute for bias in the decision problem was the median of the median values over the first 20 years (to avoid know bias in the Fry and Downing methods in the most recent years of estimation) of the 250 simulations (Table 1), while the measureable attribute for precision was measured as the range in the 5th to 95th percentile median values over the 250 simulations. I calculated median percent bias for lambda estimates in a similar manner to the bias in abundance. First I calculated the annual change in the population size, lambda ($\lambda_t = N_{t+1} / N_t$) for true and estimated abundances starting in year two. The annual bias in lambda is then calculated the same way the annual bias in abundance is calculated, subtracting the true lambda from the estimated lambda and dividing by the true lambda, ($[\hat{\lambda} - \lambda]/\lambda$), then finding the median over the analysis period (20 years) and simulations (250). I used the 5th to 95th percentile range in error over the simulations as my measure of precision in the lambda estimate.

To ease interpretation, I converted the bias and lambda measures into units representing the numbers of individuals by which the estimation methods would have erred relative to a true population size of 5,000 individuals. In the case of lambda, I used the resulting difference in population size over a ten year period assuming the true population was stable. For example, a percent bias in abundance value of 1 would indicate the estimated abundance was twice the actual abundance, while a percent bias of -0.5 would indicate the estimated abundance was one half the actual abundance. Using number of individuals as my units, bias values of 1 and -0.5, would produce abundance estimates of 10,000 and 2,500, errors of 5,000 and 2,500 individuals. A bias in lambda of 0.001 indicates the estimated lambda is 1.001 times the actual lambda. For example a bias in lambda value of 0.001 would result from an estimated lambda of 1.001 (i.e., population growth of 0.1% per year) when the true lambda is 1.00 (i.e., the population is stable). This bias in lambda of 0.001 would equate to an error 50 individuals over a ten year period with an initial population size of 5,000 individuals. When used in the decision analysis context I take the absolute value of these measures with the desired direction being minimization. In this way negative and positive bias (e.g., an error of 100 or -100 individuals) are both treated in the same way (an error of 100 individuals) and given the same performance score.

As a point of comparison, the performance of the abundance estimates and the lambda estimates were also assessed with the Coefficient of Error (CE) summary statistic used by Millspaugh et al (2009). The CE in abundance expressed as a percentage calculated as:

$$CE = \frac{\sqrt{\widehat{MSE}}}{\left(\frac{\sum_{i=j}^{n}\sum_{j=1}^{y} N_{ij}}{ny}\right)} * 100, \text{ where}$$

$$\widehat{MSE} = \frac{1}{n}\sum_{i=1}^{n}\left[\frac{\sum_{j=1}^{y}\left(\hat{N}_{ij} - N_{ij}\right)^{2}}{(y-1)}\right],$$

y is the number of years being compared (y = 40), n is the number of simulations (n = 100), N_{ij} is the true population for simulation i and year j, and $\hat{N}_{ij}$ is the associated abundance estimate. The CE in lambda is calculated the same way, but substituting $\hat{\lambda}_{ij}$ and λ_{ij} for $\hat{N}_{ij}$ and N_{ij}:

3.3.5.2 *Disease Detection, Cost, and Public Engagement (Decision Objectives 4-7)*

I developed estimates of the monitoring program impacts on disease detection, costs, and public engagement through an interview of Chris Bernier of the VT Fish and Wildlife Department. Based on the interview responses, the probability of detecting disease with a necropsy monitoring program was 75%, and 20% if necropsy was not conducted (C. Bernier pers. comm., Vermont Fish and Wildlife Department, Objective 5, Table 5).

The cost of the monitoring programs was estimated to be $120,000 with necropsy and effort surveys, and $70,000 for the without necropsy and survey alternative (C. Bernier pers. comm., Vermont Fish and Wildlife Department, Objective 6, Table 5).

The highest level of public engagement would be achieved by conducting necropsies and effort surveys. The necropsy process involves a number of volunteers and academic institutions often participate to collect additional data as well. This level of participation involves the public and presents an opportunity for communication between game species managers and the public. There was not a natural scale measurement that well-represented the degree that the public engagement objective is achieved, so a constructed scale between 0 and 10 was used. A score of ten was assigned to the best possible outcome for the trapper engagement and the public and academic institution objectives, with the remaining scores relative to the best alternative. The trapper engagement as well as the public and academic engagement objective received scores of 10 for the "with necropsy" alternatives, and a 6 for the without-necropsy alternatives (C. Bernier pers. comm., Vermont Fish and Wildlife Department, Objective 7 & 8, Table 5).

3.3.6 Decision Trade-Offs – Decision analysis

For use in decision analyses, consequences are often organized into a consequence table as shown in Table 5. A consequence table stores the predicted outcome of each alternative for each of the objectives.

Once the consequences have been determined, the 6 decision alternatives were scored across all objectives, given their weights, using a SMART analysis (Simple Multi-Attribute Ranking Technique) (Von Winterfeldt and Edwards 1986). I conducted the SMART trade-off analysis in `AMharvest` using the `smartDA` function

(Donovan et al. in preparation). There are three steps in this process, normalizing consequences, applying objective weights, and summing the weighted results. Normalizing consequences places the outcomes of each of the objectives on a standard scale such that the best outcome for each objective receives a score of 1, the worst a 0, and the mid-point between the best and worst outcomes would receive a normalized consequence score of 0.5. This is accomplished by dividing the outcome of each alternative for each objective by the range of outcomes for each objective for maximization objectives, and one minus this value for minimization objective.

Once the normalized consequences have been calculated, they are multiplied by the objective weights for each objective, and summed for each alternative to provide a final score for each alternative. The alternative with the highest total score is then the one that fulfills the objectives for the decision to the greatest degree.

3.4 Results

3.4.1 Estimator Performance

Considering only decision objectives 1-4, I found that the best with-necropsy monitoring program alternatives performed better than the without-necropsy alternatives (Figure 3.7), with the N-Fry and N-Downing, WO-Index and WO-SAK methods obtaining scores of 51.37, 53.52, 48.56, 35.62. However, within the with-necropsy alternatives, which estimator performed best depended on the objective. The sex-age-kill (N-SAK) method when used with necropsy data performed best for the bias in abundance estimate objective (Table 5, objective 4). The N-Fry method was best for the precision in abundance objective (Table 5, objective 2), and the N-Downing method produced the least biased and most precise estimates of lambda (Table 5, objectives 1 and 3). The N-Fry and N-Downing estimates were often quite similar, performing best or second best for the precision in abundance, bias in lambda, and precision in lambda objectives.

Based on the CE analysis of Millspaugh et al. (Millspaugh et al. 2009), the relative performance of the alternative monitoring programs differed for abundance estimation and lambda estimation. The CE in abundance values by estimation method were: 52.1, 56.1, 22.7, 30.3, 22.1, and 26.1 for the N-Downing, N-Fry, N-Index, N-SAK, WO-Index, and WO-SAK methods respectively. Without necropsy (and the addition of errors in data collection), the CE slightly improved for the sex-age-kill method (see Chapter 2), whereas these errors in data collection did not affect the index method because it uses totals only. In terms of population trend, lambda, N-Downing method performed best for CE in lambda (Figure 5). Thus, the selection of the best monitoring program depends heavily on the weighting (importance) of each of the four monitoring objectives centered on bias and precision. However, the remaining four objectives must be considered.

3.4.2 Decision Analysis

I used a SMART analysis to consider all 8 monitoring objectives simultaneously. A score of 100 would indicate that an alternative was best for all objectives, a score of zero that it was worst, and a score of 50 that the alternative’s outcomes averaged half-way between the best and worst alternative’s outcomes across all objectives. Given the objective weights in Table 1, I found that N-Downing was the best alternative with a score of 73.5, followed closely by the N-Fry alternative with a score of 71.4 (Figure 6). The N-Downing method performed well for most of the objectives, ranking in the top two for all but the bias in abundance and cost objectives where it performs poorly. The Sex-Age-Kill with necropsy program was the lowest scoring monitoring program alternative, given the objective weights in Table 1.

While there were some unexpected benefits of the without-necropsy approach in terms of estimator performance, necropsy provided numerous benefits that resulted in necropsy-based alternatives performing best overall. The main benefits of the without necropsy alternatives was their reduction in cost. However, based on the importance weights provided, the increased probability of disease detection gained by necropsy compensated for the reduction in cost of the without necropsy alternatives. After the cost of the necropsy method is compensated for by disease detection the benefits of the necropsy methods are accounted for by the benefits of citizen engagement and the availability of the Fry and Downing estimation methods accounted for in the increased score of the N-Downing and N-Fry alternatives relative to the without necropsy alternatives.

3.4.3 Sensitivity Analysis

I assessed how changing the weights for each objective affected the relative ranking of the 6 alternative monitoring programs. I found that the ranking of the N-Downing alternative as the best method was robust to changing the objective weights. Considering only estimator performance (by setting the weights of objectives 5-8 to 0, while the weights on objectives 1-4 remained unchanged) resulted in alternative scores of 53.5, 51.4, 19.5, 37.3, 48.6, and 35.6 for the N-Downing, N-Fry, N-Index, N-SAK, WO-Index, and WO-SAK alternatives respectively (Figure 7). While keeping the other

7 weights constant (at the weights in Table 1), weight on the bias in abundance objective needed to be increased to an importance score (weight) of at least 20 in order for the WO-Index alternative to score highest, and increased to 35 for the WO-SAK estimate to outperform the N-Downing estimate. The weight of the precision in abundance objective needed to be increased to 42 (while the other 7 objectives retained their Table 1 weights) for the Fry estimation performance to exceed the Downing estimation performance.

When the performance of the estimation methods was ignored (setting weights for objectives 1-4 to 0 while objectives 5-8 retained their initial weights), the necropsy alternatives all received an outcome score of 20 and the without necropsy alternatives received a score of 12 (Figure 8). In order for the without necropsy alternatives to be favored (while ignoring estimator performance), either the benefit of reducing the cost must have received an increased importance score of greater than 20 (with objectives 1-4 at zero, and 5, 7, and 8 at their initial weights), or the combined disease detection and engagement objective weights must have received a score of less than 12 (with objectives 1-4 at zero, and 6 at its initial weight).

Therefore, robustness of the N-Downing alternative was due to necropsy outscoring without necropsy overall for the objectives unrelated to estimator performance, and it being the best performing estimation method when all estimation performance measures are considered.

3.5 Discussion

I demonstrated an approach for evaluating among alternative monitoring programs, given multiple objectives for managing the fisher population in Vermont.

Multiple Criteria Decision Analyses like this one have been applied to many natural resource problems (Linkov et al. 2006, Mendoza and Martins 2006, Huang et al. 2011, Davies et al. 2013), with several applications to wildlife management (Peterson and Evans 2003, Converse et al. 2011, Irwin et al. 2011, Converse et al. 2013, Runge 2013), but none specific to management and monitoring of harvested wildlife species that I are aware of. My approach, however, could be used by other agencies, with unique objectives and monitoring program alternatives and consequence elicitation and simulations specific to their species and management setting.

I found that game species managers in VT should conduct necropsies and use the Downing estimation method given the relative importance of fisher monitoring program objectives. This result demonstrated some robustness to objective weights, as it typically required doubling the importance of objectives favoring another alternative to change the ranking of the alternatives. Therefore, managers can be confident that the cost of conducting necropsies is warranted based on the monitoring program objectives and their relative importance, particularly given that the disease detection and citizen engagement benefits are perceived to provide greater value than the reduction in cost from cessation of necropsies.

There are numerous examples of the benefits of increasing engagement. As an example, a single year worth of necropsy analysis provided data collection opportunities for two college research projects (Bernier and Adler 2012). A Johnson State College study examined the *E. coli* present in the digestive systems harvest animals in an effort to develop a library of *E. coli* strains by species for subsequent use in identifying the presence of games species in watersheds. Researchers from Green Mountain College also collected tissue samples to conduct population genetic analysis and to test for canine Parvo virus. Additional studies have examined mercury levels in fishers (C. Bernier, pers. comm., Vermont Fish and Wildlife Department).

The selection of the Downing method from the necropsy supported estimation methods is largely due to its more consistent estimates. The consistency of the Downing estimation method across simulations and changes in population growth rate was likely due to the pooling of adults and the calculation of abundance using a cohort approach that considers observations across multiple years. Combining observations over multiple years likely dampens the impacts of an unusual year’s worth of data. However, while the Downing estimation method performed best for the full set of objectives and the objective weights specified, this method is strongly and negatively biased in its estimate of abundance, and it is more inaccurate at estimating population status in the most recent years (Davis et al. 2007). If there is a way to compensate for this poor performance through the creation of another alternative, then a better alternative may be found than those examined here. For example, perhaps the sex-age-kill method can be used to provide abundance estimates for the most recent year in conjunction with the Downing method estimates for past years. Alternatively, even though the Downing abundance estimate is strongly (negatively) biased, the precision is good; thus it may be “predictably biased.” Perhaps a formula for a robust positive adjustment, on the order of doubling, to the Downing method’s abundance estimates can be found that eliminates its negative bias, or the abundance can be estimated through other data collection and analysis methods.

The confidence in selection of the Downing estimation method found here would not be possible from the coefficient of error (CE) evaluation alone. The coefficient of error evaluation revealed a strong trade-off between the ability to estimate abundance and the ability to estimate lambda. Downing and Fry had the best CE for estimating lambda, but the worst CE for estimating abundance. However, the relative contributions of bias and precision to the evaluation of estimator performance were also unavailable by using the CE method alone. The explicit specification of what estimation performance measures to consider, and how important they are, facilitates clarity in the selection procedure and the subsequent decision that is unavailable from a statistical measure of performance alone.

Using a structured decision approach in natural resource management is challenging, but the benefits may be great (Gregory et al. 2012, Conroy and Peterson 2013). Selecting the appropriate objectives requires management agencies to reflect on the goals of management and their values. Once objectives are specified, an additional challenge is how to measure performance of each alternative with respect to each objective. Based on conversations with the VFWD managers, I selected median bias and 5th to 95th percentile range as the performance measures for estimator abundance and lambda estimation quality. However, there are many performance measures available for evaluating population estimator performance, such as mean square error, root mean square error, absolute error, raw error, r-squared, AIC, and more (Willmott 1982, Willmott and Matsuura 2005, Cummings et al. 2011). The selection of performance measures that accurately capture the objectives of estimation is important, as the outcome of the evaluation can depend on what performance measures are selected (Cummings et al. 2011). There may also be more relevant performance measures for the other objectives, such as a telephone survey that measures the knowledge and perception of fisher management for the general public, academics, and trappers that quantifies the outcome of the citizen engagement objective, or a direct study of disease detectability to quantify the outcome of the disease detection objective.

There are also other ways of quantifying the relative benefit of outcomes relative to decision objectives. I assumed that the value derived from the achievement of an objective is linear with respect to a change in the outcome of a measurable attributes value for that objective. That is, if the measurable attribute (e.g., probability of disease detection) doubles, the value derived from the achievement of that objective doubles. It is possible that this linearity does not accurately reflect the perception of value, in which case alternative value functions should be used, because the selection of value functions can impact the selection of wildlife management models (Cummings et al. in review).

This decision analysis approach to monitoring program selection can provide clarity where typical evaluation procedures are inconclusive, as the CE evaluation was here. This approach also provides transparency to the process, as well as a tool for managers to validate and communicate why a particular monitoring program was chosen. Furthermore, due to the flexibility of the `AMharvest` package, this type of decision analysis can be repeated with other species, population demographics, harvest rates, data collection regimes, and estimators to provide insight into many wildlife management decisions.

3.6 Acknowledgements

I thank J. Pontius, J. Murdoch, and R. Mickey for their assistance through review of this chapter. Thanks to Kim Royar and Scott Darling for their input on fisher management and Chris Bernier, all with the Vermont Fish and Wildlife Department, for input on the objectives, alternatives and consequences of monitoring programs. Funding was provided by the Vermont Fish and Wildlife Department and the United States Geological Survey.

3.7 References – Chapter 3

Bernier, C., and M. B. Adler. 2012. Vermont furbearer management newsletter. Pages 7-8. Vermont Fish & Wildlife Department, Springfield, Vermont, USA.

Buskirk, S. W., L. Bowman, and J. H. Gilbert. 2012. Population biology and matrix demographic modeling of american martens and fishers. Pages 77-92 *in* K. B. Aubry, W. J. Zielinski, M. G. Raphael, G. Proulx, and S. W. Buskirk, editors. Biology and conservation of martens, sables, and fishers : a new synthesis. Comstock Pub. Associates, Ithaca, New York, USA.

Conroy, M. J., and J. T. Peterson. 2013. Decision making in natural resource management: a structured, adaptive approach. Wiley, Hoboken, New Jersey, USA.

Converse, S. J., C. T. Moore, M. J. Folk, and M. C. Runge. 2013. A matter of tradeoffs: Reintroduction as a multiple objective decision. Journal of Wildlife Management **77**:1145-1156.

Converse, S. J., K. J. Shelley, S. Morey, J. Chan, A. LaTier, C. Scafidi, D. T. Crouse, and M. C. Runge. 2011. A decision-analytic approach to the optimal allocation of resources for endangered species consultation. Biological Conservation **144**:319-329.

Cummings, J. W., and T. M. Donovan. in preparation. Effects of measurement error on population estimation of harvested species.

Cummings, J. W., M. J. Hague, D. A. Patterson, and R. M. Peterman. 2011. The impact of different performance measures on model selection for Fraser River sockeye salmon. North American Journal of Fisheries Management **31**:323-334.

Cummings, J. W., R. M. Peterman, M. J. Hague, and D. Patterson. in review. Effect of asymmetric valuation of losses on model selection for Fraser River sockeye salmon. North American Journal of Fisheries Management.

Davies, A. L., R. Bryce, and S. M. Redpath. 2013. Use of multicriteria decision analysis to address conservation conflicts. Conservation Biology **27**:936-944.

Davis, M. L., J. Berkson, D. Steffen, and M. K. Tilton. 2007. Evaluation of accuracy and precision of downing population reconstruction. Journal of Wildlife Management **71**:2297-2303.

Decker, D. J., G. R. Goff, and Wildlife Society. New York Chapter. 1987. Valuing wildlife : economic and social perspectives. Westview Press, Boulder.

Donovan, T. M., J. W. Cummings, K. Rinehart, and S. Hafner. in preparation. The R package harvest: simulating game species populations for monitoring evaluation.

Douglas, C. W., and M. A. Strickland. 1987. Fisher. Pages 510-529 Wild Furbearer Management and Conservation in North America. Ontario Trappers Association and Ontario Ministry of Natural Resources, Ontario, Canada.

Downing, R. L. 1980. Vital statistics of animal populations. Pages 247-267 *in* S. D. Schemnitz, editor. Wildlife techniques manual. The Wildlife Society, Washington, D.C., USA.

Eberhardt, L. L. 1960. Estimation of vital characteristics of Michigan deer herds. Michigan Department of Conservation Game Division, East Lansing, Michigan, USA.

Fry, F. E. J. 1949. Statistics of a lake trout fishery. Biometrics **5**:27-67.

Gregory, R., L. Failing, M. Harstone, G. Long, T. McDaniels, and D. Ohlson. 2012. Structured decision making: A practical guide to environmental management choices. Wiley-Blackwell, West Sussex, UK.

Hammond, J. S., R. L. Keeney, and H. Raiffa. 1999. Smart choices : a practical guide to making better decisions. Harvard Business School Press, Boston, Massachusetts, USA.

Huang, I. B., J. Keisler, and I. Linkov. 2011. Multi-criteria decision analysis in environmental sciences: Ten years of applications and trends. Science of the Total Environment **409**:3578-3594.

Irwin, B. J., M. J. Wilberg, M. L. Jones, and J. R. Bence. 2011. Applying structured decision making to recreational fisheries management. Fisheries **36**:113-122.

Koen, E. L., J. Bowman, and C. S. Findlay. 2007. Fisher survival in eastern Ontario. Journal of Wildlife Management **71**:1214-1219.

Krohn, W. B., S. M. Arthur, and T. F. Paragi. 1994. Mortality and vulnerability of a heavily trapped fisher population. Pages 137-145 *in* S. Buskirk, A. S. Harestad,

M. G. Raphael, and R. A. Powell, editors. Martens, sables, and fishers : biology and conservation. Comstock Pub. Associates, Ithaca, New York, USA.

Linkov, I., F. K. Satterstrom, G. Kiker, C. Batchelor, T. Bridges, and E. Ferguson. 2006. From comparative risk assessment to multi-criteria decision analysis and adaptive management: Recent developments and applications. Environment International **32**:1072-1093.

Lyons, J. E., M. C. Runge, H. P. Laskowski, and W. L. Kendall. 2008. Monitoring in the context of structured decision-making and adaptive management. Journal of Wildlife Management **72**:1683-1692.

Mendoza, G. A., and H. Martins. 2006. Multi-criteria decision analysis in natural resource management: A critical review of methods and new modelling paradigms. Forest Ecology and Management **230**:1-22.

Millspaugh, J. J., J. R. Skalski, R. L. Townsend, D. R. Diefenbach, M. S. Boyce, L. P. Hansen, and K. Kammermeyer. 2009. An evaluation of sex-age-kill (SAK) model performance. Journal of Wildlife Management **73**:442-451.

Paragi, T. F., S. M. Arthur, and W. B. Krohn. 1994. Seasonal and circadian activity patterns of female fishers, *Martes pennanti*, with kits. Canadian Field-Naturalist **108**:52-57.

Peterson, J. T., and J. W. Evans. 2003. Quantitative decision analysis for sport fisheries management. Fisheries **28**:10-21.

Powell, R. A. 1994. Structure and spacing of *Martes* populations. Pages 101-121 *in* S. Buskirk, A. S. Harestad, M. G. Raphael, and R. A. Powell, editors. Martens, sables, and fishers : biology and conservation. Comstock Pub. Associates, Ithaca, New York, USA.

Powell, R. A., S. W. Buskirk, and W. J. Zielinski. 2003. Fisher and Martin: *Martes pennanti* and *Martes americana* Pages 635-649 *in* G. A. Feldhamer, B. C. Thompson, and J. A. Chapman, editors. Wild mammals of North America : biology, management, and conservation. Johns Hopkins University Press, Baltimore, Maryland, USA.

Powell, R. A., and W. J. Zielinski. 1994. Fisher. Pages 38-73 *in* L. F. Ruggiero, K. B. Aubry, S. W. Buskirk, L. J. Lyon, and W. J. Zielinski, editors. American marten, fisher, lynx, and wolverine in western United States. United States Forest Service, General Technical Report RM-254, Fort Collins, Colorado, USA.

Rinehart, K., and T. M. Donovan. in preparation. Models, data, and cost: Efficient population estimates for wildlife managers.

Roseberry, J. L., and A. Woolf. 1991. A comparative evaluation of techniques for analyzing white-tailed deer harvest data. Wildlife Monographs:3-59.

Runge, M. C. 2013. Active adaptive management for reintroduction of an animal population. Journal of Wildlife Management **77**:1135-1144.

Skalski, J. R., M. V. Clawson, and J. J. Millspaugh. 2012. Model evaluation in statistical population reconstruction. Wildlife Biology **18**:225-234.

Skalski, J. R., K. E. Ryding, and J. J. Millspaugh. 2005. Wildlife demography: analysis of sex, age, and count data. Elsevier Academic Press, Amsterdam and Boston, Massachusetts, USA.

Van Why, K. R., and W. M. Giuliano. 2001. Fall food habits and reproductive condition of Fishers, *Martes pennanti*, in Vermont. Canadian Field-Naturalist **115**:52-56.

Von Winterfeldt, D., and W. Edwards. 1986. Decision analysis and behavioral research. Cambridge University Press, Cambridge UK and New York, USA.

Willmott, C. J. 1982. Some Comments on the Evaluation of Model Performance. Bulletin of the American Meteorological Society **63**:1309-1313.

Willmott, C. J., and K. Matsuura. 2005. Advantages of the mean absolute error (MAE) over the root mean square error (RMSE) in assessing average model performance. Climate Research **30**:79-82.

Table 3.1 List of fisher monitoring program categories, objectives, the desired direction for the objectives, how the objectives are measured, and their relative importance.

Category	Objective	Direction	Measureable Attribute	Weight (relative importance)
Maintain sustainable population	1. Precision of lambda estimate	Maximize	5th to 95th percentile range of median	20
	2. Precision of abundance estimate	Maximize	5th to 95th percentile range of median	18
	3. Bias in lambda estimate	Minimize	Median error in lambda estimate	16
	4. Bias in abundance estimate	Minimize	Median error in abundance estimate	14
	5. Disease detection	Maximize	Probability of detection	12
Cost	6. Cost	Minimize	Thousands of dollars	12
Public knowledge and engagement	7. Trapper knowledge and engagement	Maximize	Constructed 0-10 scale	5
	8. Academic and public knowledge and engagement	Maximize	Constructed 0-10 scale	3

Table 3.2 List of the alternatives, their short names, input data, and the estimation method they used with and without necropsy analysis

	With Necropsy - Index	With Necropsy - Fry	With Necropsy - Downing	With Necropsy - SAK	Without Necropsy - Index	Without Necropsy - SAK
Short Name	N-Index	N-Fry	N-Downing	N-SAK	WO-Index	WO-Index
Data Type	Annual Harvest Count Age at Harvest Sex of Harvest	Annual Harvest Count Age at Harvest Sex of Harvest	Annual Harvest Count Age at Harvest Sex of Harvest	Annual Harvest Count Age at Harvest Sex of Harvest	Annual Harvest Count	Annual Harvest Count Age Group of Harvest with error Sex of Harvest with error
Estimation Method	Index	Fry	Downing	Sex-Age-Kill	Index	Sex-Age-Kill

Table 3.3 List of models used for simulating the fisher population.

Model Name	Model Type	Transformation	Stochastic	Parameters
1. Birth Rate	Birth rate	Log	Yes, by simulation	intercept = U(0.245,0.375) AGE = 0.09 AGE2 = -0.008
2. Pre-BS Females	Pre-breeding survival females	Logit	Yes, by simulation	intercept* = U(0.875,0.1.11) AGE = 1.65 AGE2 = -0.16
3. Pre-BS Males	Pre-breeding survival males	Logit	Yes, by simulation	intercept = intercept* AGE = 1.5 AGE2 = -0.125
4. Post-BS Females	Pre-breeding survival females	Logit	No	intercept = 1.85 AGE = 0.45 AGE2 = -0.028
5. Post-BS Males	Pre-breeding survival males	Logit	No	intercept = 2.25 AGE = 0.4 AGE2 = -0.02
Effort	Effort covariate (simeffort)	None	Yes, by simulation	intercept = U(11.3,19.2)
6. Harvest Rate Females	Annual harvest rate females	Logit	Yes, annually	intercept = -1.777 simeffort= 0.0325 AGE = -0.325 AGE2 = 0.03
7. Harvest Rate Males	Annual harvest rate males	Logit	Yes, annually	intercept = -1.9 simeffort=0.0325 AGE = -0.25 AGE2 = 0.02

Table 3.4 List of models used in simulating the data collection process with and without necropsy

Monitoring Program	Model Name	Model Type	Transformation	Stochastic	Parameters
With Necropsy (N)	100% Reporting Rate Females	reporting rate females	None	No	intercept = 1
	100% Reporting Rate Males	reporting rate males	None	No	intercept = 1
	No Error – Females	gender classification females	None	No	intercept = 1
	No Error – Males	gender classification males	None	No	intercept = 1
	No Age Error	age error	polynomial	No	-25
Without Necropsy (WO)	95 % Reporting Rate Females	reporting rate females	None	No	intercept = 0.95
	95% Reporting Rate Males	reporting rate males	None	No	intercept = 0.95
	10% Error – Females	gender classification females	None	No	intercept = 0.9
	10% Error – Males	gender classification males	None	No	intercept = 0.9
	10% Age Error	age error	polynomial	No	-2.791

Table 3.5 Consequence Table. The outcome of each alternative is listed for each objective, with the best result for each objective in bold.

	Alternatives					
Objective	N-Index	N-Fry	N-Downing	N-SAK	WO-Index	WO-SAK
1. Precision of lambda estimate	5,733	4,992	**4,762**	13,019	5,471	10,340
2. Precision of abundance estimate	2,914	**1,563**	1,747	3,606	2,815	3,247
3. Bias in lambda estimate	124	46	**37**	94	67	57
4. Bias in abundance estimate	-67	-2545	-2338	**-5**	-201	-67
5. Disease detection	**75%**	**75%**	**75%**	**75%**	20%	20%
6. Cost	$120,000	$120,000	$120,000	$120,000	**$70,000**	**$70,000**
7. Trapper knowledge and engagement	**10**	**10**	**10**	**10**	6	6
8. Academic and public knowledge and engagement	**10**	**10**	**10**	**10**	6	6

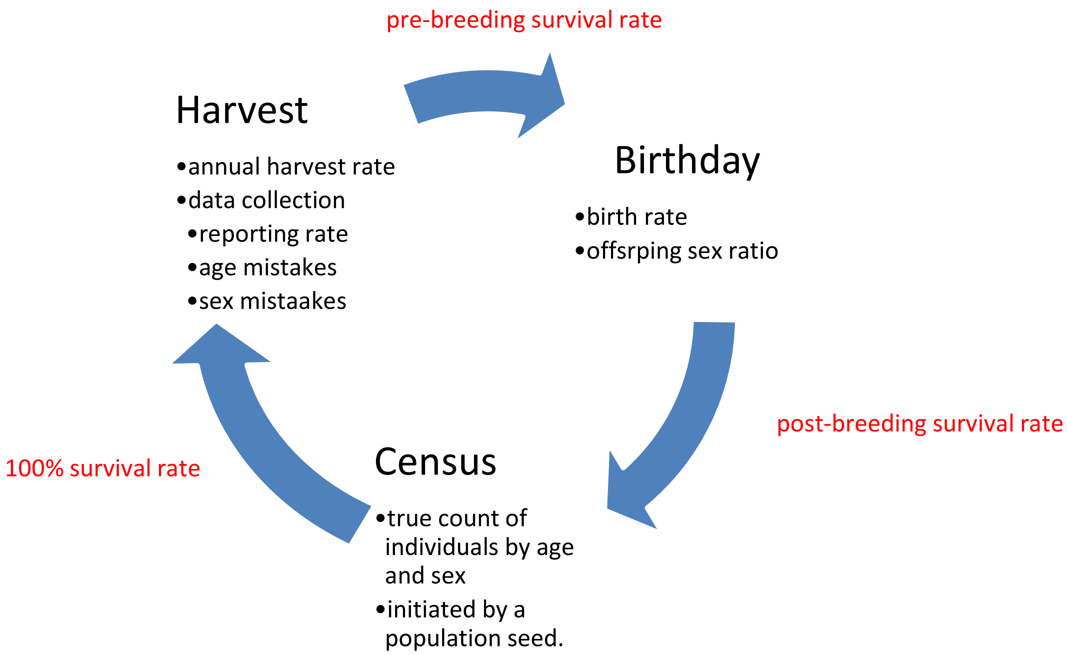


Figure 3.1 Simulated Life Cycle. An annual census occurs at which time the true count of the number of individuals is determined. 100% of individuals survive from the time of the census until the harvest occurs, at which time all mortality is assumed to be due to harvest. Harvest is determined by the simulated harvest rate, with errors resulting in the count of the harvest depending on the error model used. Following the harvest individuals may survive until their birthdays based on the pre-breeding survival rate, at which time they advance in age by one year and reproduce based on the birth rate. Following the birthday individuals advance to the next census depending on the post-breeding survival rate.

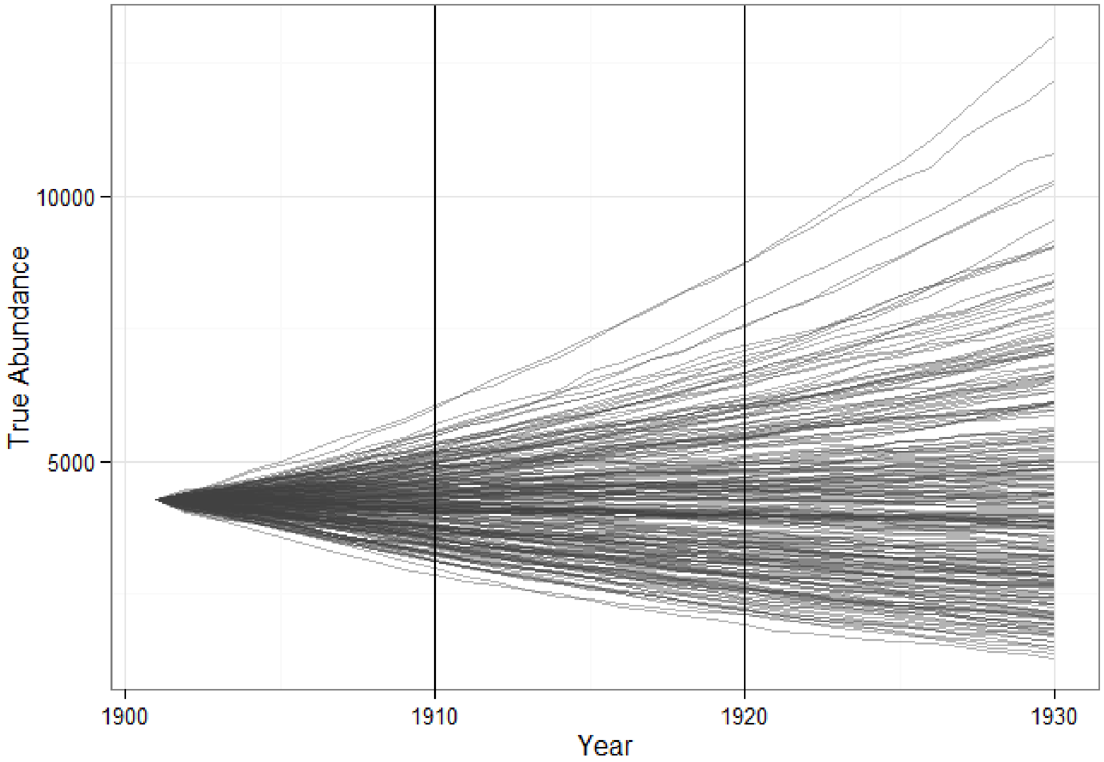


Figure 3.2 Simulated Population Trajectories. Each line shows the true population size by year for each of the 250 simulations.

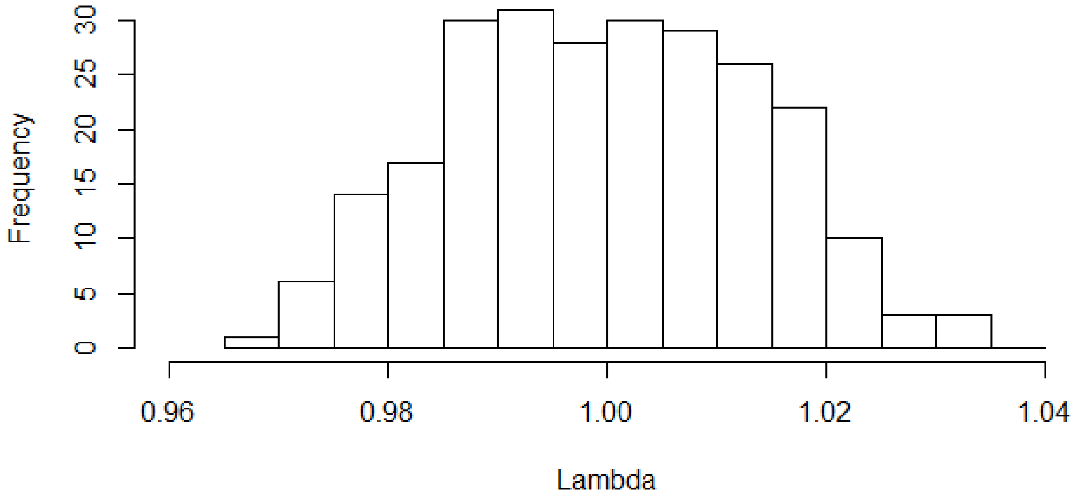


Figure 3.3 Histogram of simulated population growth rates with the number of population growth rates from the 250 simulations that fall in each of the 16 bins from 0.96 to 1.04 by 0.05 increments.

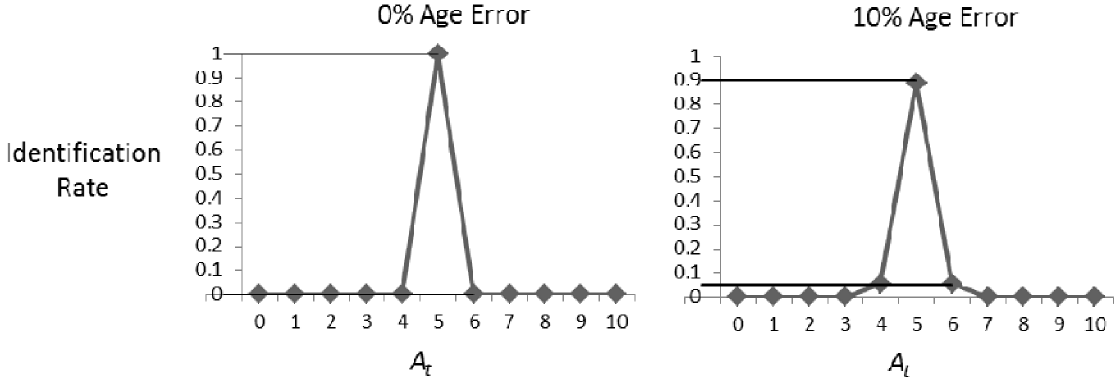


Figure 3.4 Example age classification rate for individuals that are truly 5 years old. The y-axis shows the rate at which 5 year olds are classified into each of the ages shown on the x-axis. The left panel show the rates for no error in age (0% age error). The right panel shows the rates with age error included (10% age error).

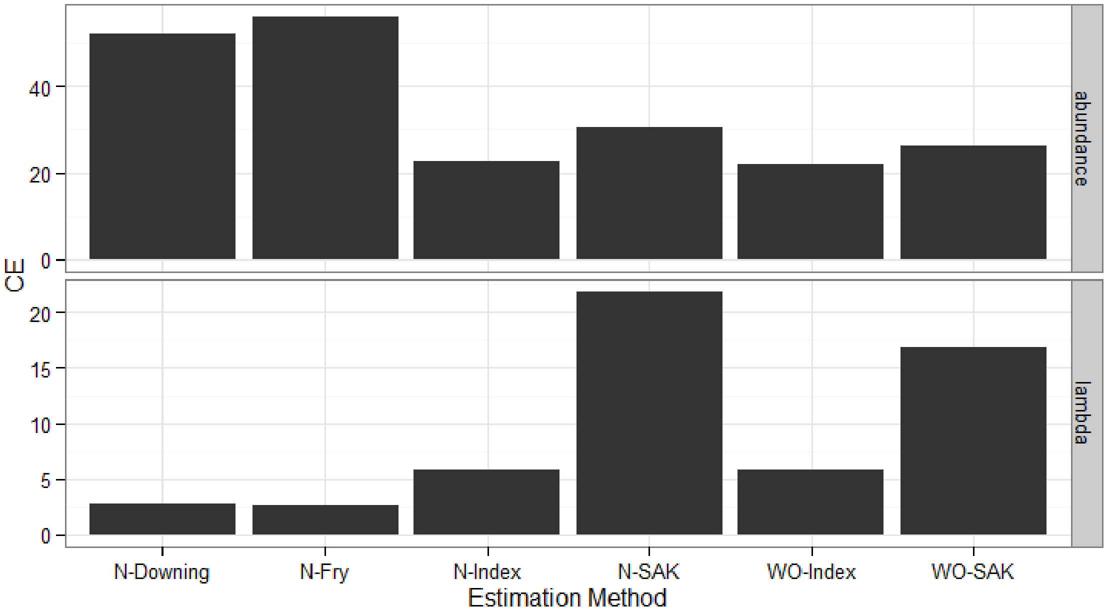


Figure 3.5 Coefficient of Error in abundance (Top Panel) and lambda (Bottom Panel) for each alternative monitoring program, where lower scores indicate better performance. A CE of zero would indicate perfect performance. Each panel contains a bar for each of the six monitoring program estimation methods (N-Downing, N-Fry, N-Index, N-SAK, WO-Index, and WO-SAK from left to right).

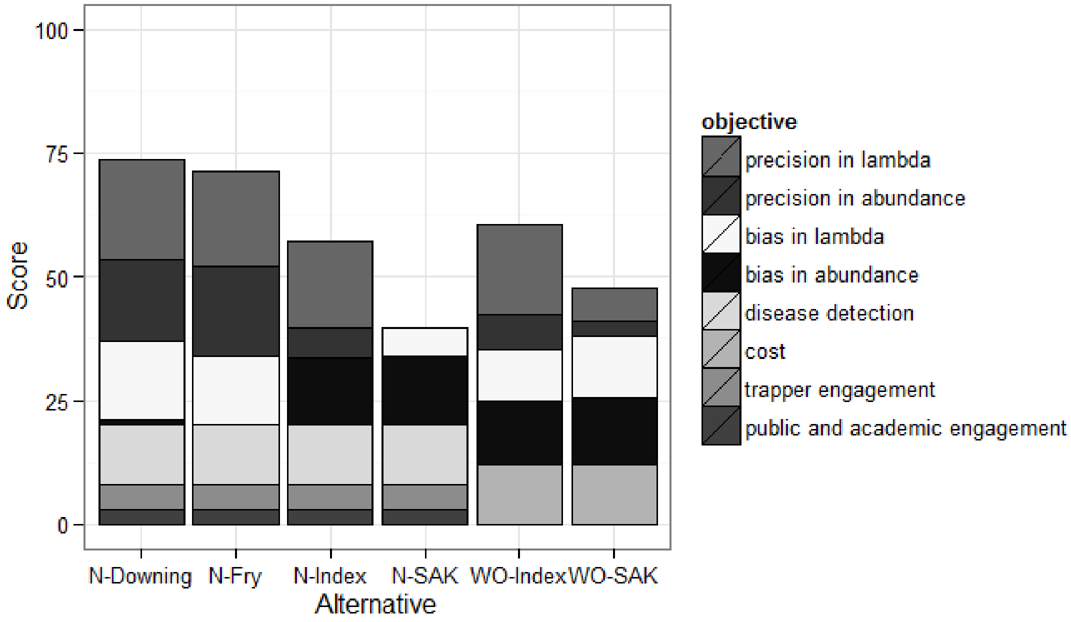


Figure 3.6 Decision analysis scores by alternative monitoring program (N-Downing, N-Fry, N-Index, N-SAK, WO-Index, and WO-SAK from left to right) with the contribution from each objective from objective 1 to 8 (top to bottom) as stacking. A higher score indicates better performance. A score of zero results for an alternative with the worst outcome for all objectives, while a score of 100 results if an alternative scores the best for all objectives.

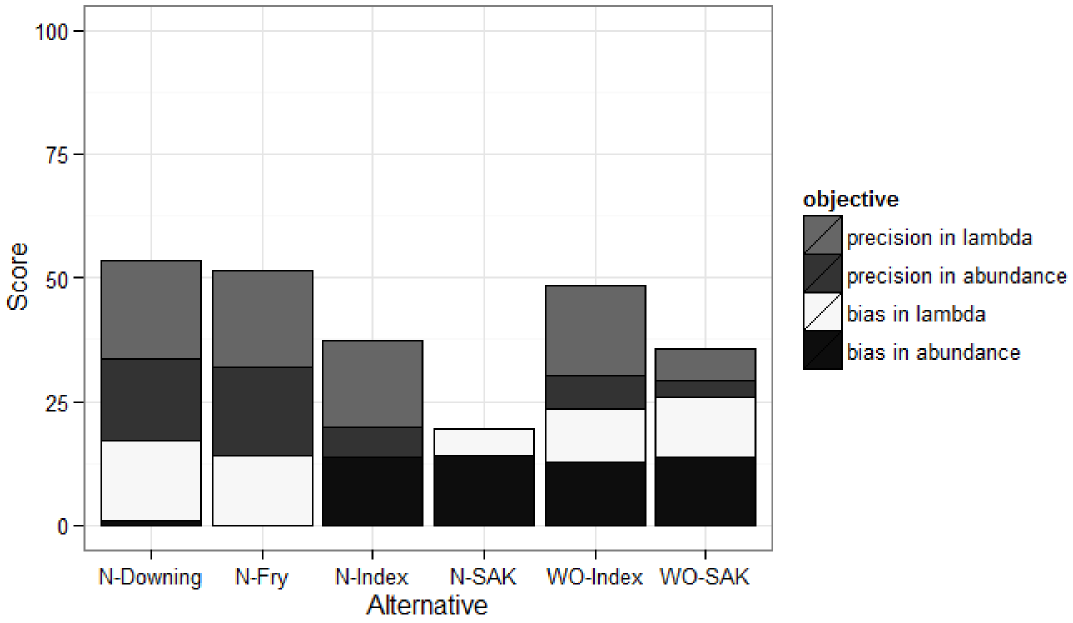


Figure 3.7 Decision analysis scores by alternative monitoring program with the contribution to the score from estimation performance only stacked from objective 1 to 4 top to bottom. Objectives 5-8 were given weights of zero, while the importance scores for objectives 1-4 remain the same. A higher score indicates better performance for an alternative. A score of zero would result if an alternative was worst for each objective and 68 if an alternative was best for all four.

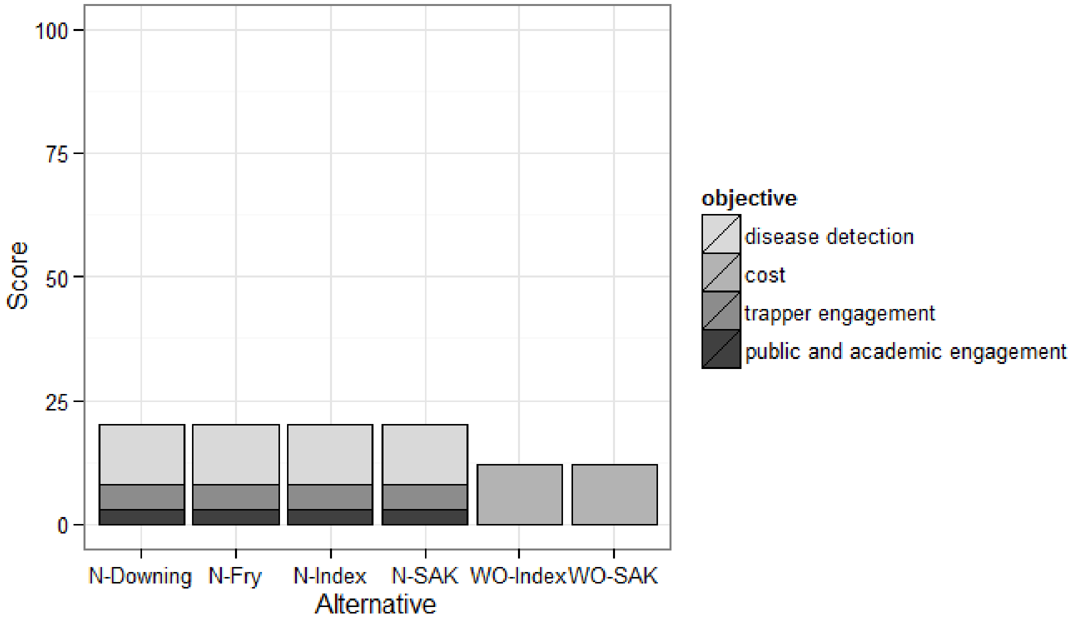


Figure 3.8 Decision analysis scores by alternative monitoring program with the contribution to the score from objectives 5-8 only stacked from objective 5-8 top to bottom. Objectives 1-4 were given weights of zero, while the importance scores for objectives 5-8 remain the same. A higher score indicates better performance for an alternative. A score of zero would result if an alternative was worst for each objective and 32 if an alternative was best for all four.

CHAPTER 4. THE VALUE OF MAPS IN NATURAL RESOURCE MANAGEMENT: AN APPLICATION OF EXPECTED VALUE OF SAMPLE INFORMATION

4.1 Abstract

Many of today's most pressing challenges such as climate change, human population growth and development are often assessed at the landscape scale. Consequently, demand for spatially explicit scientific information has increased. However, mapping scientific information is costly and often includes many sources of uncertainty. This creates challenges when evaluating whether a desired management outcome will be achieved and whether the benefits of mapping are cost effective. Here, we apply the Expected Value of Sample Information methodology to spatial information analyses as a means of addressing issues of uncertainty and cost. The method: 1) allows an assessment of the benefits of investment in improved mapping efforts, 2) enables an analysis of the relative gains of mapping efforts in comparison to acting with current knowledge, and 3) allows comparisons of one potential mapping effort with another. We demonstrate the method with several hypothetical examples that involve the use of maps in natural resource decision making. As these examples illustrate, using this method allows identification of a map's value, enabling the selection of mapping efforts that will be of greatest value and efficient allocation of budgets to the most beneficial projects.

Key Words: Value of Information, Spatial Analysis, EVSI, Landscape Ecology, Structured Decision Making, Applied Science, Mapping

4.2 Introduction

Applied landscape ecology is a key component of successful natural resource management (Poiani et al. 2000, Hilty and Groves 2008). Managers face challenges at multiple scales, but many of the most pressing challenges such as climate change, human population growth and landscape development operate at the landscape scale (Schwartz 1999). Addressing these challenges requires management considerations not just at the individual species scale, but also at a system scale (Schwartz 1999). Consequently, demand for spatially explicit scientific information has increased, enabling land managers to evaluate alternative management actions and choose an action that optimizes their management goals (Noon et al. 2012).

There are multiple examples of the need for spatial information in natural resource management. Spatial information is essential in the design and selection of sites for reserve networks used to maintain biodiversity (Csuti et al. 1997, Araujo and Williams 2000, Cabeza and Moilanen 2001). Spatial information is often used to determine the risk of colonization by invasive species (Gormley et al. 2011), or the probability of colonization and range expansion for wildlife reintroductions (Carden et al. 2010, Cook et al. 2010, Zimmermann et al. 2011). Maps provide the spatial information for effective habitat management to maintain ecosystems and target populations.

While spatial information may be used in a variety of ecological applications, its value in natural resource management is related to the reliability of the spatial information. Many sources of uncertainty exist in mapping, including the size of the minimum mapping unit, the bias and precision of classification algorithms, image registration error and discontinuity in scale between spatial coverages, and the resource in question (Aerts et al. 2003). These uncertainties result in outcome uncertainty, or uncertainty that a management decision (based on the uncertain spatial information) will produce the desired management outcome. For instance, in reserve design problems, the reserve selection algorithms can only produce recommendations that are as accurate as the spatial information upon which they are based. The resource manager then uses this information to determine, for example, which parcels of land to protect within the reserve system to maximize conservation of a target species. The success of this action, in part, is determined by the quality and accuracy of initial spatial data.

While reducing the error and uncertainty in spatial information can improve management decisions, an important limitation to spatial information is the cost of obtaining that information. Natural resource management often occurs on a limited budget. If managers allocate too much of their budget to spatial information now, they may be left without the means to conduct on-the-ground management in the future. However, if managers allocate too little of their budget to spatial information, they may use highly uncertain information, or not include information that would be useful in choosing among alternative management options. What is needed is a tool that allows managers to weigh the costs and benefits of increasing map accuracy with the costs and benefits to the resources that are being managed.

In this paper, we demonstrate how a decision analysis framework called Value of Information (VoI) can provide an estimate of the value of spatial information to managers. For clarity, we use “map” as a term for a visual representation of spatial information and use “spatial information” and “map” interchangeably as terms for spatial input to management decisions. VoI analyses compare the expected outcome of taking an action or making a decision with additional information to the expected outcome of taking an action or making a decision with the current, more limited set of information (Morgan and Henrion 1990). A VoI analysis determines how much better the outcome of the action or decision is expected to be with the additional information, where the value of the information is equal to the improvement in the outcome when the information is used. The type of VoI analysis we demonstrate is referred to as Expected Value of Sample Information (EVSI) where the value of the information contained in a sample (e.g. a survey, map, field data, etc.) is being determined.

As a hypothetical example, suppose one is managing the spillway of a dam for farm irrigation purposes, with a goal to maximize harvest. Each day, the manager decides whether to release water. The decision to release water depends on several factors, including the current condition of the field (which is known) and the future condition of the field (which is unknown and depends on future precipitation). The decision may be improved if the manager had information about likely precipitation in the future. The uncertainty in upcoming rainfall can be reduced by producing a long term weather forecast. The VoI contained in the weather forecast is measured as the difference between the expected outcome of spillway management with the weather forecast and the expected outcome of the spillway management without the forecast. For example, if the farmers lost $5,000 worth of crops due to spillway management without the weather forecast, and lost $1,000 due to spillway management with a perfect weather forecast, the VoI in the weather forecast is $4,000. Technically, this is called the expected value of perfect information (EVPI) if the forecast is 100% accurate, without error (Morgan and Henrion 1990). Therefore, the spillway manager should be willing to pay up to $4,000 for the weather forecast data. With VoI analysis, the change in outcome (measured in dollars in this example) is the expected value of obtaining the additional information. Using VoI analysis, the manager can determine if the weather forecast is a worthy investment. If the cost is greater than the VoI, the forecast isn’t worth it, and vice versa. Unlike this example, predictions are rarely 100% accurate. Most predictions are imperfect and are based on a sample of the truth. Using the VOI technique described with samples, where the information may not be perfect, produces an EVSI.

The EVSI approach can similarly be used to provide an estimate of the value of spatial information for natural resource management purposes. By predicting the expected value of obtaining additional spatial information, managers can better target their management and research budget to acquire spatial information when it improves the expected outcome of their management decisions. Here we demonstrate how the EVSI methodology can inform the use of spatial data layers for natural resource management. Our specific objectives were to: 1) Provide a framework for evaluating the value of developing or improving spatial information, and 2) demonstrate flexibility in the framework by applying it to natural resource management scenarios.

4.3 Methods

4.3.1 Framework for map value of information

We considered management decisions that could result in one of two outcomes for a given management objective: 1 = successful outcome, 0 = unsuccessful outcome. For example, a wildlife manager may be tasked with making a decision that will lead to the recovery (1) or failed recovery (0) of a resource, such as a species of concern. The management objective (or the goal the manager wishes to achieve) includes a measureable attribute (e.g. species population status), along with a target, standard, or threshold for that attribute. For example, the management objective may be average occupancy probability (the measurable attribute) reaching 0.60 (the target) across an area of interest. In mapping terms, each mapping unit (e.g. a pixel or polygon in the spatial data layer) contains a probability of occupancy which depends on the landscape conditions associated with the pixel; the target of 0.60 represents the average probability of occupancy across all mapping units in the study area (for example see Noon et al. 2012).

In addition to metrics for the decision outcomes, VoI analyses also require an estimate of the current resource status in relation to the target. There is often uncertainty about this status. Continuing our example, if the last species status assessment was some time ago, the species status may have changed across the entire study area, or disproportionately in its distribution across space. A consultant specializing in occupancy modeling may be available to develop a new occupancy map of the species that can resolve some of the uncertainty about the current status. However, obtaining this map requires paying the consultant’s fee.

The manager has two linked decisions to make in this scenario. The first is whether or not to pay money for a map to determine the current status of the resource (with its associated error), and the second is whether or not to take any management action based on that assessment. The management outcome (successful, unsuccessful) of these decisions is affected by three sets of probabilities. The first set is the probability (P) that the predicted, current status (PS) is at or above the target *t*, $P(PS_{\geq t})$. $P(PS_{<t})$ is the probability that the predicted status is below the target, which is 1-$P(PS_{\geq t})$. Although the actual status (AS) of the resource does not change based on the predicted status, the *probability* that the actual status is at or above the target *is* conditional on the predicted status. Consequently, the second set is the probability that the actual (but unknown) status is at or above the target, $P(AS_{\geq t})$ or below the target, $P(AS_{<t})$, given the predicted status. A natural resource manager is specifically interested in these probabilities as they relate directly to the outcome: unsuccessful (0) or successful (1). The third set is the probability that any management actions that are taken will successfully alter the true, current status to achieve an outcome of 1 (recovery), designated by $P(M_s)$.

The first two probability sets (predicted and actual status relative to the target) can be depicted and calculated using a conjoint probability table (Table 4.1a). The table is populated with two inputs: (1) *p*, which is the probability that the *predicted status* (symbolized above as PS) is correct, and (2) *a*, which is the probability that the *actual status* (symbolized above as AS) is at or above the target threshold, *t*. If *a* is the marginal probability that the *actual status* achieves the target, 1- *a* is the marginal probability that the *actual status* is below the target. Given the *actual* target is achieved, the joint probability that the *predicted status* also achieves the target is $a * p$, and the joint probability that the *predicted status* is below the target is $a * (1\text{-}p)$. Similarly, given that the actual target is not achieved, the joint probability that the *predicted status* achieves the target is $(1 - a) * (1 - p)$, and the joint probability that the *predicted status* is below the target is $(1\text{-} a) * p$. From this information, the first set of probabilities can be calculated. The marginal probability that the *predicted status* is at or above the target is:

$$P(PS_{\geq t}) = ap + (1-a)(1-p) \qquad \text{Eq 1.}$$

and the marginal probability the *predicted status* is below the target is:

$$P(PS_{<t}) = (1-a)p + a(1 - p) = 1 - P(PS_{\geq t}). \qquad \text{Eq 2.}$$

From here it is straightforward to calculate the second set of probabilities, which are conditional probabilities, by dividing the joint probability by the appropriate marginal probability. For example, the conditional probability that the *actual status* achieves the target, given the *predicted status* achieves the target is $ap/P(PS_{\geq t})$.

Table 4.1b puts these probabilities back into the management context. When the species is truly at or above the target, the management objective will be met and the outcome will be successful; otherwise it will be unsuccessful. Thus, the marginal probabilities $P(AS_{\geq t})$ and $P(AS_{<t})$ represent the probabilities of these two outcomes, respectively. When the prediction is that the species achieves the target, a manager will not take a management action; when the prediction is that the species is below the target, a manager will take action. Thus, the marginal probabilities $P(PS_{\geq t})$ and $P(PS_{<t})$ represent the probability of no management action and the probability of management action, respectively.

Note that each column in Table 4.1a (conjoint table) and 4.1b (management implications) contains an assessment error. When the actual status is at or above the target but is predicted to be below the target, a manager will take action even when action is not required (a false assessment). The resultant cost is the cost of the unnecessary management action. When the actual status is below the target but is predicted to be at or above the target, the lack of management is an error resulting in an unsuccessful outcome (a false assessment). This error is detrimental in that the species does not achieve the target; associated costs of this error may include legal ramifications, loss of ecosystem services, further decline of the species, etc.

Improving the accuracy of the predicted status through spatial information such as a map could reduce the likelihood of both false assessment errors described above. Thus, the first decision a manager faces is whether to purchase a map. The second decision is whether to manage or not, where the success of the management action is our third probabilistic event. These decisions and probabilistic outcomes can be collectively represented as a decision tree (Figure 4.1). A decision tree is a visual representation of the outcomes of a decision, or series of decisions, and the probabilistic chain of events that must occur to result in each possible outcome. Our primary interest is in whether the natural resource management objective is met (1) or not (0) while minimizing the cost associated with each outcome. The decision tree allows us to compute the expected value of a decision to purchase a map in terms of these objectives.

To demonstrate calculating VoI of a map (Figure 4.1), we consider the case where a manager must decide whether to purchase a map to predict the species status across the area of interest ("Purchase Map?"). Thus, the first split is whether a map is purchased or not. For this example, we assume the cost of spatial information and its processing, i.e. the map cost is $2,500. The upper branches of the tree following this split depict the information necessary to determine the expected cost given the map, while the lower branches of the tree depict the expected cost of carrying on using current knowledge without the addition of a map. For our calculations, we will assume that the probability that the predicted status is correct, p using current information is 0.6, whereas $p = 0.9$ with a purchased map that has greater map accuracy. A manager assigning these values should reflect on their past predictive skills with the current information at their disposal, as well as the predictive accuracy with an improved map to arrive at these values. We will also assume the probability the actual status is at or above the target threshold, $a = 0.75$. Thus, $P(AS_{\geq t}) = 0.75$, and without management there is a 75% chance of a successful outcome and a 25% chance of an unsuccessful outcome.

Based on these inputs, we calculate the first set of probabilities which are associated with the predicted status probability nodes (Figure 4.1, Probability Set 1). With the purchased map (upper branches of the decision tree following the "Purchase Map?" split), the probability that the predicted status is at or above the target, $P(PS_{\geq t}) = 0.9*0.75 + (1-0.9)*(1-0.75) = 0.7$ (Equation 1) and the probability that the predicted status is below the target, $P(PS_{<t})$ is then 0.3 (Equation 2). With the current information (lower branches), the probability that the predicted status is at or above the target, $P(PS_{\geq t}) = 0.6*0.75 + (1-0.6)*(1-0.75) = 0.55$ (Equation 1) and probability that the predicted status is below the target, $P(PS_{<t})$ is then 0.45 (Equation 2).

Based on these predictions of species status, the manager decides whether to conduct management or not. If the prediction is that the species is already at the target, the manager would decide not to take action ("No Mgt Action"), while a prediction that the current status is below the target results in deciding to take the management action ("Mgt Action"). For this example, we assume that the cost of management, if undertaken, is \$20,000.

Once the management action is selected, the next set of probability nodes in Figure 4.1 represents the probability of the actual status being above or below the target, *given the predicted status*. Since the predicted status differs depending on whether a map is purchased or not, these probabilities will differ between the upper and lower branches of the tree. We focus now on the two topmost branches of the tree (Figure 4.1), where the predicted status suggests the target has been met and no management action is necessary. For the upper most branch leading to leaf tip i, the probability that the actual status is at the target, P($AS_{\geq t}$), given the predicted status, P($PS_{\geq t}$), is at or above the target can be expressed in many ways:

$$P(AS_{\geq t})|P(PS_{\geq t}) = \frac{P(PS_{\geq t})|P(AS_{\geq t}) * P(AS_{\geq t})}{P(PS_{\geq t})|P(AS_{\geq t}) * P(AS_{\geq t}) + P(PS_{\geq t})|P(AS_{<t}) * P(AS_{<t})}$$

$$= \frac{a * p}{P(PS_{\geq t})} = \frac{0.675}{.7} = 0.964$$

The second expression demonstrates the application of Bayes' Theorem to compute P($AS_{\geq t}$) | P($PS_{\geq t}$), but the third expression can be easily intuited from Table 4.1. The Bayesian formulation, however, makes it clear that the hypotheses of interest to the manager are the probability that the actual status is above or below the target.

This upper most tree branch results in a successful outcome (1), and the cost incurred by the manager is the cost of the map (Figure 4.1, leaf tip i).

Similarly, the probability that the actual status is less than the target, P(AS$_{<t}$), given the predicted status, P(PS$_{\geq t}$), is at or above the target can be expressed in many ways:

$$P(AS_{<t})|P(PS_{\geq t}) = \frac{(PS_{\geq t})|P(AS_{<t}) * P(AS_{<t})}{P(PS_{\geq t)}|P(AS_{\geq t}) * P(AS_{\geq t}) + P(PS_{\geq t})|P(AS_{<t}) * P(AS_{<t})}$$

$$= \frac{(1-p)(1-a)}{P(PS_{\geq t})} = \frac{(1-0.9)(1-0.75)}{0.7} = 0.0357$$

This tree branch results in a failed outcome (0), and the cost incurred by the manager is the cost of the map, plus the cost of failing to meet the resource objective, including economic loss, loss of ecosystem services, and potential legal costs (Figure 4.1, leaf tip ii). The remaining actual status conditional probabilities in the tree (Figure 4.1, probability set 2) are calculated in a similar manner.

In cases where management action is called for (i.e., P(PS$_{<t}$)), the final set of probability nodes (Figure 4.1, Management Success) represent the probability of the management action successfully altering the species status. This is the third probability set used in the VoI analysis. We assume that the probability of successful management P(M_s) is 0.8 and is independent of the other two probability nodes, making the probability of failed management 0.2 for our example. For example, if the management is habitat manipulation, there is an 80% chance that the management will be successful in moving the attribute (occupancy) to the target (0.60).

We now focus on the two bottommost branches in the top half of the tree leading to leaf tips iv and v, where the predicted status suggests the target has not been met and the actual status is below the target. The outcome and costs associated with these tips depends on whether the management action successfully altered the actual status. When management is successful, the result is a successful outcome (1), and the cost incurred by the manager is the cost of the map and the cost of the management action (Figure 4.1, leaf tip iv). When management is unsuccessful, the result is a failed outcome (0), and the cost incurred by the manager is the cost of the map, the cost of the management action, and the cost of failing to meet the resource objective, including economic loss, loss of ecosystem services, and potential legal costs (Figure 4.2, leaf tip v).

We now demonstrate the calculation of EVSI for a map, using the decision tree in Figure 4.1 and inputs $a = 0.75$ (the probability that the actual status exceeds the target), $p = 0.9$ with a map, $p = 0.6$ without a map (the probability of correctly assessing the actual status), and $P(M_s) = 0.8$ (the probability of successful management). We also assume some costs: a map costs \$2,500 to acquire, management costs total \$20,000, and the total costs of failed recovery (economic loss, lost ecosystem services, and legal costs) are valued at \$100,000. The cost of any leaf tip can be calculated using the appropriate set of these three values. For example, the value of leaf tip iv is the cost of the map and the management (\$2,500 + \$20,000 = \$22,500) as there is no cost due to failed recovery. After filling in the costs for each leaf, we determine the *expected cost* (EC) of each leaf by multiplying the leaf costs by the probabilistic chain of events leading to the branch node. For example, the expected cost of leaf iv in Figure 4.2 is $\$22{,}500 * 0.3 * 0.75 * 0.8 = \$4{,}050$, where 0.3, 0.7 and 0.8 are the $P(PS_{<t})$, $P(AS_{<t}) \mid P(PS_{<t})$, and $P(M_s)$ respectively. These expected costs are calculated for each leaf of

the decision tree and summed for the top (map) and bottom (no map) branches of the tree.

The expected cost of purchasing the map, \$15,500, is calculated by summing the EC's across the top (map) branches of the tree. The expected cost of not purchasing a map, \$22,000, is calculated by summing the EC's across the lower (no map) branches of the tree. The difference (\$6,500) provides the expected difference between the outcome of the decision using current knowledge and using the map.

If a manager doesn't yet know how much the map with cost, they would be more interested in calculating the total value of information the map provides. To calculate the EVSI provided by the map, we repeat the above calculation as if the map was free (i.e. \$22,000 - \$15,500 + \$2,500 = \$9,000). This determines the gross value of information rather than the net. Using this EVSI, a manager can directly compare the expected \$9,000 benefit the map provides to a consultant's price quote for producing the map, and select to purchase the map if it costs less than the \$9,000.

While we know it is unlikely for a map to be perfect, a manager may be interested in the maximum benefit a map could provide. By setting $p=1$, i.e. making the map perfect, which sets $P(PS_{>t}) = P(AS_{>t}) = 0.75$, the manager can determine the maximum benefit of a map relative to current knowledge. Setting $p=1$ changes the expected cost of purchasing the map to \$12,500 rather than \$15,500, making the EVPI \$12,000 (\$22,000 – \$12,500). Based on this EVPI and the assumptions that went into it the manager knows that at best a map can be worth \$12,000, so any map costing more than this isn't even worth considering.

4.3.2 Example Application: Invasive species mapping

This framework can be applied to a large variety of natural resource management decisions that involve spatial information. To exemplify this, we now examine an adaptation of the framework presented above to another management situation using a simplified model of forest management. The management objective for this situation is to minimize the economic impact of emerald ash borer (EAB; *Agrilus planipennis*) induced damage to a forest parcel. Because discussing and analyzing the full details of EAB biology, spread, and management are beyond the scope of our analysis, and EAB management efforts have limited efficacy, we present a simplified version of a management situation loosely based on EAB to demonstrate an application of spatial EVSI analysis to the current, pressing natural resource problem of invasive species management.

The management situation we will examine is that of a forester responsible for managing a parcel of land near or within the outskirts of the known extent of EAB. The manager knows EAB is an exotic invasive species already responsible for destroying millions of ash trees in North America, resulting in millions of dollars in damages (Herms et al. 2004, www.emeraldashborer.info, Kovacs et al. 2010).

Using the initial framework as our template, we make necessary adaptations and assumptions to fit the circumstances of the EAB situation (Figure 4.2). The management objective is best met if no EAB infestation occurs on the forest parcel, as the cost of EAB damages and the resulting decrease in timber value are avoided. In this example, the management action is the pre-emptive removal of large ash trees from the parcel. The 2012 silviculture recommendations from Michigan (http://www.emeraldashborer.info/files/Ash_Mgt_Guidelines.pdf) suggest that the probability of EAB destroying the ash trees in a parcel can be reduced by removing the largest trees in a parcel (referred to as thinning). Although this action has since been shown to be ineffective (Klooster et al. 2013), we proceed as if successful EAB management is a possibility for the purposes of demonstrating EVSI analysis.

With this assumption the combinations of possible EAB infestation status (infested, not infested) and management actions (thinning, no action) results in four possible outcomes: 1) Full timber value results when no EAB presence occurs without thinning, allowing the stand to fully mature and be harvested when value is maximized (assumed to be $500 thousand dollars); 2) Damaged timber value results when EAB infestation occurs without thinning, leaving only what little value can be salvaged from the damaged trees ($55 thousand); 3) Managed timber value results when thinning prevents EAB infestation providing the value of the thinned trees and the eventual maximum value of the remaining trees ($400 thousand), and 4) Managed and damaged timber value results when thinning occurs, but is unsuccessful at preventing EAB infestation leaving the value of the thinned trees and what little can be salvaged from the remaining damaged trees ($75 thousand).

Currently the manager is uncertain about the status of EAB in the area surrounding the forest parcel. EAB can spread at a rate of 0.5 miles per year or more in large dense EAB populations (Mercader et al. 2009, Mercader et al. 2012), so the greater the probability of EAB in the surrounding area, the greater the likelihood of the parcel becoming infested in the near future. Although the known locations of EAB are often marked and mapped (e.g., http://www.emeraldashborer.info/files/MultiState_EABpos.pdf), unmarked locations may or may not have EAB. They could be uninfested or infested but not detected. An alternative to mapping only the known locations of EAB is to develop a predictive map that shows the relative threat of EAB across the landscape, such as might be generated with a MaxEnt analysis (e.g., Phillips et al. 2006), or to develop a predictive map that shows the probability of infestation, such as might be generated with a MaxLike analysis (e.g., Royle et al. 2012).

Based on the uncertainty of current knowledge and using our framework, the decisions are whether to purchase a map delimiting the threat of EAB and whether to manage preemptively based on current knowledge. Regardless of whether of a map is purchased, the first step for the manager is to determine the management threshold *t*, i.e. the level of EAB threat within a given distance of the parcel at which the management action may be warranted. That is, the level of EAB threat that makes the expected value of ash thinning become greater than the expected value of not taking action. For example, suppose the manager determines this threshold occurs at 0.4, any prediction indicating less than this level of EAB threat in the surrounding area suggests there is little risk of infestation so management is unlikely to be necessary, while a prediction of 0.4 or greater suggests there is a risk of infestation and management is likely prudent. This threshold is used like the target level in objective one for the VoI analysis. Unlike our first example, in this scenario, the manager may choose to manage even if the threshold is not met, and may choose not to manage if the threshold is exceeded.

With a set of input probabilities we can now examine the expected value of the mapping decision using the decision tree (Figure 4.2). The upper branches of the tree, the half above the purchase map split, depict the information necessary to determine the expected value obtained from the timber parcel given the map, while the lower branches depict the expected value of the parcel when the manager uses current knowledge. For our calculations, we will assume that the probability that the predicted status (*p)* of EAB is accurate (i.e. on the correct side of the 0.4 threshold) using current information is p =0.5, whereas p = 0.75 with a purchased map that has greater accuracy. If the manager really has no knowledge of what EAB risk is in neighboring areas, the 0.5 probability using current information is akin to setting equal odds to this risk. We will also assume the probability the actual status of EAB is at or above the management threshold, a = 0.2. Thus, the probability that EAB is truly present in the area, $P(AS_{present}) = 0.2$, and without management there is a 20% chance of a EAB infestation and an 80% chance of no EAB infestation.

To correspond with the circumstances of this situation, we need to slightly modify values calculated by Equations 1 and 2. Because the management action will be taken when the threshold is met, the antithesis of our initial species example in objective one where action was taken if the target was not met, Equation 1 now applies to the probability the prediction is above the threshold and Equation 2 now applies to the probability the prediction is below the threshold. Therefore, given the inputs, with the map (upper branches) the probability that the predicted status is at or above the threshold, $P(PS_{\geq t}) = a*p + (1-a)*(1-p) = 0.2*0.75 + 0.8*0.25 = 0.35$ (Equation 1), and the probability that the predicted status is below the threshold, $P(PS_{<t})$ =

1 - 0.35 = 0.65 (Equation 2). With current information (lower branches), the probability that the predicted status is at or above the target, $P(PS_{\geq t}) = a*p + (1-a)*(1-p)$ = 0.2*0.5 + 0.8 *0.5 = 0.5 and the probability that the predicted status is below the target, $P(PS_{<t})$ = 1 – 0.5 = 0.5. These probabilities are found just above and below the predicted status probability nodes in Figure 4.2.

Following these predictions, the manager decides whether to take a management action ("Thinning") or not ("No Action"), with the outcome depending on the actual status of EAB risk and the probability that thinning is effective. The upper two leaves (i and ii, Figure 4.2) and the branches leading to them depict the outcomes when no management action is taken, even though $PS_{\geq t}$. Leaves iii, iv, and v and their branches depict the outcomes when management action given $PS_{\geq t}$.

Recall that the actual probability that EAB is present or absent, given the predicted status, is a conditional probability which can be calculated by multiplying the appropriate probability of prediction and actual status and dividing by the probability that the given prediction was made. For example, if we want the probability that EAB is truly present $P(AS_{present})$ given the map predicts that EAB exceeds the threshold, $(PS_{\geq t})$, we multiple the probability EAB is present, $a = 0.2$, by the probability the map is accurate (because the prediction is correct here), $p = 0.75$, and divide by the probability that the map predicts $(PS_{\geq t}) = 0.35$ (calculated with equation 1 above), giving the $P(AS_{present} | PS_{\geq t}) = 0.43$ (Figure 4.2, top branch).

The expected values can now be calculated by supplying the probability of management success. As previously stated, for demonstration purposes while acknowledging that EAB is a successful colonist, we will assume management has a

40% chance of effectively preventing EAB infestation in the parcel, i.e. P(M_s) = 0.4. Rolling back the decision tree by multiplying the tree probabilities by the outcomes for each leaf tip gives the *expected value* (EV) of each leaf tip (Figure 4.2, leaf EVs). (The term "expected value" is used in this example because we are interested in maximizing value of ash trees, whereas in our previous example the term "expected cost" was used because our interest was in minimizing cost).

Because managers have two decisions to make, the mapping decision and the subsequent management decision to make when deciding whether to manage for EAB, the expected value calculations require an additional step. In rolling back the decision tree the expected values from each leaf are first summed for the set of branches following the management action. For example, summing the EVs in leaf tip i and ii ($8.25 thousand plus $100 thousand) provides the EV ($108.25 thousand) of taking no action given the decision to purchase a map which predicts the EAB probability is at or above the threshold (Figure 4.2). Leaf tip iii, iv, and v sum to give the EV ($110.75 thousand) of thinning when the map is purchased and its prediction is at or above the threshold (Figure 4.2). In order to maximize the EV the manager would therefore choose to take action and thin if the map is purchased and its $PS_{\geq t}$, eliminating no action from consideration by pruning these branches from the tree (Figure 4.2, double tick marks). After pruning to remove the lower EV branches, only the remaining branches with the higher EV from the "Mgt Action?" nodes are then used to determine the EV for the map decision (Figure 4.2, branches without double tick marks).

We find that the expected value of managing with a map is $413.5 thousand (while the expected value of managing with current knowledge is $411 thousand. Note that the decision tree was constructed without any cost to obtain a regional EAB threat map because the costs of producing a regional map likely would have been born by a state or regional body; therefore the EVSI contained in the map in regards to managing this parcel is $2.5 thousand.

To compute these results, the parcel manager made two key assumptions in the analysis: (1) the probability the actual status of EAB is at or above the management threshold (a) = 0.2 and (2) the probability that the predicted status (p) of EAB is accurate = 0.5 without a map and 0.75 with a map. These assumptions may not be correct and the actual values are difficult to obtain (but see **Discussion,** *Challenges Estimating VoI).* To account for this, sensitivity analyses can be used to examine the effect of the range of reasonable uncertainty present about any input (Morgan and Henrion 1990). For example, if the manager believes the probability of correctly identifying whether EAB is at or above the management threshold given a map is 0.8 rather than 0.75, the value of p for the map is changed to 0.8, the probabilities are recalculated in the decision tree and the analysis is repeated. This would produce an EVSI of $8 thousand rather than the $2.5 thousand we reported above. The analysis can be repeated with adjustments to the other probabilities and timber values to determine their impact on the resulting EVSI as well.

A sensitivity analysis can also be used to determine thresholds, such as the probability of EAB presence, a, or the probability of management success, $P(M_s)$, below which there is no EVSI. For example, keeping the other inputs constant while changing a or $P(Ms)$, the EVSI drops to zero if a is below 0.182 or if $P(Ms)$ is below 0.349 (Figure 4.3). Therefore, if the probability that EAB is present at the management threshold level is less than 18.2% or the probability of successfully managing for EAB less than 34.9% in our example a manager would expect to obtain no benefit from additional information.

While our discussion of Figure 4.2 focuses on a one-time decision for the parcel manager, the decision tree also enables iterative analysis of this problem. For example, imagine the manager chose to map in 2012 and took no action based on the map's predicted status, and a new upgrade to the map is being proposed. Now, because the parcel has not been thinned the situation will repeat itself with the information from the 2012 map acting as the current information with its p of 0.75, and the newly proposed map will have some new p value, such as 0.8. Repeating the EVSI analysis with these new values produces an EVSI of $5.5 thousand. Over time the analysis can also be repeated to account for advances in methodology, or technology. For example, these advances can be accounted for updating the probability of management success $P(M_s)$, or mapping accuracy (p) as a response to better management, surveying, or mapping techniques and repeating the analysis.

4.4 Discussion

EVSI methodology is one of many techniques in the field of structured decision making (Gregory et al. 2012) and represents an important approach for identifying and reducing uncertainties in adaptive resource management programs (Williams et al. 2011a). The application of EVSI methodology to spatial information analyses discussed here provides a means of: 1) assessing the benefits of investment in improved mapping efforts, 2) enabling an analysis of the relative gains of mapping efforts in comparison to acting with current knowledge, and 3) comparing one potential mapping effort with another. With this assessment, the mapping efforts that will be of greatest value can be selected and budgets can be allocated to the most beneficial projects, improving efficiency and the overall productivity of management agencies.

While there are many theoretical discussions of VoI analyses, as well as a number of specific applications, the applications of VoI analyses to natural resource management are quite limited. Past applications either focus on a description of the data required for VoI analyses (e.g. objectives and economic valuation) with a rather general description of the methodology (e.g. Macauley 2006, Kangas et al. 2010), or on evaluating the VoI to a limited situation, with a focus on the results for that situation rather than on the implementation of VoI methodology (e.g. Costello et al. 2010, Moore et al. 2011, Moore and Runge 2012). We aimed to complement these approaches by focusing on the methodology used in VoI analysis, demonstrating its general application to enable understanding and replication, as well as demonstrating its adaptability to realistic natural resource management situations. To this end we provide a template spreadsheet and the list of specific input assumptions to guide the use of this methodology for a range of natural resource applications (See Supplement).

4.4.1 Challenges Estimating VoI.

While VoI methodology is a useful means of determining the benefits of information, it has some limitations. For example, an error free VoI analysis requires error-free estimates of the probabilities, benefits, and costs used in the analysis, which can be difficult, impractical, or even impossible to fully obtain. Assigning accurate probabilities to events can be particularly difficult if management in a similar situation has not been tried, similar mapping techniques to those proposed have not been applied, the quality of the predictive method is not well known, or the true state of the system is poorly understood. However, the alternative to using the VoI approach is to make a decision about mapping and management action without a formal approach, implicitly estimating the expected value calculations. Therefore, at some level, prediction of these probabilities and outcomes is occurring whenever a decision is being made. By making the probabilities and expected outcomes explicit, VoI analysis allows better documentation of the decision process. Additionally, an explicit analysis enables evaluation, replication and potential improvement for future attempts; it increases the ability to learn from experience, both one's own, and with documentation, the experience of others. The dependence of VoI on map accuracy should also alert land managers to the importance of considering accuracy when maps are used during the management process.

In addition to estimating probabilities in the VoI analysis, determining the benefits or costs of a management action in monetary terms, such as the cost of thinning, can be challenging. However, there are many examples of methods for assessing the economic value of natural resources (Costanza et al. 1997, Bockstael et al. 2000, de Groot et al. 2002, Farber et al. 2002). These methods are not always easy or affordable to implement (Turner et al. 2003, Chee 2004). An alternative to economic valuation techniques is expected utility theory (utility here is being used in the economic sense, meaning the amount of satisfaction, or dissatisfaction, obtained from an outcome) and the use of even swaps (Keeney and Raiffa 1976, Hammond et al. 1998). Rather than using money to measure preferences for something, preferences for outcome A are measured by how much of another outcome, B, one would trade for outcome A and still obtain the same degree of benefit. For example, if you are twice as satisfied by a chocolate bar as you are by a granola bar, and you would pay $1.25 for the granola bar, based on even swaps you would pay $2.50 for the chocolate bar, or twice as many units on another non-monetary utility scale.

4.4.2 Applications of EVSI to mapping.

VoI analysis in a mapping context provides an opportunity to determine the level of spatial accuracy needed for management applications. All models, and therefore all maps, being spatial models, have error, quantified by their user and producer error, that is the rate at which they predict something is in a location when it is not (user), or fail to predict something is in a location when in fact it is (producer) (Congalton 1991). In addition to varying in these error rates, maps also can vary in the resolution (pixel size), minimum mapping unit, and spatial extent, all of which can potentially affect the probability of predicting the actual status of a resource, and potentially the success of a management action (Aerts et al. 2003). Some regions of the world are mapped at low resolution (100m by 100m pixels rather than the more standard 30m by 30m pixels) and some regions on maps have been classified using a greater or lesser number of distinctions than others, with categories that may not match the scale of the local system of interest or are poorly validated (Sales-Luis et al. 2012).

The analysis presented here allows one to evaluate the value provided as map information varies based on components of map quality and their associated costs. By producing a set of branches on the decision tree for each map alternative that is being proposed, providing the estimated map accuracy and costs for the proposed map as inputs, managers can compare the value of a range of maps. In this way, by using decision trees with multiple map branches emanating from the purchase map decision node, rather than the single map branch shown here, managers can compare maps with different costs and error rates, choosing the one that produces the greatest expected value, or least expected cost.

While our work focused on evaluating a single set of spatial information, a productive extension of this work is to include multiple management decisions using the same map. For example, national mapping programs in the USA such as the Multi-Resolution Land Characterization Consortium (www.mrlc.gov) generates maps such as the National Land Cover Database (NLCD) that are used by federal, state, town governments, NGO's, water districts, planning districts, and many other agencies for a variety of purposes such as management of water quality, ecosystem heath, and wildlife habitat, as well as land use planning (www.mrlc.gov). The agencies tasked with constructing such maps have a goal of providing sound spatial data that can be used to address multiple management needs in a cost effective manner (www.mrlc.gov). To estimate the value of such maps, map producers could survey the maps' potential users, asking them to conduct individual EVSI analyses for the map's proposed uses focusing on the decision or decisions relevant to each individual agency. By aggregating the results of each EVSI analysis, managers of these multi-user mapping efforts could determine the most cost-effective level of effort to devote to producing the map. For example, the full expected value of a regional EAB map would be the sum of the EVSI results from all of the local parcel managers within the area of the map's coverage.

In summary, we believe the VoI approach will be useful for a wide range of natural resource managers making decisions about spatial information acquisition.

4.5 Acknowledgements

Support for this work was provided by U.S. Geological Survey. We thank Jennifer Pontius, Kimberley Wallin, James Murdoch, Ruth Mickey, and Daniel Herms for case study suggestions and comments on a draft manuscript. Any use of trade, firm, or product names is for descriptive purposes only and does not imply endorsement by the U.S. Government. The Vermont Cooperative Fish and Wildlife Research Unit is jointly sponsored by U.S. Geological Survey, the Vermont Fish and Wildlife Department, the University of Vermont, and the Wildlife Management Institute.

4.6 References – Chapter 4

Aerts, J. C. J. H., M. F. Goodchild, and G. B. M. Heuvelink. 2003. Accounting for spatial uncertainty in optimization with spatial decision support systems. Transactions in GIS **7**:211-230.

Araujo, M. B., and P. H. Williams. 2000. Selecting areas for species persistence using occurrence data. Biological Conservation **96**:331-345.

Bockstael, N. E., A. M. Freeman, R. J. Kopp, P. R. Portney, and V. K. Smith. 2000. On measuring economic values for nature. Environmental Science & Technology **34**:1384-1389.

Cabeza, M., and A. Moilanen. 2001. Design of reserve networks and the persistence of biodiversity. Trends in Ecology & Evolution **16**:242-248.

Carden, R. F., C. M. Carlin, F. Marnell, D. McElholm, J. Hetherington, and M. P. Gammell. 2010. Distribution and range expansion of deer in Ireland. Mammal Review **41**:313-325.

Chee, Y. E. 2004. An ecological perspective on the valuation of ecosystem services. Biological Conservation **120**:549-565.

Congalton, R. G. 1991. A review of assessing the accuracy of classifications of remotely sensed data. Remote Sensing of Environment **37**:35-46.

Cook, C. N., D. G. Morgan, and D. J. Marshall. 2010. Reevaluating suitable habitat for reintroductions: lessons learnt from the eastern barred bandicoot recovery program. Animal Conservation **13**:184-195.

Costanza, R., R. dArge, R. deGroot, S. Farber, M. Grasso, B. Hannon, K. Limburg, S. Naeem, R. V. Oneill, J. Paruelo, R. G. Raskin, P. Sutton, and M. vandenBelt. 1997. The value of the world's ecosystem services and natural capital. Nature **387**:253-260.

Costello, C., A. Rassweiler, D. Siegel, G. De Leo, F. Micheli, and A. Rosenberg. 2010. The value of spatial information in MPA network design. Proceedings of the National Academy of Sciences of the United States of America **107**:18294-18299.

Csuti, B., S. Polasky, P. H. Williams, R. L. Pressey, J. D. Camm, M. Kershaw, A. R. Kiester, B. Downs, R. Hamilton, M. Huso, and K. Sahr. 1997. A comparison of reserve selection algorithms using data on terrestrial vertebrates in Oregon. Biological Conservation **80**:83-97.

de Groot, R. S., M. A. Wilson, and R. M. J. Boumans. 2002. A typology for the classification, description and valuation of ecosystem functions, goods and services. Ecological Economics **41**:393-408.

Farber, S. C., R. Costanza, and M. A. Wilson. 2002. Economic and ecological concepts for valuing ecosystem services. Ecological Economics **41**:375-392.

Gormley, A. M., D. M. Forsyth, P. Griffioen, M. Lindeman, D. S. L. Ramsey, M. P. Scroggie, and L. Woodford. 2011. Using presence-only and presence-absence data to estimate the current and potential distributions of established invasive species. Journal of Applied Ecology **48**:25-34.

Gregory, R., L. Failing, M. Harstone, G. Long, T. McDaniels, and D. Ohlson. 2012. Structured decision making: A practical guide to environmental management choices. Wiley-Blackwell, West Sussex, UK.

Hammond, J. S., R. L. Keeney, and H. Raiffa. 1998. Even swaps: A rational method for making trade-offs. Harvard Business Review **76**:137+.

Herms, D. A., D. G. McCullough, and D. R. Smitley. 2004. Under attack: The current status of the emerald ash borer infestation and the program to eradicate it. American Nurseryman **200**:20-27.

Hilty, J. A., and C. R. Groves. 2008. Conservation planning: new tools and new approaches.*in* R. L. Knight and C. White, editors. Conservation for a New Generation: Redefining Natural Resources Management. Island Press, Washington, D.C., USA.

Kangas, A. S., P. Horne, and P. Leskinen. 2010. Measuring the Value of Information in Multicriteria Decisionmaking. Forest Science **56**:558-566.

Keeney, R. L., and H. Raiffa. 1976. Decisions with multiple objectives: preferences and value tradeoffs. Cambridge University Press, New York, USA.

Klooster, W. S., D. A. Herms, K. S. Knight, C. P. Herms, D. G. McCullough, A. Smith, K. J. K. Gandhi, and J. Cardina. 2013. Ash (*Fraxinus spp.*) mortality, regeneration, and seed bank dynamics in mixed hardwood forests following invasion by emeral ash borer (*Agrilus planipennis*). Biological Invasions **15**.

Kovacs, K. F., R. G. Haight, D. G. McCullough, R. J. Mercader, N. W. Siegert, and A. M. Liebhold. 2010. Cost of potential emerald ash borer damage in US communities, 2009-2019. Ecological Economics **69**:569-578.

Macauley, M. K. 2006. The value of information: Measuring the contribution of space-derived earth science data to resource management. Space Policy **22**:274-282.

Mercader, R. J., N. W. Siegert, A. M. Liebhold, and D. G. McCullough. 2009. Dispersal of the emerald ash borer, Agrilus planipennis, in newly-colonized sites. Agricultural and Forest Entomology **11**:421-424.

Mercader, R. J., N. W. Siegert, and D. G. McCullough. 2012. Estimating the influence of population density and dispersal behavior on the ability to detect and monitor *Agrilus planipennis* (*Coleoptera: Buprestidae*) populations. Journal of Economic Entomology **105**:272-281.

Moore, J. L., and M. C. Runge. 2012. Combining structured decision making and value-of-information analyses to identify robust management strategies. Conservation Biology **26**:810-820.

Moore, J. L., M. C. Runge, B. L. Webber, and J. R. U. Wilson. 2011. Contain or eradicate? Optimizing the management goal for Australian acacia invasions in the face of uncertainty. Diversity and Distributions **17**:1047-1059.

Morgan, M. G., and M. Henrion. 1990. Uncertainty: a guide to dealing with uncertainty in quantitative risk and policy analysis. Cambridge University Press, Cambridge, UK.

Noon, B. R., L. L. Bailey, T. D. Sisk, and K. S. McKelvey. 2012. Efficient species-level monitoring at the landscape scale. Conservation Biology **26**:432-441.

Phillips, S. J., R. P. Anderson, and R. E. Schapire. 2006. Maximum entropy modeling of species geographic distributions. Ecological Modelling **190**:231-259.

Poiani, K. A., B. D. Richter, M. G. Anderson, and H. E. Richter. 2000. Biodiversity conservation at multiple scales: Functional sites, landscapes, and networks. Bioscience **50**:133-146.

Royle, J. A., R. B. Chandler, C. Yackulic, and J. D. Nichols. 2012. Likelihood analysis of species occurrence probability from presence-only data for modelling species distributions. Methods in Ecology and Evolution **3**:545-554.

Sales-Luis, T., J. A. Bissonette, and M. Santos-Reis. 2012. Conservation of Mediterranean otters: the influence of map scale resolution. Biodiversity and Conservation **21**:2061-2073.

Schwartz, M. W. 1999. Choosing the appropriate scale of reserves for conservation. Annual Review of Ecology and Systematics **30**:83-108.

Turner, R. K., J. Paavola, P. Cooper, S. Farber, V. Jessamy, and S. Georgiou. 2003. Valuing nature: lessons learned and future research directions. Ecological Economics **46**:493-510.

Williams, B. K., M. J. Eaton, and D. R. Breininger. 2011. Adaptive resource management and the value of information. Ecological Modelling **222**:3429-3436.

Zimmermann, H., H. Von Wehrden, M. A. Damascos, D. Bran, E. Welk, D. Renison, and I. Hensen. 2011. Habitat invasion risk assessment based on Landsat 5 data, exemplified by the shrub Rosa rubiginosa in southern Argentina. Austral Ecology **36**:870-880.

Table 4.1 a. Conjoint probability table used in calculating *predicted* status probabilities given *a*, the probability the *actual* status is at or above the target, and *p*, the probability the *predicted* status is correct. b. Associated management implications of the four possible combinations of *predicted* status and *actual* status.

		Conjoint Table				Management Implications		
		Predicted Status				Predicted Status		
		≥ t	< t	**Marginal**		≥ t	< t	**Mgt Objective**
Actual Status	**≥ t**	$a * p$	$a * (1-p)$	$\mathbf{P(AS_{\geq t}) = \boldsymbol{a}}$		True Assessment No mgt action	False Assessment Cost of mgt action	**P(Successful)**
	< t	$(1-a) * (1-p)$	$(1-a) * p$	$\mathbf{P(AS_{<t}) = 1-\boldsymbol{a}}$		False Assessment Cost of mgt inaction	True Assessment Mgt action	**P(Unsuccessful)**
	Marginal	$\mathbf{P(PS_{\geq t})}$	$\mathbf{P(PS_{<t})}$			**P(No Mgt Action)**	**P(Mgt Action)**	

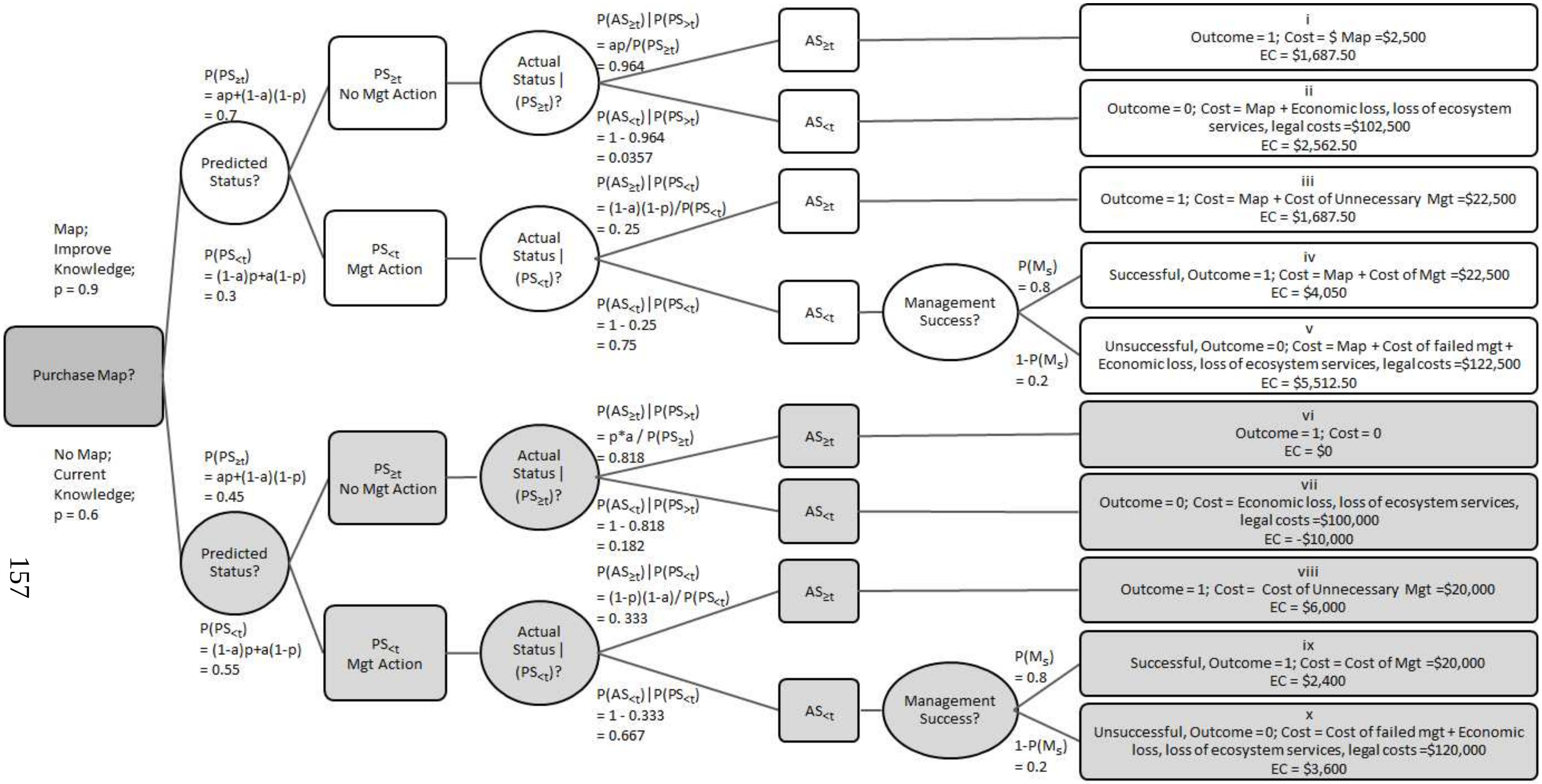


Figure 4.1 Decision Tree calculating the expected cost of species management with and without a species occupancy map. Decision nodes are represented by rectangles, probability nodes are represented by ovals. The tree begins at the far left with branches emanating from the purchase map decision node and splits into additional branches at the probability nodes. Branches terminate at 'leaf tips' labeled i through x at the far right. Each probability node is accompanied by the appropriate probability from its associated probability set.

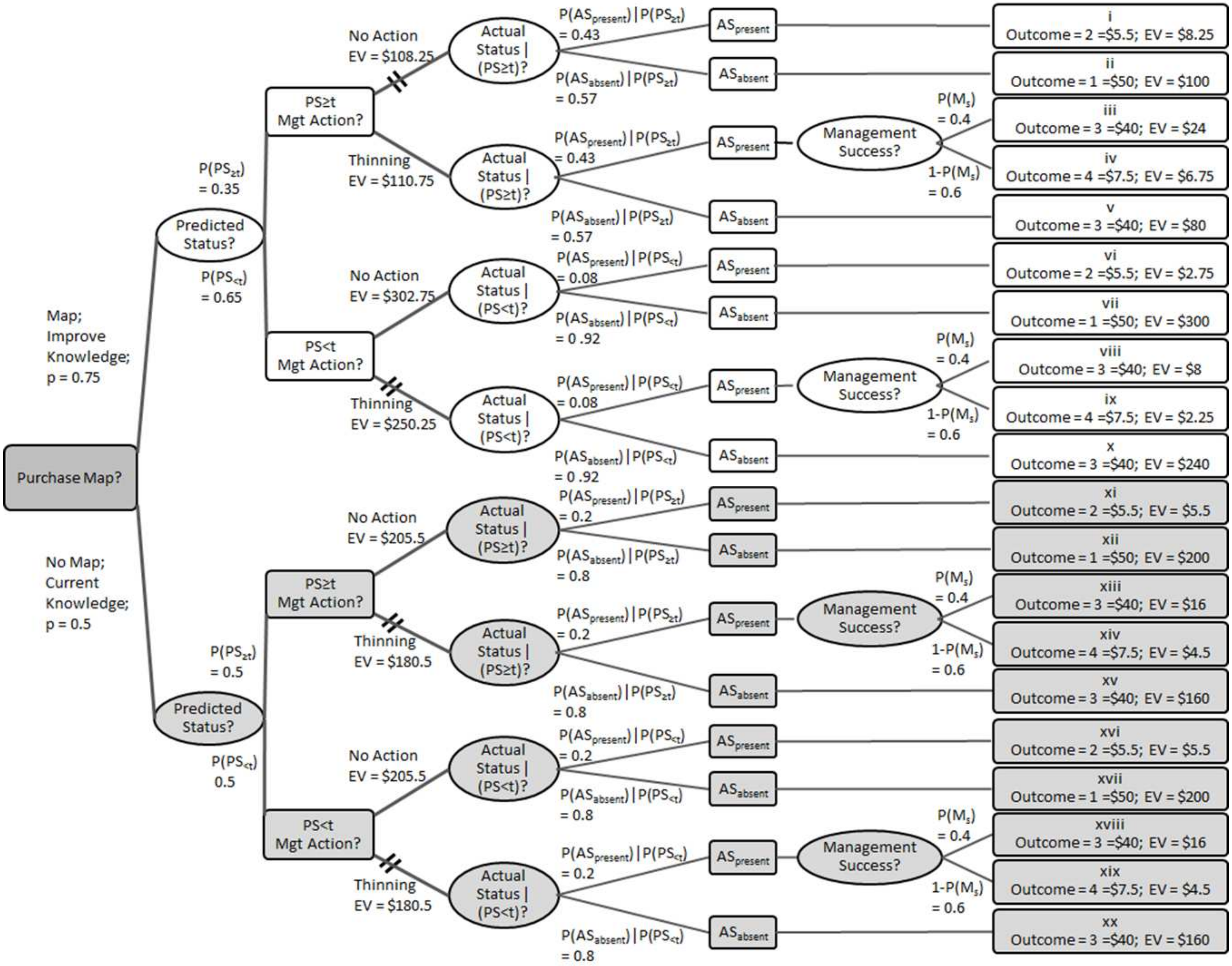

Purchase Map?
Map; Improve Knowledge; p = 0.75
No Map; Current Knowledge; p = 0.5
Predicted Status?
$P(PS_{\geq t})$ = 0.35
$P(PS_{<t})$ = 0.65
PS≥t Mgt Action?
PS<t Mgt Action?
No Action EV = $108.25
Thinning EV = $110.75
No Action EV = $302.75
Thinning EV = $250.25
Actual Status | (PS≥t)?
Actual Status | (PS<t)?
$P(AS_{present}) | P(PS_{\geq t})$ = 0.43
$P(AS_{absent}) | P(PS_{\geq t})$ = 0.57
$P(AS_{present}) | P(PS_{<t})$ = 0.08
$P(AS_{absent}) | P(PS_{<t})$ = 0 .92
$AS_{present}$
AS_{absent}
Management Success?
$P(M_s)$ = 0.4
$1-P(M_s)$ = 0.6
i Outcome = 2 =$5.5; EV = $8.25
ii Outcome = 1 =$50; EV = $100
iii Outcome = 3 =$40; EV = $24
iv Outcome = 4 =$7.5; EV = $6.75
v Outcome = 3 =$40; EV = $80
vi Outcome = 2 =$5.5; EV = $2.75
vii Outcome = 1 =$50; EV = $300
viii Outcome = 3 =$40; EV = $8
ix Outcome = 4 =$7.5; EV = $2.25
x Outcome = 3 =$40; EV = $240
$P(PS_{\geq t})$ = 0.5
$P(PS_{<t})$ 0.5
No Action EV = $205.5
Thinning EV = $180.5
No Action EV = $205.5
Thinning EV = $180.5
$P(AS_{present}) | P(PS_{\geq t})$ = 0.2
$P(AS_{absent}) | P(PS_{\geq t})$ = 0.8
$P(AS_{present}) | P(PS_{<t})$ = 0.2
$P(AS_{absent}) | P(PS_{<t})$ = 0.8
xi Outcome = 2 =$5.5; EV = $5.5
xii Outcome = 1 =$50; EV = $200
xiii Outcome = 3 =$40; EV = $16
xiv Outcome = 4 =$7.5; EV = $4.5
xv Outcome = 3 =$40; EV = $160
xvi Outcome = 2 =$5.5; EV = $5.5
xvii Outcome = 1 =$50; EV = $200
xviii Outcome = 3 =$40; EV = $16
xix Outcome = 4 =$7.5; EV = $4.5
xx Outcome = 3 =$40; EV = $160

Figure 4.2 Decision Tree calculating the expected value of emerald ash borer management with and without a map of the probability of neighboring emerald ash borer infestation. Outcomes and expected values (EV) are in leaf tips i-xx are in thousands of dollars. Double tick marks on branches emerging from the “Mgt Action?” decision nodes indicate branches that are pruned due to the lesser EV of those branches relative to their alternatives.

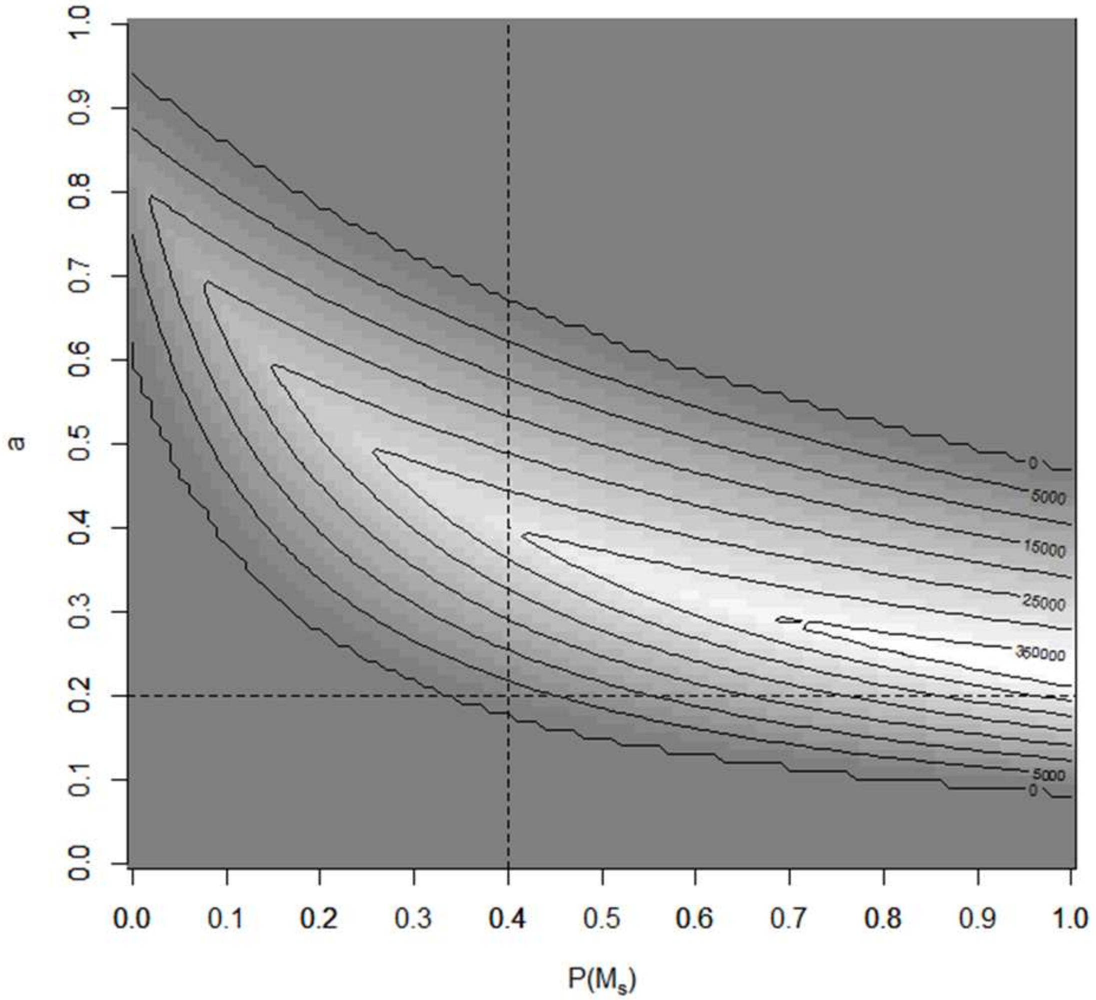


Figure 4.3 Contour plot of EVSI over the range of possible values of *a* (the probability the actual status is at or above the target) and P(M_s) (the probability that a management action will be successful). The probability that the predicted status is correct, *p*, was set at 0.75 with a map and 0.5 with current information. Lines at *a* = 0.2, and P(M_s) = 0.4, correspond to the values described in the example application for invasive species mapping, intersecting at the EVSI value of $2,500. Following the line at *a* = 0.2 shows the impact of changes to P(*Ms*) on EVSI when *a* is constant at 0.2.

APPENDIX A. EXECUTIVE SUMMARY

A.1 Chapter 2

In chapter 2 I evaluated the index, sex-age-kill, Fry, and Downing estimation methods. For those estimators I found:

- Estimating abundance is more difficult than estimating population change
- There is a tradeoff between estimating abundance and estimation population change in the estimation methods selected
- The sex-age-kill estimation method (`sakEst`) is best for abundance
- The Fry (`fryEst`) and Downing (`downingEst`) estimation methods and are best for estimating population change
- The performance of these estimation methods declines when populations are unstable (growing or declining)

Error in data collection impacts the performance of the estimation methods in the following ways:

- Reporting error (incomplete reporting) results in underestimates of abundance
- Sex and age error resulted in improved abundance estimates for the sex-age-kill method by increasing the abundance estimate under the simulated conditions

Some implications to be aware of:

- The declining performance for unstable populations could cause a lag in the recognition of populations changes, making it more difficult to determine when to take management actions, and difficult to recognize an effect of management action

- Of the error types, allocating resources to reporting error will have the biggest impact on reducing bias

A.2 Chapter 3

In chapter 3 I evaluated the performance of two fisher monitoring programs (with and without necropsy) and the estimation methods they enable. I found that based on the weights (importance scores) provided:

- The Downing (downingEst) estimation method performs best
- Performing necropsies is worth the cost of doing so because the value obtained from disease detection and public engagement is greater than the value obtained from the reduced cost from not conducting necropsies.
- The use of the Downing estimation method with necropsies performs best, but does not perform well in terms of minimizing bias in the abundance estimate

Some comments on the methodology to be aware of:

- The results, while fairly robust to the weights and consequences found here, are dependent on the objectives and weights identified.
- Should the objectives, their weights, or the consequences change; the analysis can be readily repeated so that the Vermont Fish and Wildlife Department can adapt the monitoring program to future changes in values.

A.3 Chapter 4

In chapter 4 I demonstrate the use of Expected Value of Sample Information (EVSI) to evaluate the benefits of collecting and analyzing spatial information (conducting mapping efforts). The method enables analysis of:

- The relative gains of mapping efforts vs. acting with current knowledge
- The benefits of investing in mapping efforts
- The benefits of one mapping effort vs. another

These analyses enable decision making by supporting:

- Comparison of the value of mapping efforts to their costs
- Comparison of multiple mapping efforts to each other to select the most beneficial.
- Budgeting and staffing decisions that depend on the comparisons listed above

I developed a spreadsheet to support independent EVSI analyses:

- To obtain a copy email me at jonathan.cummings@gmail.com, Subject: EVSI spreadsheet

APPENDIX B. DECISION ANALYSIS IN THE R SOFTWARE PACKAGE AMHARVEST

B.1 Abstract

I present a portion of the software package (`harvest`) that facilitates decision analysis through R functions and database storage. The software's associated database supports storage of the information accumulated during the structured decision making process, including the problem, objectives, and alterative, the predictive models, and the decision outcome. The software linking to the database calculates the consequences and trade-offs of the decision, which can also be stored in the database to track decision making over time. The package is written in the R programming language and is available through the Comprehensive R Archive Network (CRAN; http://cran.r-project.org/). Here, I describe the uses of the database and decision analysis functions provided by the `harvest` package harvest and demonstrate its use on a hypothetical natural resource management.

Keywords: Decision Analysis, Structured Decision Making, MCDA, SMART, smartDA

Note:

Names of Access database items are displayed in Calibri, while names of items and functions in R are displayed in `Courier New`.

B.2 Introduction

The use of structured decision making (SDM, Gregory et al. 2012, Conroy and Peterson 2013) and decision analysis (Keeney and Raiffa 1976) is expanding, particularly in the environmental sciences (Huang et al. 2011) as they become more familiar. The first portion of structured decision making process centers on problem framing, or laying out the decision to be made and the components that affect the structure and outcome of the decision. With assistance or experience with the structured decision making process decision makers tend to be comfortable and effective at this completing this stage of the structured decision making process. However, after using the structured decision making process to frame a problem a decision maker still needs to determine the consequences of the decision and needs to conduct the decision analysis to identify the best course of action. Currently managers tend to rely on decision analysts to conduct the decision analysis due to the complexity of the stage in the process and the complexity and cost of the currently commercially available decision analysis software.

Expansion in the use decision analysis along with the spreading idea that management actions can be tracked over time in form of scientific observation has placed a greater emphasis on making transparent, repeatable decisions and on recording the performance of management actions over time. For example, a key component of adaptive management is monitoring what decisions were made and what actions were taken in the past and present so that learning can occur over time and improve future decisions (Walters 2001).

Environmental and natural resources managers, and decision makers generally will likely benefit from a freely available means of evaluating the predicted outcomes of decisions, recording what decisions were made, and tracking the results of those decisions. The use of database software in conjunction with the R programming language (CRAN; http://cran.r-project.org/) makes this possible. Here I present the use of a Microsoft Access linked MySQL database and R based decision analysis functions in a means to conduct decision analysis and track decision making over time using the newly developed R package `harvest`.

My objectives are to: 1) Describe the methods for entering inputs to a decision analysis in the `harvest` package database; 2) Describe the steps for conducting the decision analysis in `harvest`; 3) Describe this process in term of an example problem, describing the decision analysis and its results along the way.

B.3 Decision analysis and decision information storage with `AMharvest`

The R package `AMharvest` links to a database to store decision analysis inputs and output while R functions are used to predict consequences and to conduct the decision analysis. I describe these components using the structured decision making approach to problem framing and decision analysis (Gregory et al. 2012, Conroy and Peterson 2013), which follows the abbreviation PrOACT (Hammond et al. 1999). PrOACT refers to the process of identifying the **Pr**oblem, describing the **O**bjectives, enumerating the **A**lternatives, predicting the **C**onsequences, and evaluating the **T**rade-offs. Here I demonstrate the data entry and decision analysis in `AMharvest` for a hypothetical decision regarding the management of a park

(Centennial Woods) in light of a declining population of Bowtruckle following the steps of the PrOACT process.

B.3.1 Database

The `AMharvest` package comes with a downloadable MySQL database to store data for decisions and an accompanying Microsoft Access front-end for data entry and retrieval. I designed the database to be flexible to a range of decision problems and components as I discuss below. Decisions and their components are entered into the Access front-end using the Decisions forms under the Decision Analysis header in the `AMharvest` package's database (Figure A.1). I encourage readers to open the database so that they may follow along while reading this manuscript.

B.3.2 Problem

The first step in structured decision making is defining the problem. Defining the problem is also the first step for decision analysis with `AMharvest` which is done by entering the problem definition into the database (Figure A.2). Problems are stored by name and automatically given an identification number (`pkdecisionid`). I named my example problem “Centennial Woods Habitat Management Problem” which was assigned a `pkdecisionid` of 5. For linked decisions the id that the decision is linked to is entered as well (`fklinkeddecisionid`). My problem has no linked decision, but as an example, an annual harvest management decision would likely depend on the decision a year prior. Therefore the `pkdecisionid` for the prior year's decision would be entered as the `fklinkeddecisionid` for the current year's decision.

Information about the decision to be made and the background information about that decision are entered in the Decision Question and Problem Definition portions of the Decisions form. The Decision Question is a succinct statement of the decision to be made, often defined as the irrevocable allocation of resources under consideration (Dale and English 1999). For my example the Decision Question is, "What habitat management action should be taken to meet the needs of Bowtruckles and the public?" The problem definition is a fuller explanation of the situation the decision maker is facing. A problem definition typically includes a number of components such as the location, scale, frequency, and timing of the decision, who the decision maker or decision makers are, any significant uncertainties that could influence the outcome of the decision, the nature of any linked decisions, any key stakeholders in the decision process or the result of the decision, and or any other important considerations in the decision making process. In my example I provided a brief problem definition (Figure A.2, Problem Definition).

The remaining components to enter for a decision are the type of decision analysis to conduct, the outcome, and the date of the decision. Currently the analysis function available for use in the package is the `smartDA` function, while future iteration of the package will include an option to conduct portfolio type decision analyses with the `portfolioDA` function. The analysis used for my example problem is the `smartDA` approach. The description of the outcome of the decision is entered in Outcome while the date the decision was made, or the selected alternative was implemented is entered in Date. These fields are not filled in until after the decision analysis is conducted and the decision is actually made and implemented. In my example after analysis a protected area was established on 4/29/2014 (Figure A.2, Date) that increased Bowtruckle abundance at a low cost (Figure A.2, Outcome).

B.3.3 Objectives

The second step in structured decision making is describing the objectives. Objectives are the criteria used to evaluate the outcome of a decision, determined by the values of the individuals making the decision. Objectives are entered in the Objectives section of the Decisions form (Figure A.3). The name of the decision is repeated (Figure A.3, Decision) for reference while entering the components of an Objective.

Objectives are selected by name from the list of objectives in the drop down Objective. To enter an objective that isn't in the drop down list select the Edit Objectives button and enter the name of a new objective (Figure A.4).

An objective has a number of associated components. The Measureable Attribute is the units used to assess the status of an objective. Measureable attributes also go by a number of other names such as criteria, measure, attribute, metric, performance measure, or performance metric depending on the decision analysis or decision analyst. Regardless of the name the measureable attribute is the item being counted, qualified, quantified, or otherwise recorded to determine the state of the world relative to what is desired. In my example the measureable attribute for the abundance objective is the number of Bowtruckle present in Centennial Woods. Each measureable attribute also has an associated measurement technique.

The Measurement Technique is the means of assessing the status of a measureable attribute. That is, the description of the measurement technique answers the question, “how is the amount of the measured unit being predicted, counted or otherwise determined?” For my example the number of Bowtruckles objective is being measured using the output of a predictive model that forecasts the abundance of Bowtruckle in Centennial Woods.

The Description is used to elaborate on the name of the objective in order to better communicate what the desire associated with an objective is. The purpose behind the description field is to clarify the intent of an objective, share the values an objective represents, and more clearly communicate the purpose of an objective than is possible through an objective’s name. For example the desire for the example objective is to maximize the number of Bowtruckles in Centennial Woods.

Each objective also has a desired direction. The Direction for each objective has one of four possible values: maximize – the more of the measurable attribute the better, minimize – the less the better, target – the closer to a target value the better, or constraint – either the objective is achieved (Yes/1) or not (No/0) relative to the constraint level. In the case of my example objective the desired direction is maximize, meaning the desire is to have as many Bowtruckles in Centennial Woods as possible.

An objective also has a relative importance or weight. The weight is the value, benefit, or utility derived from the range of possible outcomes for this objective relative to the utility derived from the other objectives for the decision in question. My example objective has a weight of 0.35 out of a total of 1 across the objective in my example, indicating that going from the worst to the best possible outcomes in terms of the number of Bowtruckles would provide 35% of the possible benefit of going from the overall worst to best possible Bowtruckle abundance outcomes.

The full set of objectives in the example Centennial Woods Habitat Management Problem are to maximize the number of Bowtruckles, to maximize the percentage of Centennial Woods visitors that see a Bowtruckle, to maximize Centennial Woods visitation, to maximize the enjoyment of visitors (the visitor experience), and to minimize the cost of management (Table A.1). Each objective is associated with one or more (for multiple model prediction) models that are used to assess the status of the objective and predict the consequences of selecting a particular alternative.

B.3.4 Models

In decision analysis models predict the status of an objective for an alternative as if the alternative is selected. That is, models are used to forecast the consequences of a decision. Each objective has an associated model and these models also have beta values for each of the model's covariates that influence the status of an objective. The model for each objective and that model's beta values are selected using the Models and Keys sub-forms that are shown in the Objectives entry section (Figure A.5).

Models are selected from a list of Models using the Model drop down. If a new model is needed models are added by selecting the Edit Models button and entering the new model's information in the Models form. For example, if the Bowtruckle Abundance Model did not yet exist it would be entered as shown in Figure A.6. A pkmodelid is automatically assigned to each model, while fkparentmodelid references an earlier version of the same model (using the methodology described for linking decisions with fklinkeddecisionid) if the model beta values change over time. There are two fkmodeltype values to select from for modeling the status of an objective in a decision analysis: consequence.predicted – for predictive models that are forecasting the future state of an objective and consequence.observed – for models that are storing the results of the observed state of an objective. For example, the status of the visitor experience objective from my example decision is the result of a survey of Centennial Woods visitors conducted specifically for this decision, so in this case the model stores values that would produce those observed survey results. The name stores the name of the model, transformation stores the type of transformation that occurs between the inputs and output of a model, Bayesian stores whether the model includes uncertainty in its parameters such that it can be used in Bayesian modeling, and description stores a description of the model. For decision analysis purposes fkspeciesid is an optional link to a species name if a model is used for a particular species and the user wishes to track this. The formula can be left blank for decision analysis purposes.

For decision analysis the model keys can also be referred to as model betas, or the rate of change in the model output that results from one unit of change in the beta or key (fkkeyid) selected. I further discuss the keys in the Alternatives section. The key for each model beta is selected using the fkkeyid drop down. If a key is not present a new key can be added by selecting the Edit Keys (Model Betas) button that opens the Keys form (Supplement A.6.1). The beta value for each key is entered in the valuenum column. If the number in the valuenum column is a dummy coding for a character or factor value the character or factor the dummy code is associated with is stored in the valuechar column. For decision analysis purposes the remaining columns are left blank under most circumstances (Supplement A.6.2). The model betas can either be entered in the Model Keys section of the Models form or by clicking the + to the left of the model drop down in the Models section of the Objectives form.

While I describe entering a single model for each objective, `AMharvest` supports multi-model predictions as well. By selecting multiple models in the model sub-form for each objective more than one model can be linked to an objective. The output from each of the selected models is then averaged to produce a single output value using model weights for the selected models. Model weights are added as an additional key (model beta) for each of the models being combined (Supplement A.6.3)

B.3.5 Alternatives

The third step in structured decision making is enumerating the alternatives. Alternatives are the actions that one is choosing between. Alternatives are entered in the final section of the Decisions form; the Alternatives section (Figure A.7). The name of the decision is repeated (Figure A.7, Decision) for reference while entering the components of an Alternative.

Like objectives, alternatives are selected by name from a list of alternatives, in this case using the Alternative drop down. For my example the Alternative name for the first alternative is “Protected Area”. To enter an alternative that isn’t included in the list for the drop down, click the Edit Alternatives button and enter the name of a new alternative, the pkalternativeid will be filled in automatically (Figure A.8).

In addition to an alternative’s name the database stores a description of the alternative; the decision analysis score for the alternative, and whether or not the alternative was selected for implementation when the decision was made (Table A.2).

Alternatives are also made up of one or more action elements, which describe the degree to which an action is taken.

The description – which communicates the details of what would be done if the alternative is selected – of an alternative, is entered in the Description box. For my example protected area alternative, the description is, "Set aside a region of Centennial Woods that is off limits to visitors."

An alternative's score field should be left blank at this point. The score value will be filled in when a decision analysis function is run. For my example the decision analysis has already been conducted, returning a score of 0.766792 for the protected area alternative.

The selected check box can be set to unchecked when an alternative is first entered for a decision. Once the decision is made, the alternative that is implemented should have its selected box checked, while the selected box for the other alternatives remain unchecked. In my example the protected area alternative had the highest score and was selected for implementation, so the selected box is checked.

The remaining sections of the Alternatives form store the action elements associated with an alternative. A range of terminology has been used to describe pieces of alternatives (called action elements here) and the combination of action elements into sets that one chooses between (alternatives here). Here I use alternative to mean either the single action taken and action element value implemented if the alternative is selected or the combination or set of actions (action elements) taken if the alternative is selected. So from a decision analysis perspective the set of alternatives to select from always represents the set of implementable items from which to select, whether there is one or more actions associated with each of the alternatives. Other terms have been used for alternatives when they contain combinations of actions, such as strategies, or portfolios, but I use alternative to mean both a portfolio or actions one can select or a single unique action that can be selected. A number of terms have been used for action elements or pieces that make up an alternative as well. They have been referred to as alternatives themselves, actions, components, constituent alternatives, and elements. Here I refer to the parts or pieces of an alternative as action elements.

In my usage an action element is the quantifiable action that is taken when an alternative is implemented. Where an objective is made up of a desired direction and a unit of measure an alternative is made up of one or more action elements that have names and a value enumerating the degree to which the action element is enacted. These action elements are also the covariate inputs to the models I use to determine the status of my decision objectives.

Action elements and the models they feed into are selected in the Action Elements sub-form. Action elements are selected from the list of action elements in the Action Element (Key, fkkeyid) drop down. Like adding new model betas, to add new action elements click the Edit Action Element (Keys) button and enter new action elements there. For my example the action element shown is the intercept action element. To match an objective's model to an alternative each of the model betas for the objective's model also needs a corresponding action element associated with each alternative the model is used for. The outcome of selecting the protected area alternative in terms of the Bowtruckle abundance is predicted using the "Bowtruckle Abundance Model" which has model betas of intercept, protected.area, viewing.area, and entry.fee. Therefore, the protected area alternative also needs the intercept, protected.area, viewing.area, and entry.fee actions elements (Table A.3).

The status of each of these elements if an alternative were selected is entered in the Action Value and Action Character fields. That is, the degree to which an action is taken is entered. As with the model betas if the number in the Action Value field is a dummy coding for a character or factor value the character or factor the dummy code is associated with is stored in the Action Character field. For my example decision each action element is either taken or not taken for each alternative, so the action character values are either Yes or No with yes stored as a 1 in the Action Value field and No stored as 0. If a model output depends on the value of an action, say the size of the protected area where one of the alternatives creates a 10 acres protected area the Action Value field for the protected.area would be 10.

The last step in entering an alternative's action element is to select the models for which the action element value is a covariate. This is done by selecting the names of those models in the fkmodelid column of the Models sub-form. The models should already be in the list if they were entered along with the objectives, but clicking the Edit Models button allows the entry of new models from the Alternatives section of the Decision form as well should a user wish to enter information in a different order that starts with alternatives. At this point all of the inputs to a decision analysis have been entered into the database and the decision analysis can be conducted.

B.4 R functions

B.4.1 Consequences

The fourth step in structured decision making is predicting the consequences. Consequences link alternatives to objectives by predicting the outcome of each alternative in terms of the measureable attributes for each of the objectives. In my framework the consequences involve determining the sum of the model betas (entered during the objectives section) multiplied by the model covariates (entered as action elements during the alternatives section). For example, the consequence for the abundance objective and the protected area alternative in my example is determined using the Bowtruckle abundance model (Table A.4). This model multiplies the `Model Beta` value for each key by the `Action Value` for that key, and sums the result for each key. In this case 10*1 + 90*1 + 30*0 + 50*0 for the four keys to the model equals 100, so the predicted consequence of the protected area alternative for the abundance objective is an abundance of 100 Bowtruckles.

These calculations take place in the `consequencesDA` function. The `consequencesDA` function requires two arguments as function inputs, the `db.name` and the `decision.id`. The `db.name` is the name of the database where the decision data is stored. This is the name you gave the database when you downloaded it with the `AMharvest` package, I named ours “HARVESTR”. The `decision.id` is the id number that was assigned to the decision problem back at the first step of data entry. In my example the Centennial Woods Habitat Management Problem as assigned a `decision.id` of 5. The example code to run `consequencesDA` on my example is therefore `consequencesDA("HARVESTR",5)`.

The output of the `consequencesDA` function is the resulting consequences for the decision, which are uploaded to the database selected using the `db.name` argument input to the function. The uploaded consequences are stored in tblconsequence for use in a decision analysis function. The consequences for my example decision are shown in Table A.5.

B.4.2 Trade-offs

The fifth step in structured decision making is conducting the decision analysis and evaluating the trade-offs. There are three parts of the decision analysis portion of trade-off evaluation process. The first part of the process is to normalize the consequences in order place the status of each of the objectives on the same scale. The normalized scores in the consequence table result in scores of 1 for the best outcome for each objective, scores of 0 for the worst outcome per objective, with the remaining outcomes receiving a score relative to how far it is from the best outcome. For example, the mid-point between the best and worst outcomes would receive a normalized consequence score of 0.5.

The second part of the process is to apply the weights for each objective to the normalized consequences. By multiplying the weight or relative importance of each objective by its normalized consequence, rather than having the best outcome for each objective score a 1, the best outcome for each objective would receive a score equal to that objective's weight. For my example, the abundance objective has a weight of 0.35, so the best outcome for the abundance objective receives a weighted consequence score of 0.35 instead of the 1 it received during the normalization step.

The third part of the process is to sum the weighted consequence scores for each alternative to arrive at the total score for the alternative across the full set of objectives. The alternative with the highest total score is then the one that fulfills the objectives for the decision to the greatest degree. The decision analysis process just described is also referred to as the simple multiple attribute rating technique (SMART, Von Winterfeldt and Edwards 1986).

The decision analysis processes described above are carried out by the `smartDA` decision analysis function. The `smartDA` function has four input arguments, `db.name`, `decision.id`, `database`, and `consequences.csv`. The `database` argument specifies whether or not the function will obtain values from a database and upload the results to a database. The default value of database is `TRUE`, indicating the database will be used, in which case the `consequence.csv` argument retains its default value of `NULL`. When the database is used the `db.name` and `decision.id` arguments are required. Like the `consequencesDA` function the `db.name` is the name of the database where the decision data is stored ("HARVESTR" in my example) and the `decision.id` is the id number that was assigned to the decision problem (`decision.id` = 5 in my example). The code to run the decision analysis for my example is therefore: `smartDA("HARVESTR",5)`.

When the database is used the function obtains a consequence table from the database and formats it for analysis (Table A.6). If a user does not enter a decision into the database and calculate the consequences using `consequencesDA` they can instead enter a consequence table directly into R by setting the `database` argument equal to FALSE and providing the name of a csv file containing a consequence table. The format of the csv file should match the format of Table A.6 with the same column names for objective, weight, and direction followed by a column for each alternative. Each row is an objective with its corresponding values. If my example had a consequence table stored in the csv file named "Centennial Woods Problem" the `smartDA` function could be run without using the database with the following code: `smartDA (db.name=NA, decision.id=NA, database=FALSE, consequence.csv=”Centennial Woods Problem”)`.

The output of `smartDA` is the score for each alternative. The scores for my example problem indicate that the protected area is the highest scoring alternative (Table A.7). For my example, the objectives weights sum to 1. Therefore the range of possible alternative scores ranges from 0 (worst case outcome for all objectives) to 1 (best case outcome for all objectives). Any values can be used for the weights, but assigning weights such that they sum of 1 or to 100 makes interpreting the scores easiest. Because the weights sum to 1 in this example the protected area alternative with its score of ~0.767 can be described as obtaining 76.7 percent of the best case outcomes relative to the worst case outcomes.

Based on the results of the example decision analysis I would select the protected area alternative for implementation. In order to track the selection of this alternative the selected check box for this alternative is checked on the Alternatives section of the Decision entry form in the database. Once the outcome of the selected alternative is clear a description of the outcome is entered in the `outcome` field in the decision entry form.

B.5 Conclusion, Extensions, and Additional functions

Here I presented the simple multiple attribute rating technique (SMART, Von Winterfeldt and Edwards 1986) approach to decision analysis and storing the results of the structured decision making process. The use of structured decision making and the AMharvest package provides a means to easily store the results of a decision process, facilitating transparency and communication as well as learning over time from the results of previous decisions.

For demonstration purposes the example decision I presented was a relatively more straight forward and less complex one. There are a number of possible extensions to the decision analysis presented here that deal with more complex forms of decision analysis. Some of the possible extensions are currently supported by the AMharvest package while others are not but may be developed for future versions of the package.

For the decision presented only one action was taken per alternative, but the analysis can be conducted with multiple action elements being implemented per alternative and at with different levels of implementation for the action elements. This would be done using the `smartDA` function as well, but with a greater number of combinations action elements and variety of action element values per alternative. The yet to be released `portfolioDA` function will use the SMART approach to decision analysis as well, but rather than running the analysis with a predetermined combination of action elements the function use optimization to select the optimal combination of action elements to produce the best possible alternative. The also yet to be released `optimizationDA` function extends this further, removing the need to preselect the action value associated with each action element. The function then optimizes not only the combination of action elements, but the action value for each of those action elements, arriving at the best possible alternative given the action elements available.

The final extension available but not discussed in the example is the ability to enter multiple models per objective and entering model weights for each of those models. The predictions from multiple models can then be combined to support a model averaging approach to consequence prediction (Supplement A.6.3)

Currently the consequenceDA makes a single prediction for each model, making a deterministic prediction. Possible extensions for further development of this package include developing R functions that support sensitivity analysis and uncertainty in the model predictions and developing functions that support variability in risk attitudes and the use of non-linear utility functions.

B.6 Supplement

B.6.1 Entering Keys

Keys, model betas for decision analysis, are entered in the Keys form (Figure A.9). The pkkeyid is assigned automatically for each key, name stores the name of the key, and description stores a description of the key. The fkkeytype for a key stores what the keytype is for the selected key from the list of keytypes (Table A.8). The fksettingtype will autofill following selection of the fkkeytype. Keys can have one of four datatypes: numeric, character, factor, or date/time that are stored in datatype.

B.6.2 Additional Columns in the Model Keys entry form

The remaining columns in the Model Keys form will rarely be used for decision analyses. The `enudensitystage` and `enudensitypop` columns are only used for simulating populations where the simulation is dependent on the abundance of the population. The `enudensitystage` refers to the stage in the annual lifecycle of the population at which the abundance is assessed and `enudensitypop` refers to the portion of the population whose abundance is considered. If there is a standard error associated with a model beta it is stored in the `se` column.

B.6.3 Predicting consequences with multiple models

To predict consequences from multiple models an objective must be associated with more than one model. This is done by selected multiple models in the model drop down in the objectives section of the decision form. An additional model beta is also selected for each of these models, their model weights. The model weights must be between 0 and 1 for each model, with a sum of 1 for a full set of models predicting the consequences of an objective. The weight for each model provides the relative influence of that model's prediction relative to the other models in the set. For example if model A has a weight of 0.75 and model B has a weight of 0.25, with predictions of 1 and 2 respectively, the multiple model prediction is the sum of the model predictions by their weights. In this case 0.75 + 0.5 the multiple model prediction is 1.25 (0.75+0.5).

B.7 References – Appendix B

Conroy, M. J., and J. T. Peterson. 2013. Decision making in natural resource management: a structured, adaptive approach. Wiley, Hoboken, New Jersey, USA.

Dale, V. H., and M. R. English. 1999. Tools to aid environmental decision making. Springer, New York.

Gregory, R., L. Failing, M. Harstone, G. Long, T. McDaniels, and D. Ohlson. 2012. Structured decision making: A practical guide to environmental management choices. Wiley-Blackwell, West Sussex, UK.

Hammond, J. S., R. L. Keeney, and H. Raiffa. 1999. Smart choices : a practical guide to making better decisions. Harvard Business School Press, Boston, Massachusetts, USA.

Huang, I. B., J. Keisler, and I. Linkov. 2011. Multi-criteria decision analysis in environmental sciences: Ten years of applications and trends. Science of the Total Environment **409**:3578-3594.

Keeney, R. L., and H. Raiffa. 1976. Decisions with multiple objectives: preferences and value tradeoffs. Cambridge University Press, New York, USA.

Von Winterfeldt, D., and W. Edwards. 1986. Decision analysis and behavioral research. Cambridge University Press, Cambridge UK and New York, USA.

Walters, C. J. 2001. Adaptive management of renewable resources. Blackburn Press, Caldwell, New Jersey, USA.

Table A.1 Objectives and their components for my example Centennial Woods Habitat Management Problem decision.

Objective Name	Direction	Weight	Measureable Attribute	Measurement Technique	Description
Abundance	maximize	0.35	Number of Bowtruckles	Predictive model of the number of Bowtruckles present in Centennial woods.	Maximize the abundance of Bowtruckles in Centennial Woods.
Sightings	maximize	0.175	Percentage of visitors with a Bowtruckle sighting	Predictive model of the Bowtruckle sighting rate.	Maximize the percentage of visitors to Centennial Woods that see a Bowtruckle during their visit.
Visits	maximize	0.085	Number of visitors per week.	Predictive Model of the number of visits per week.	Maximize the average number of individuals that visit Centennial Woods per week.
Visitor Experience	maximize	0.27	Average rating (0-10).	Observed response to an opinion survey of current visitors to Centennial Woods and a random sample of the local public.	Maximize the visitor experience of those who visit Centennial Woods.
Cost	minimize	0.12	Number of park ranger hours.	Predictive Model of the number of hours required to successfully manage the park.	Minimize the number of hours required for park rangers to manage Centennial Woods.

Table A.2 Alternatives, their descriptions, decision analysis score, and whether or not they were selected for implementation in my example Centennial Woods Habitat Management Problem.

Alternative Name	Description	Score	Selected
Protected Area	Set aside a region of Centennial Woods that is off limits to visitors.	0.7668	1 – Yes
Viewing Area	Develop a viewing station that directs visitors to a Bowtruckle viewing sight that minimizes negative effects to Bowtruckles.	0.7517	0 – No
Status Quo	Maintain the status quo management of Centennial Woods	0.16	0 – No
Entry Fee	Charging visitors an entry fee to enter Centennial Woods.	0.4221	0 – No

Table A.3 Alternatives with their action elements, action values, action character values, and models.

Alternative	Action Element	Action Value	Action Character	Models*
Protected Area	intercept	1		1,2,3,4,5
	entry.fee	0	No	1,2,3,4,5
	viewing.area	0	No	1,2,4,5
	protected.area	1	Yes	1,2,3,4,5
Viewing Area	intercept	1		1,2,3,4,5
	viewing.area	1	Yes	1,2,4,5
	entry.fee	0	No	1,2,3,4,5
	protected.area	0	No	1,2,3,4,5
Status Quo	intercept	1		1,2,3,4,5
	protected.area	0	No	1,2,3,4,5
	entry.fee	0	No	1,2,3,4,5
	viewing.area	0	No	1,2,4,5
Entry Fee	intercept	1		1,2,3,4,5
	entry.fee	1	Yes	1,2,3,4,5
	protected.area	0	No	1,2,3,4,5
	viewing.area	0	No	1,2,4,5

*1 – Bowtruckle Abundance Model, 2 – Bowtruckle Sighting Model, 3 – Centennial Woods Visit Model, 4 – Centennial Woods Visitor Survey, 5 – Centennial Woods Management Cost Model

Table A.4 The inputs to the Bowtruckle Abundance Model that models the consequences for the Abundance objective and Protected Area alternative for my example problem.

Objective	Alternative	Model	Transformation	Key	Model Beta Value	Action Value	Action Character
Abundance	Protected Area	Bowtruckle Abundance Model	none	intercept	10	1	
Abundance	Protected Area	Bowtruckle Abundance Model	none	protected.area	90	1	Yes
Abundance	Protected Area	Bowtruckle Abundance Model	none	viewing.area	30	0	No
Abundance	Protected Area	Bowtruckle Abundance Model	none	entry.fee	50	0	No

Table A.5 Consequences by objective and alternative for the example problem.

	Alternatives			
Objectives	Protected Area	Viewing Area	Status Quo	Entry Fee
Abundance	100	40	10	60
Sightings	55	95	20	25
Visits	175	250	250	50
Visitor Experience	5	7	2	6
Cost	8	12	20	40

Table A.6 Example layout of csv file for use with the smartDA function with three objective columns and a column for each alternative.

objective	weight	Direction	Entry Fee	Protected Area	Status Quo	Viewing Area
Abundance	0.35	maximize	60	100	10	40
Cost	0.12	minimize	40	8	20	12
Sightings	0.175	maximize	25	55	20	95
Visitor Experience	0.27	maximize	6	5	2	7
Visits	0.085	maximize	50	175	250	250

Table A.7 Decision analysis scores for each of the alternatives in the example problem.

Entry Fee	Protected Area	Status Quo	Viewing Area
0.4221111	0.7667917	0.16	0.7516667

Table A.8 List of key types by name with their descriptions.

name	description
dataset.column	A column of a dataset (does NOT include annual or daily covariates). All keys entered in CAPS.
function.argument	A key used as arguments for R function arguments, such as mean, sd, dataset, etc.
model.beta	A beta for a model, either for simulation or estimated.
covariate.column	A column in tblcovariate (includes annual and daily covariates)
popmod.key	A key created by and used in the popmod function for simulating a population through time.
analysis.output	An output from an analysis
distribution.parameter	Keys used that define a parameter of a statistical distribution.
beta.info	Additional information related to a model beta, such as se, uci, lci
model.info	A key that provides additional information about a model, such as its weight or aic score.
covariate.value	The value that is fed into a model and multiplied by a beta
sim.species	Keys that identify a species life history
sim.mark	Keys used for simulating a marked population
sim.pop	Keys used to simulate population dynamics
sim.harvest.data	Keys used for simulating agency handling of harvest data
sim.harvest	Keys used to simulate the harvest
sim.season	Identifies the type of harvest season (e.g., rifle, bow, etc)

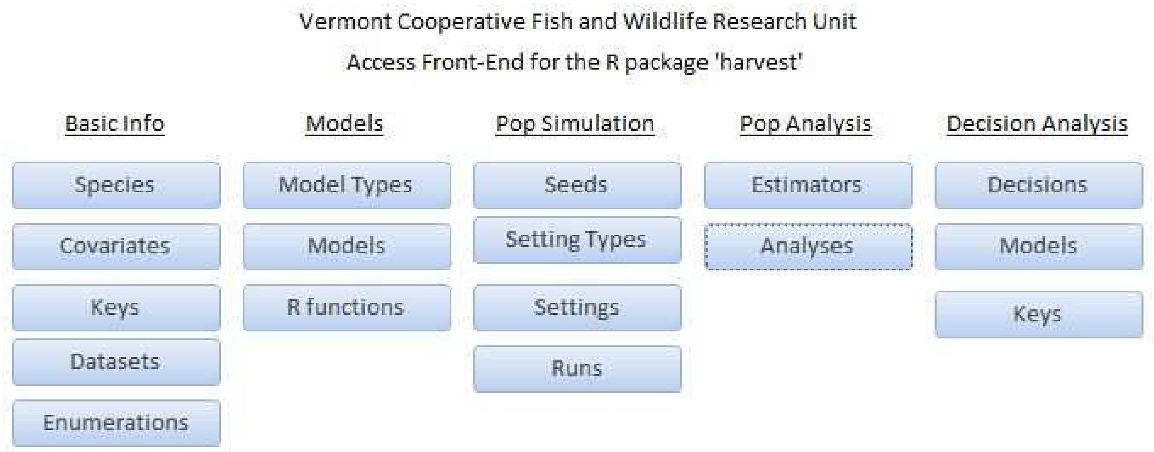
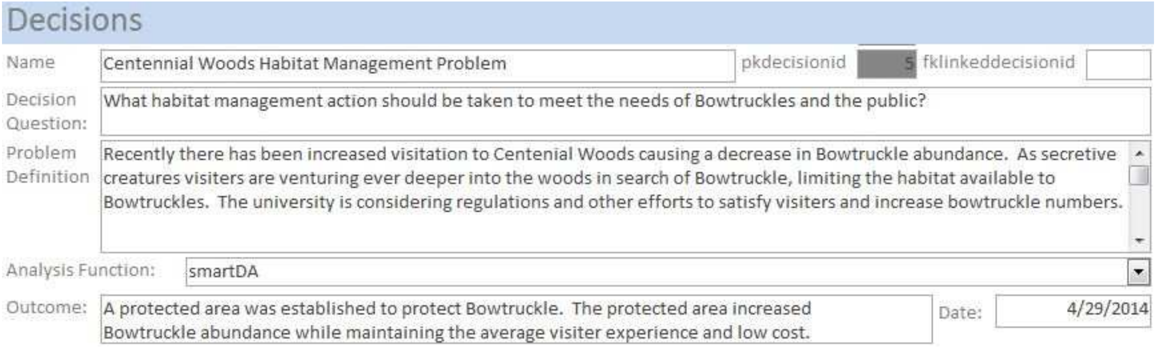


Figure A.1 The home page for Microsoft Access database used in the R package AMharvest. The majority of the decision analysis functionality is linked to the buttons under the Decision Analysis header. To enter information about a decisions select the Decisions button. To enter models used in the consequences step select the Models button. To enter model betas and action elements select the Keys button.



Name: Centennial Woods Habitat Management Problem

pkdecisionid: 5

fklinkeddecisionid:

Decision Question: What habitat management action should be taken to meet the needs of Bowtruckles and the public?

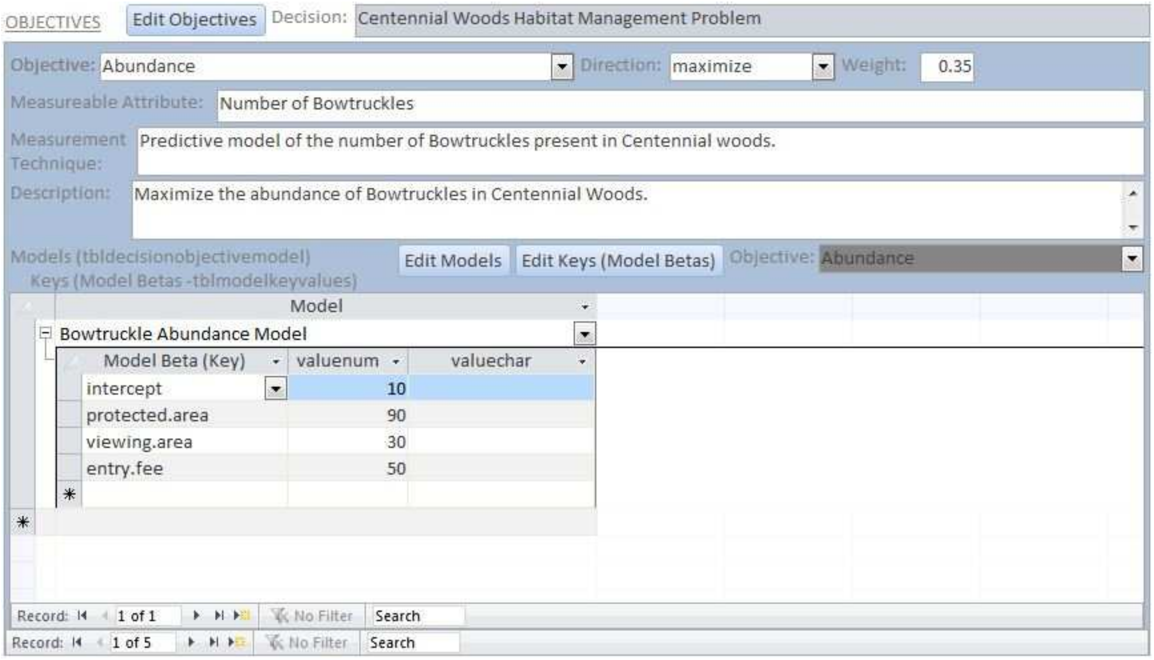
Problem Definition: Recently there has been increased visitation to Centenial Woods causing a decrease in Bowtruckle abundance. As secretive creatures visiters are venturing ever deeper into the woods in search of Bowtruckle, limiting the habitat available to Bowtruckles. The university is considering regulations and other efforts to satisfy visiters and increase bowtruckle numbers.

Analysis Function: smartDA

Outcome: A protected area was established to protect Bowtruckle. The protected area increased Bowtruckle abundance while maintaining the average visiter experience and low cost.

Date: 4/29/2014

Figure A.2 Decisions are entered in the Decisions form. The Name, pkdecisionid, fklinkeddecisionid, Decision Question, Problem Definition, Analysis Function, Outcome, and Date are entered and displayed in this form. Name is the name given to the decision. The pkdecisionid is the id assigned to the decision, while fklinkeddecision id store the id this displayed decision links to, if there is one. The Decision Question is the decision to be made, while the Problem Definition provides the background information on the decision. The Analysis Funcition is the R function used for the decision analysis. The Outcome is the result of the decision and the Date is the date the decision was made.



Decision: Centennial Woods Habitat Management Problem

Objective: Abundance

Direction: maximize

Weight: 0.35

Measureable Attribute: Number of Bowtruckles

Measurement Technique: Predictive model of the number of Bowtruckles present in Centennial woods.

Description: Maximize the abundance of Bowtruckles in Centennial Woods.

Models (tbldecisionobjectivemodel)
Keys (Model Betas -tblmodelkeyvalues)

Objective: Abundance

Model: Bowtruckle Abundance Model

Model Beta (Key)	valuenum	valuechar
intercept	10	
protected.area	90	
viewing.area	30	
entry.fee	50	

Record: 1 of 1

Record: 1 of 5

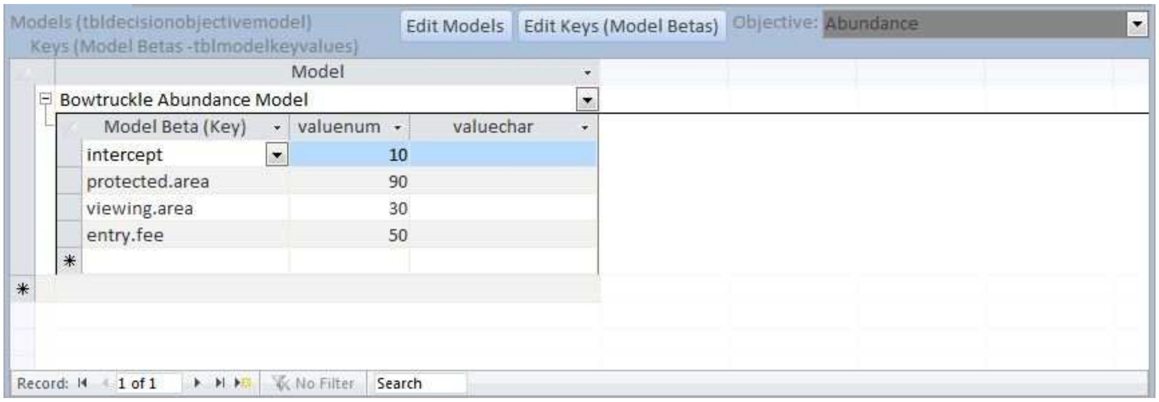
Figure A.3 Objectives are entered in the Objectives form. The Objective, Direciton, Weight, Measureable Attribute, Measurement Technique, are entered and displayed in this form. The decision the objective is a part of (Decision) and the button for editing or entering new objectives (Edit Objecitves) are just above the objectives section of the form. Objective is the name given to the objective. Direction is the desired state of the objecitve. Weight is the relative importance of the objective. The Measureable Attribute is the units the objective is assessed with, and the Measurment Technique is the means for assessing how many of the measured unit result from the decision.

Objectives (tblobjective)

pkobjectiveid: 11

Name: Cost

Figure A.4 Objective names are added or edited in the form linked to by the Edit Objectives button.

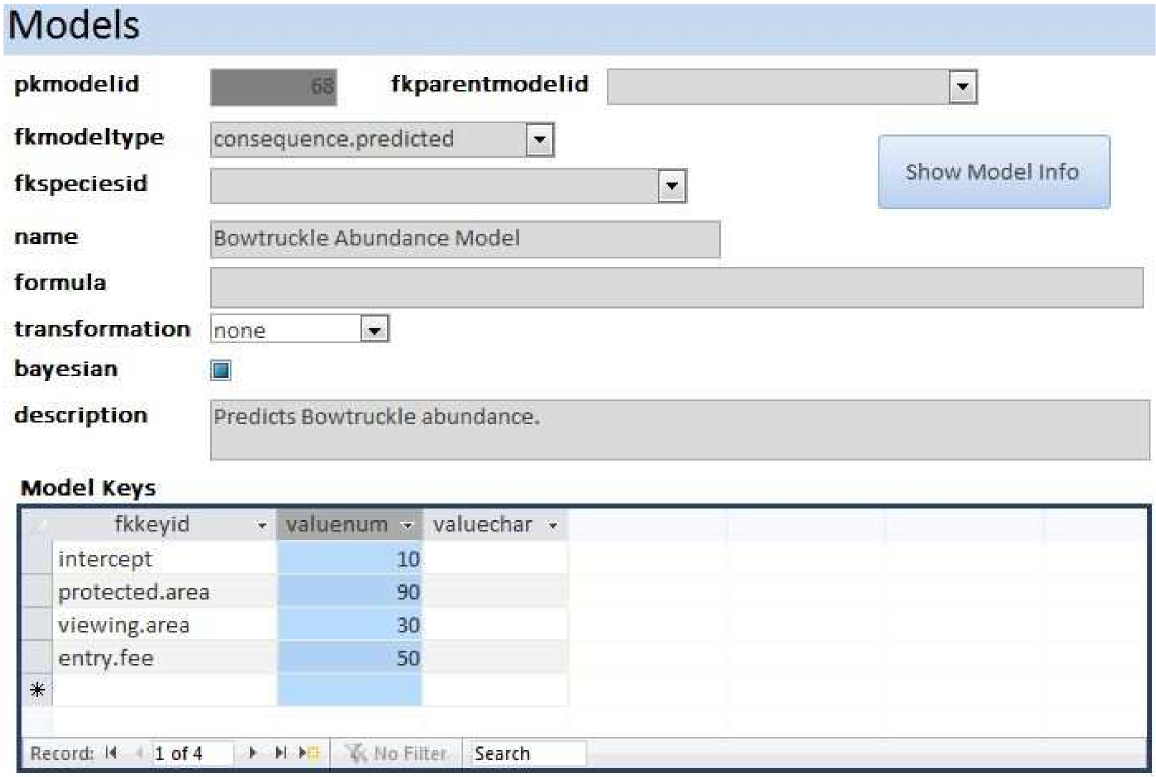


Objective: Abundance

Model: Bowtruckle Abundance Model

Model Beta (Key)	valuenum	valuechar
intercept	10	
protected.area	90	
viewing.area	30	
entry.fee	50	

Figure A.5 Model and their model betas (Keys) are entered in the Model and Keys sub-forms. The Model, the Model Beta values, and the valuenum and valuechar values are entered in these sub-forms. Model is the name of the model used. Model Beta is the name of the beta used in the model. The valuenum is the numeric value of the beta, and valuechar an the character value of beta if applicable.



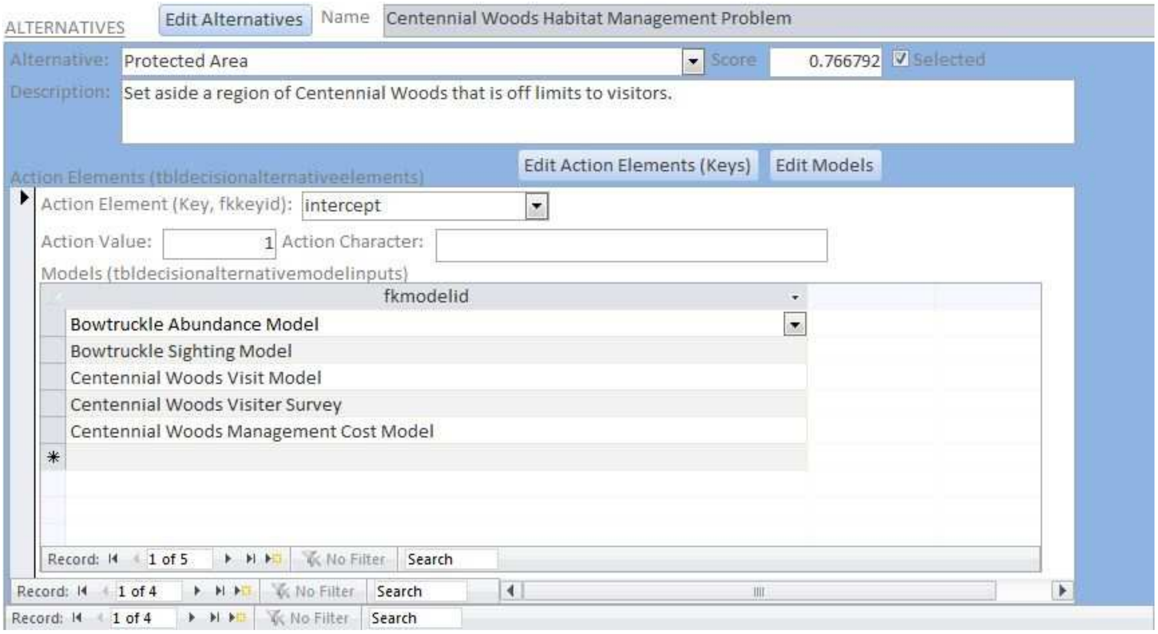
Models

pkmodelid	68
fkparentmodelid	
fkmodeltype	consequence.predicted
fkspeciesid	
name	Bowtruckle Abundance Model
formula	
transformation	none
bayesian	☑
description	Predicts Bowtruckle abundance.

Model Keys

fkkeyid	valuenum	valuechar
intercept	10	
protected.area	90	
viewing.area	30	
entry.fee	50	
*		

Figure A.6 Model editing can also be conducted in Model form. The fields in the model form are pkmodelid, fkparentmodelid, fkmodeltype, fkspeciesid, name, formula, transformation, bayesian, and description. The pkmodelid and fkparentmodelid fields store the id for the current model, and the id for the parent model if the current model is an iteration of an earlier version of the model. The fkmodeltype is the type of the model, and the fkspeciesid is the species the model makes a prediction about if applicable. The name field store the name of the model. The formula field stores the model formula if needed for use in R, while transformtion stores and transformation of the model output that occurs. The bayesian check box is used if the model includes bayesian uncertainty. The description field is a text description of the model. The Model Keys sub-form stores the keys associated with a model (fkkeyid), and there numeric (valuenum) or character values (valuechar).



Name: Centennial Woods Habitat Management Problem

Alternative: Protected Area

Score: 0.766792

☑ Selected

Description: Set aside a region of Centennial Woods that is off limits to visitors.

Action Elements (tbldecisionalternativeelements)

Action Element (Key, fkkeyid): intercept

Action Value: 1

Action Character:

Models (tbldecisionalternativemodelinputs)

fkmodelid
Bowtruckle Abundance Model
Bowtruckle Sighting Model
Centennial Woods Visit Model
Centennial Woods Visiter Survey
Centennial Woods Management Cost Model

Figure A.7 Alternatives are entered in the Alternatives form. The Alternative, Description, Score, and Selected values, as well as the action elements and their values are entered and displayed in this form. The decision the alternative is a part of (Decision) and the button for editing or entering new alternatives (Edit Alternatives) are just above the alternatives section of the form. Alternative is the name given to the objective. Description is a text description of the alternative. Score is the decision analysis result for the alternative and selected is check if the alternative was selected for implementation. The Action Elements sub-form stores the action elements, the action element values (Action Value) for the alternative and action element character values (Action Character) if applicable. The models that the action elements are covariates of are stored in the Models sub-form fkmodelid drop down.

Alternatives (tblalternative)

pkalternativeid: 16

Name: Fence

Figure A.8 Alternative names are added or edited in the form linked to by the Edit Alternatives button.

pkkeyid	80
name	protected.area
fkkeytype	model.beta
fksettingtype	
datatype	numeric
description	Whether or not a protected area is established.

Figure A.9 Keys are entered in the Keys form. The pkkeyid, name, fkkeytype, fksettingtype, datatype, and description field for keys are stored and displayed in this form. The pkkeyid is the automatic id for each key, the fkkeytype is the type of key it is, fksettingtype is the key's setting type if applicable, and datatype is the key's type of day stored with the key. The name field is the name of the key and the description field is the key's description.

APPENDIX C. ANALAYSIS OF VARIANCE IN ESTIMATOR PERFORMANCE

To test the significance of the differences in mean performance by estimation method, and as a function of error I conducted Tukey's HSD tests. Based on this analysis there is a significant difference in the performance of all of the estimators in terms of their ability to predict abundance as measured by the bias of the estimators (Table C.1). In terms of the ability to predict population change (lambda) measure by bias in lambda there is a significant difference between the sex-age-kill method (`sakEst`) and the other three methods, but the other three methods are not significantly different from each other (Table C.2).

In terms of ability to predict abundance including error in data collection resulted in significantly different performance from one error type to another with two exceptions (Table C.3). , When reporting error and all error, as well as sex error and age error (Table C.3) the differences were insignificant for the index (`indexEst`), Fry, (`fryEst`) and Downing (`downingEst`) methods, but significant for the sex-age-kill method (`sakEst`) except . There were no significant effects of error in the ability to predict lambda (Table C.4).

Table C.1 Differences in the mean bias in abundance estimate by estimation method across scenarios.

Estimator comparison	Difference in means	Lower limit of 95% confidence interval on difference in means	Lower limit of 95% confidence interval on difference in means	Adjusted p-value
indexEst to fryEst	0.4895	0.4877	0.4912	0.0000
indexEst to downingEst	0.4480	0.4462	0.4497	0.0000
indexEst to sakEst	-0.0243	-0.0225	-0.0260	0.0000
fryEst to downingEst	-0.0415	-0.0432	-0.0397	0.0000

fryEst to sakEst	-0.5137	-0.5120	-0.5155	0.0000
downingEst to sakEst	-0.4723	-0.4705	-0.4740	0.0000

Table C.2 Difference in the mean bias in lambda estimate by estimation method across scenarios.

Estimator comparison	Difference in means	Lower limit of 95% confidence interval on difference in means	Lower limit of 95% confidence interval on difference in means	Adjusted p-value
indexEst to fryEst	0.0014	-0.0003	0.0032	0.1497
indexEst to downingEst	0.0012	-0.0005	0.0030	0.2608
indexEst to sakEst	-0.0184	-0.0166	-0.0201	0.0000
fryEst to downingEst	-0.0002	-0.0019	0.0016	0.9920
fryEst to sakEst	-0.0198	-0.0180	-0.0215	0.0000
downingEst to sakEst	-0.0196	-0.0178	-0.0213	0.0000

Table C.3 Difference in the mean bias in abundance estimate for by error type across estimation methods and by estimator.

Scenario comparison	All estimation methods	indexESt	fryEst	downingEst	sakEst
stable.null to stable.reporting	0.0000	0.0000	0.0000	0.0000	0.0000
stable.null to stable.sex	0.0000	0.0000	0.0000	0.0000	0.0000
stable.null to stable.age	0.0000001	0.0000	0.0000	0.0000	0.0000
stable.null to stable.all	0.0000	0.0000	0.0000	0.0000	0.0000
stable.reporting to stable.sex	0.0000	0.0000	0.0000	0.0000	0.0000
stable.reporting to stable.age	0.0000	0.0000	0.0000	0.0000	0.0000
stable.reporting to stable.all	0.0000	0.9317	0.3516	0.9444	0.0000
stable.age to stable.sex	0.3310	0.8638	0.1687	0.5798	0.0000008
stable.age to stable.all	0.0000	0.0000	0.0000	0.0000	0.0000
stable.sex to stable.all	0.0000	0.0000	0.0000	0.0000	0.0000

Table C.4 Difference in the mean bias in lambda estimate for by error type across estimation methods and by estimator.

Scenario comparison	All estimation methods	indexEst	fryEst	downingEst	sakEst
stable.null to stable.reporting	0.9999	0.9999	0.9999	0.9981	0.9996
stable.null to stable.sex	0.8447	0.9999	0.7880	0.7684	0.6798
stable.null to stable.age	0.9960	0.9999	0.9459	0.9569	0.9866
stable.null to stable.all	0.6605	0.9999	0.9968	0.9954	0.5557
stable.reporting to stable.sex	0.9071	0.9999	0.8399	0.9092	0.7983
stable.reporting to stable.age	0.9995	0.9999	0.9679	0.9949	0.9981
stable.reporting to stable.all	0.7527	0.9999	0.9991	0.9999	0.6863
stable.age to stable.sex	0.9659	0.9998	0.9951	0.9899	0.9276
stable.age to stable.all	0.8646	0.9999	0.9949	0.9979	0.8544
stable.sex to stable.all	0.9976	0.9999	0.9353	0.9346	0.9997

APPENDIX D. FULL REFERENCE LIST

Aerts, J. C. J. H., M. F. Goodchild, and G. B. M. Heuvelink. 2003. Accounting for spatial uncertainty in optimization with spatial decision support systems. Transactions in GIS **7**:211-230.

Araujo, M. B., and P. H. Williams. 2000. Selecting areas for species persistence using occurrence data. Biological Conservation **96**:331-345.

Artelle, K. A., S. C. Anderson, A. B. Cooper, P. C. Paquet, J. D. Reynolds, and C. T. Darimont. 2013. Confronting uncertainty in wildlife management: performance of grizzly bear management. PLoS One **8**:9.

Asmus, J., and F. W. Weckerly. 2011. Evaluating precision of cementum annuli analysis for aging mule deer from Southern California. Journal of Wildlife Management **75**:1194-1199.

Atwood, E. L. 1956. Validity of mail survey data on bagged waterfowl. Journal of Wildlife Management **20**:1-16.

Ayyub, B. M. 2001. Elicitation of expert opinions for uncertainty and risks. CRC Press, Boca Raton, Florida, USA.

Bernier, C., and M. B. Adler. 2012. Vermont furbearer management newsletter. Pages 7-8. Vermont Fish & Wildlife Department, Springfield, Vermont, USA.

Bockstael, N. E., A. M. Freeman, R. J. Kopp, P. R. Portney, and V. K. Smith. 2000. On measuring economic values for nature. Environmental Science & Technology **34**:1384-1389.

Buskirk, S. W., L. Bowman, and J. H. Gilbert. 2012. Population biology and matrix demographic modeling of american martens and fishers. Pages 77-92 *in* K. B.

Aubry, W. J. Zielinski, M. G. Raphael, G. Proulx, and S. W. Buskirk, editors. Biology and conservation of martens, sables, and fishers : a new synthesis. Comstock Pub. Associates, Ithaca, New York, USA.

Cabeza, M., and A. Moilanen. 2001. Design of reserve networks and the persistence of biodiversity. Trends in Ecology & Evolution **16**:242-248.

Carden, R. F., C. M. Carlin, F. Marnell, D. McElholm, J. Hetherington, and M. P. Gammell. 2010. Distribution and range expansion of deer in Ireland. Mammal Review **41**:313-325.

Chee, Y. E. 2004. An ecological perspective on the valuation of ecosystem services. Biological Conservation **120**:549-565.

Congalton, R. G. 1991. A review of assessing the accuracy of classifications of remotely sensed data. Remote Sensing of Environment **37**:35-46.

Conn, P. B. 2007. Bayesian analysis of age-at-harvest data with focus on wildlife monitoring programs. Colorado State University, Fort Collins, Colorado, USA.

Conn, P. B., D. R. Diefenbach, J. L. Laake, M. A. Ternant, and G. C. White. 2008. Bayesian analysis of wildlife age-at-harvest data. Biometrics **64**:1170-1177.

Conroy, M. J., and J. T. Peterson. 2013. Decision making in natural resource management: a structured, adaptive approach. Wiley, Hoboken, New Jersey, USA.

Converse, S. J., C. T. Moore, M. J. Folk, and M. C. Runge. 2013. A matter of tradeoffs: reintroduction as a multiple objective decision. Journal of Wildlife Management **77**:1145-1156.

Converse, S. J., K. J. Shelley, S. Morey, J. Chan, A. LaTier, C. Scafidi, D. T. Crouse, and M. C. Runge. 2011. A decision-analytic approach to the optimal allocation of resources for endangered species consultation. Biological Conservation **144**:319-329.

Cook, C. N., D. G. Morgan, and D. J. Marshall. 2010. Reevaluating suitable habitat for reintroductions: lessons learnt from the eastern barred bandicoot recovery program. Animal Conservation **13**:184-195.

Costanza, R., R. dArge, R. deGroot, S. Farber, M. Grasso, B. Hannon, K. Limburg, S. Naeem, R. V. Oneill, J. Paruelo, R. G. Raskin, P. Sutton, and M. vandenBelt. 1997. The value of the world's ecosystem services and natural capital. Nature **387**:253-260.

Costello, C., A. Rassweiler, D. Siegel, G. De Leo, F. Micheli, and A. Rosenberg. 2010. The value of spatial information in MPA network design. Proceedings of the National Academy of Sciences of the United States of America **107**:18294-18299.

Csuti, B., S. Polasky, P. H. Williams, R. L. Pressey, J. D. Camm, M. Kershaw, A. R. Kiester, B. Downs, R. Hamilton, M. Huso, and K. Sahr. 1997. A comparison of reserve selection algorithms using data on terrestrial vertebrates in Oregon. Biological Conservation **80**:83-97.

Cummings, J. W., and T. Donovan. in preparation-a. A decison analysis approach to selecting a program for monitoring population size of game species.

Cummings, J. W., and T. M. Donovan. in preparation-b. Effects of measurement error on population estimation of harvested species.

Cummings, J. W., M. J. Hague, D. A. Patterson, and R. M. Peterman. 2011. The impact of different performance measures on model selection for Fraser River sockeye salmon. North American Journal of Fisheries Management **31**:323-334.

Cummings, J. W., R. M. Peterman, M. J. Hague, and D. Patterson. in review. Effect of asymmetric valuation of losses on model selection for Fraser River sockeye salmon. North American Journal of Fisheries Management.

Dale, V. H., and M. R. English. 1999. Tools to aid environmental decision making. Springer, New York.

Dankel, D. J., U. Dieckmann, and M. Heino. 2007. Success in fishery management by reconciling stakeholder objectives in Hilborn's "Zone of new consensus". International Council for the Exploration of the Sea Annual Science Conference 2007, Helsinki, Finland.

Davies, A. L., R. Bryce, and S. M. Redpath. 2013. Use of multicriteria decision analysis to address conservation conflicts. Conservation Biology **27**:936-944.

Davis, M. L., J. Berkson, D. Steffen, and M. K. Tilton. 2007. Evaluation of accuracy and precision of downing population reconstruction. Journal of Wildlife Management **71**:2297-2303.

de Groot, R. S., M. A. Wilson, and R. M. J. Boumans. 2002. A typology for the classification, description and valuation of ecosystem functions, goods and services. Ecological Economics **41**:393-408.

Decker, D. J., G. R. Goff, and Wildlife Society. New York Chapter. 1987. Valuing wildlife : economic and social perspectives. Westview Press, Boulder.

DeLury, D. B. 1947. On the Estimation of Biological Populations. Biometrics **3**:145-167.

Donovan, T. M., J. W. Cummings, K. Rinehart, and S. Hafner. in preparation. The R package harvest: simulating game species populations for monitoring evaluation.

Douglas, C. W., and M. A. Strickland. 1987. Fisher. Pages 510-529 Wild Furbearer Management and Conservation in North America. Ontario Trappers Association and Ontario Ministry of Natural Resources, Ontario, Canada.

Downing, R. L. 1980. Vital statistics of animal populations. Pages 247-267 *in* S. D. Schemnitz, editor. Wildlife techniques manual. The Wildlife Society, Washington, D.C., USA.

Eberhardt, L. L. 1960. Estimation of vital characteristics of Michigan deer herds. Michigan Department of Conservation Game Division, East Lansing, Michigan, USA.

Edwards, W., R. F. Miles, and D. Von Winterfeldt. 2007. Advances in decision analysis : from foundations to applications. Cambridge University Press, Cambridge, UK and New York, USA.

Farber, S. C., R. Costanza, and M. A. Wilson. 2002. Economic and ecological concepts for valuing ecosystem services. Ecological Economics **41**:375-392.

Fieberg, J. R., K. W. Shertzer, P. B. Conn, K. V. Noyce, and D. L. Garshelis. 2010a. Integrated population modeling of black bears in Minnesota: implications for monitoring and management. PLoS One **5**:11.

Fry, F. E. J. 1949. Statistics of a lake trout fishery. Biometrics **5**:27-67.

Fryxell, J. M., W. E. Mercer, and R. B. Gellately. 1988. Population dynamics of Newfoundland moose using cohort analysis. Journal of Wildlife Management **52**:14-21.

Gormley, A. M., D. M. Forsyth, P. Griffioen, M. Lindeman, D. S. L. Ramsey, M. P. Scroggie, and L. Woodford. 2011. Using presence-only and presence-absence data to estimate the current and potential distributions of established invasive species. Journal of Applied Ecology **48**:25-34.

Gould, W. R., and K. H. Pollock. 1997. Catch-effort maximum likelihood estimation of important population parameters. Canadian Journal of Fisheries and Aquatic Sciences **54**:890-897.

Gove, N. E., J. R. Skalski, P. Zager, and R. L. Townsend. 2002. Statistical models for population reconstruction using age-at-harvest data. Journal of Wildlife Management **66**:310-320.

Gregory, R., L. Failing, M. Harstone, G. Long, T. McDaniels, and D. Ohlson. 2012. Structured decision making: A practical guide to environmental management choices. Wiley-Blackwell, West Sussex, UK.

Gregory, R., and R. L. Keeney. 1994. Creating policy alternatives using stakeholder values. Management Science **40**:1035-1048.

Hammond, J. S., R. L. Keeney, and H. Raiffa. 1998. Even swaps: A rational method for making trade-offs. Harvard Business Review **76**:137+.

Hammond, J. S., R. L. Keeney, and H. Raiffa. 1999. Smart choices : a practical guide to making better decisions. Harvard Business School Press, Boston, Massachusetts, USA.

Hawken, P., A. B. Lovins, and L. H. Lovins. 1999. Natural capitalism: creating the next industrial revolution. 1st edition. Little, Brown and Co., Boston, Massachusetts, USA.

Herms, D. A., D. G. McCullough, and D. R. Smitley. 2004. Under attack: The current status of the emerald ash borer infestation and the program to eradicate it. American Nurseryman **200**:20-27.

Hilty, J. A., and C. R. Groves. 2008. Conservation planning: new tools and new approaches.*in* R. L. Knight and C. White, editors. Conservation for a New Generation: Redefining Natural Resources Management. Island Press, Washington, D.C., USA.

Howard, R. A. 1966. Decision analysis: applied decision theory.*in* International Conference on Operational Research. Wiley, New York, USA.

Howard, R. A. 1975. Social decision analysis. Proceedings of the Ieee **63**:359-371.

Howard, R. A. 1980. Assessment of decision-analysis. Operations Research **28**:4-27.

Howard, R. A. 1988. Decision-analysis - practice and promise. Management Science **34**:679-695.

Huang, I. B., J. Keisler, and I. Linkov. 2011. Multi-criteria decision analysis in environmental sciences: Ten years of applications and trends. Science of the Total Environment **409**:3578-3594.

Huggins, R. M. 1989. On the Statistical-Analysis of Capture Experiments. Biometrika **76**:133-140.

Irwin, B. J., M. J. Wilberg, M. L. Jones, and J. R. Bence. 2011. Applying structured decision making to recreational fisheries management. Fisheries **36**:113-122.

Kangas, A. S., P. Horne, and P. Leskinen. 2010. Measuring the value of information in multicriteria decisionmaking. Forest Science **56**:558-566.

Keeney, R. L. 1992. Value-focused thinking : a path to creative decisionmaking. Harvard University Press, Cambridge, Massachusetts, USA.

Keeney, R. L., and H. Raiffa. 1976. Decisions with multiple objectives: preferences and value tradeoffs. Cambridge University Press, New York, USA.

Keeney, R. L., and H. Raiffa. 1993. Decisions with multiple objectives : preferences and value tradeoffs. Cambridge University Press, Cambridge UK and New York, USA.

Kelly, G. M. 1977. Fisher (Martes pennanti) biology in the White Mountain National Forest and adjacent areas. University of Massachusetts, Amherst.

Klooster, W. S., D. A. Herms, K. S. Knight, C. P. Herms, D. G. McCullough, A. Smith, K. J. K. Gandhi, and J. Cardina. 2013. Ash (*Fraxinus spp.*) mortality, regeneration, and seed bank dynamics in mixed hardwood forests following invasion by emeral ash borer (*Agrilus planipennis*). Biological Invasions **15**.

Koen, E. L., J. Bowman, and C. S. Findlay. 2007. Fisher survival in eastern Ontario. Journal of Wildlife Management **71**:1214-1219.

Kovacs, K. F., R. G. Haight, D. G. McCullough, R. J. Mercader, N. W. Siegert, and A. M. Liebhold. 2010. Cost of potential emerald ash borer damage in US communities, 2009-2019. Ecological Economics **69**:569-578.

Krohn, W. B., S. M. Arthur, and T. F. Paragi. 1994. Mortality and vulnerability of a heavily trapped fisher population. Pages 137-145 *in* S. Buskirk, A. S. Harestad,

M. G. Raphael, and R. A. Powell, editors. Martens, sables, and fishers : biology and conservation. Comstock Pub. Associates, Ithaca, New York, USA.

Linkov, I., F. K. Satterstrom, G. Kiker, C. Batchelor, T. Bridges, and E. Ferguson. 2006. From comparative risk assessment to multi-criteria decision analysis and adaptive management: Recent developments and applications. Environment International **32**:1072-1093.

Lyons, J. E., M. C. Runge, H. P. Laskowski, and W. L. Kendall. 2008. Monitoring in the context of structured decision-making and adaptive management. Journal of Wildlife Management **72**:1683-1692.

Macauley, M. K. 2006. The value of information: Measuring the contribution of space-derived earth science data to resource management. Space Policy **22**:274-282.

Marealle, W. N., F. Fossoy, T. Holmern, B. G. Stokke, and E. Roskaft. 2010. Does illegal hunting skew Serengeti wildlife sex ratios? Wildlife Biology **16**:419-429.

Martin, T. G., M. A. Burgman, F. Fidler, P. M. Kuhnert, S. Low-Choy, M. McBride, and K. Mengersen. 2012. Eliciting expert knowledge in conservation science. Conservation Biology **26**:29-38.

Martin, W. E., H. W. Bender, and D. J. Shields. 2000. Stakeholder objectives for public lands: Rankings of forest management alternatives. Journal of Environmental Management **58**:21-32.

McBride, M. F., S. T. Garnett, J. K. Szabo, A. H. Burbidge, S. H. M. Butchart, L. Christidis, G. Dutson, H. A. Ford, R. H. Loyn, D. M. Watson, and M. A. Burgman. 2012. Structured elicitation of expert judgments for threatened species assessment: a case study on a continental scale using email. Methods in Ecology and Evolution **3**:906-920.

McFadden, J. E., T. L. Hiller, and A. J. Tyre. 2011. Evaluating the efficacy of adaptive management approaches: Is there a formula for success? Journal of Environmental Management **92**:1354-1359.

Mendoza, G. A., and H. Martins. 2006. Multi-criteria decision analysis in natural resource management: A critical review of methods and new modelling paradigms. Forest Ecology and Management **230**:1-22.

Mercader, R. J., N. W. Siegert, A. M. Liebhold, and D. G. McCullough. 2009. Dispersal of the emerald ash borer, Agrilus planipennis, in newly-colonized sites. Agricultural and Forest Entomology **11**:421-424.

Mercader, R. J., N. W. Siegert, and D. G. McCullough. 2012. Estimating the influence of population density and dispersal behavior on the ability to detect and monitor *Agrilus planipennis* (*Coleoptera: Buprestidae*) populations. Journal of Economic Entomology **105**:272-281.

Millspaugh, J. J., J. R. Skalski, R. L. Townsend, D. R. Diefenbach, M. S. Boyce, L. P. Hansen, and K. Kammermeyer. 2009. An evaluation of sex-age-kill (SAK) model performance. Journal of Wildlife Management **73**:442-451.

Moore, J. L., and M. C. Runge. 2012. Combining structured decision making and value-of-information analyses to identify robust management strategies. Conservation Biology **26**:810-820.

Moore, J. L., M. C. Runge, B. L. Webber, and J. R. U. Wilson. 2011. Contain or eradicate? Optimizing the management goal for Australian acacia invasions in the face of uncertainty. Diversity and Distributions **17**:1047-1059.

Morgan, M. G., and M. Henrion. 1990. Uncertainty: a guide to dealing with uncertainty in quantitative risk and policy analysis. Cambridge University Press, Cambridge, UK.

Noon, B. R., L. L. Bailey, T. D. Sisk, and K. S. McKelvey. 2012. Efficient species-level monitoring at the landscape scale. Conservation Biology **26**:432-441.

Otis, D. L., K. P. Burnham, G. C. White, and D. R. Anderson. 1978. Statistical inference from capture data on closed animal populations. Wildlife Monographs:3-135.

Paragi, T. F., S. M. Arthur, and W. B. Krohn. 1994. Seasonal and circadian activity patterns of female fishers, *Martes pennanti*, with kits. Canadian Field-Naturalist **108**:52-57.

Perera, A. H., C. A. Drew, and C. J. Johnson. 2012. Expert knowledge and its application in landscape ecology.

Peterson, J. T., and J. W. Evans. 2003. Quantitative decision analysis for sport fisheries management. Fisheries **28**:10-21.

Phillips, S. J., R. P. Anderson, and R. E. Schapire. 2006. Maximum entropy modeling of species geographic distributions. Ecological Modelling **190**:231-259.

Poiani, K. A., B. D. Richter, M. G. Anderson, and H. E. Richter. 2000. Biodiversity conservation at multiple scales: Functional sites, landscapes, and networks. Bioscience **50**:133-146.

Powell, R. A. 1994. Structure and spacing of *Martes* populations. Pages 101-121 *in* S. Buskirk, A. S. Harestad, M. G. Raphael, and R. A. Powell, editors. Martens, sables, and fishers : biology and conservation. Comstock Pub. Associates, Ithaca, New York, USA.

Powell, R. A., S. W. Buskirk, and W. J. Zielinski. 2003. Fisher and Martin: *Martes pennanti* and *Martes americana* Pages 635-649 *in* G. A. Feldhamer, B. C. Thompson, and J. A. Chapman, editors. Wild mammals of North America : biology, management, and conservation. Johns Hopkins University Press, Baltimore, Maryland, USA.

Powell, R. A., and W. J. Zielinski. 1994. Fisher. Pages 38-73 *in* L. F. Ruggiero, K. B. Aubry, S. W. Buskirk, L. J. Lyon, and W. J. Zielinski, editors. American marten, fisher, lynx, and wolverine in western United States. United States Forest Service, General Technical Report RM-254, Fort Collins, Colorado, USA.

Redpath, S. A., B. E. Arroyo, E. M. Leckie, P. Bacon, N. Bayfield, R. J. Gutierrez, and S. J. Thirgood. 2004. Using decision modeling with stakeholders to reduce human-wildlife conflict: a Raptor-Grouse case study. Conservation Biology **18**:350-359.

Rinehart, K., and T. M. Donovan. in preparation. Models, data, and cost: Efficient population estimates for wildlife managers.

Roseberry, J. L., and A. Woolf. 1991. A comparative evaluation of techniques for analyzing white-tailed deer harvest data. Wildlife Monographs:3-59.

Royle, J. A., R. B. Chandler, C. Yackulic, and J. D. Nichols. 2012. Likelihood analysis of species occurrence probability from presence-only data for modelling species distributions. Methods in Ecology and Evolution **3**:545-554.

Ruhl, J. B., and R. L. Fischman. 2010. Adaptive management in the courts. Minnesota Law Review **95**:424-484.

Runge, M. C. 2013. Active adaptive management for reintroduction of an animal population. Journal of Wildlife Management **77**:1135-1144.

Sales-Luis, T., J. A. Bissonette, and M. Santos-Reis. 2012. Conservation of Mediterranean otters: the influence of map scale resolution. Biodiversity and Conservation **21**:2061-2073.

Schwartz, M. W. 1999. Choosing the appropriate scale of reserves for conservation. Annual Review of Ecology and Systematics **30**:83-108.

Sinclair, A. R. E., J. M. Fryxell, and G. Caughley. 2006. Wildlife ecology, conservation, and management. 2nd edition. Blackwell Pub., Oxford, UK and Malden, Massachusetts, USA.

Skalski, J. R., M. V. Clawson, and J. J. Millspaugh. 2012. Model evaluation in statistical population reconstruction. Wildlife Biology **18**:225-234.

Skalski, J. R., K. E. Ryding, and J. J. Millspaugh. 2005. Wildlife demography: analysis of sex, age, and count data. Elsevier Academic Press, Amsterdam and Boston, Massachusetts, USA.

Skalski, J. R., R. L. Townsend, and B. A. Gilbert. 2007. Calibrating statistical population reconstruction models using catch-effort and index data. Journal of Wildlife Management **71**:1309-1316.

Starfield, A. M. 1997. A pragmatic approach to modeling for wildlife management. Journal of Wildlife Management **61**:261-270.

Starfield, A. M., and A. L. Bleloch. 1986. Building models for conservation and wildlife management. Macmillan; Collier Macmillan, New York, USA and London, UK.

Turner, R. K., J. Paavola, P. Cooper, S. Farber, V. Jessamy, and S. Georgiou. 2003. Valuing nature: lessons learned and future research directions. Ecological Economics **46**:493-510.

Van Why, K. R., and W. M. Giuliano. 2001. Fall food habits and reproductive condition of Fishers, *Martes pennanti*, in Vermont. Canadian Field-Naturalist **115**:52-56.

Von Winterfeldt, D., and W. Edwards. 1986. Decision analysis and behavioral research. Cambridge University Press, Cambridge UK and New York, USA.

Walters, C. J. 2001. Adaptive management of renewable resources. Blackburn Press, Caldwell, New Jersey, USA.

Walters, C. J. 2007. Is adaptive management helping to solve fisheries problems? Ambio **36**:304-307.

White, G. C., and B. C. Lubow. 2002. Fitting population models to multiple sources of observed data. Journal of Wildlife Management **66**:300-309.

Williams, B. K., M. J. Eaton, and D. R. Breininger. 2011a. Adaptive resource management and the value of information. Ecological Modelling **222**:3429-3436.

Williams, B. W., D. R. Etter, P. D. DeWitt, K. T. Scribner, and P. D. Friedrich. 2011b. Uncertainty in Determination of Sex From Harvested Bobcats. Journal of Wildlife Management **75**:1508-1512.

Willmott, C. J. 1982. Some comments on the evaluation of model performance. Bulletin of the American Meteorological Society **63**:1309-1313.

Willmott, C. J., and K. Matsuura. 2005. Advantages of the mean absolute error (MAE) over the root mean square error (RMSE) in assessing average model performance. Climate Research **30**:79-82.

Zimmermann, H., H. Von Wehrden, M. A. Damascos, D. Bran, E. Welk, D. Renison, and I. Hensen. 2011. Habitat invasion risk assessment based on Landsat 5 data, exemplified by the shrub Rosa rubiginosa in southern Argentina. Austral Ecology **36**:870-880.