A Risk Assessment Approach to Ecological Decision-Making

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Abstract

The conservation and management of wild populations and ecosystems almost always involves making decisions in the face of uncertainty and risk. The application of science to the ecological decision-making process was something that the late Professor Daniel Goodman thought deeply about. In this paper we outline the three main principles that Dr. Goodman espoused for good practice when conducting analyses for ecological decision-making: 1) the results should be conditioned on all relevant data and information, 2) there must be a full characterization of all uncertainty, and it should be fully propagated into the result, and 3) doing so in the correct way will result in the calculation of an accurate probability distribution (conditioned on our understanding of the state of nature) that should be used directly for ecological decision-making. Dr. Goodman believed that in the context of threatened and endangered species management Population Viability Analysis (PVA), Bayesian statistics, and structured decision-making are the most logical tools to achieve the three principles. To illustrate the application of the principles and tools in a real management setting, we discuss a Bayesian PVA that Dr. Goodman produced for the endangered Steller sea lion. We conclude by discussing the practical and philosophical impediments that may limit the full realization of the three principles and we offer some suggested solutions.

Keywords:

Population Viability Analysis (PVA); Endangered Species Act (ESA); conservation biology

1. INTRODUCTION

The conservation and management of species almost always involves making decisions based on limited information. We often do not know with precision, for example, the current state of the species we need to manage, we may not know what factors influence its dynamics, and often, we have limited knowledge of the species' recent or long-term past that brought it to its current state. Similarly, the impact of potential management actions on a species and future environmental conditions cannot be known with certainty. Because of these uncertainties and the potential for negative outcomes if we get the management decisions wrong, species management and conservation involve risk. Such risks may include failing to arrest a species' decline, causing harm to other non-target species, spending limited financial and personnel resources on ineffectual actions, or unnecessarily limiting exploitation or other human activity associated with the species or its habitat. Despite these uncertainties and risks, management decisions must be made. How to make these decisions in an optimal way regardless of the quality or quantity of information available is clearly in the purview of the field of risk analysis and management. Rarely, however, is on-the-ground ecological management and decision-making approached from the perspective of risk analysis and management[1].

The late Professor Daniel Goodman spent a great deal of his career on this question of optimal use of information for ecological decision-making, and strongly advocated for addressing decisions from a risk-focused perspective. He believed that the key to effective conservation of vulnerable species and other ecological decision-making lay in accurate estimation of the risk to a species coupled with structured decision-making that facilitated a transparent decision-making process and clear separation of scientific and policy questions. In

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this paper we describe the three main principles that Dr. Goodman advocated when making ecological decisions and the tools he believed were necessary to achieve these principles, namely, Population Viability Analysis (PVA), Bayesian statistics, and formal decision analysis. We also briefly discuss how Goodman applied these principles in a contentious management situation. Throughout the paper we focus primarily on threatened and endangered species management under the US Endangered Species Act (ESA), but the concepts we present are relevant to all ecological decision-making arenas in and outside of the US.

2. BACKGROUND ON ESA AND PVA

Goodman was an applied ecologist. He described his primary professional interest as the "application of modeling and statistics to actual environmental decision-making" [(2)]. Much of his applied worked involved ESA-related decision-making, including listing (placing a species on the endangered species list) and delisting (removing the species from the list) decisions. According to the law, listing of a species under the ESA is an indication that the species is "in danger of extinction throughout all or a significant portion of its range" (endangered), or is at risk of becoming endangered "within the foreseeable future" (threatened). Listing affords the species protective status under the law and may result in restrictions on human activity (e.g., land development, harvest, resource extraction). Once a species is listed under the ESA, the agency tasked with managing it (US Fish and Wildlife Service or National Marine Fisheries Service; collectively, the services) is required to develop a recovery plan that outlines how the agency proposes to recover the species so that it no longer requires the special protective measures of the ESA. The plan is required to contain "objective, measurable criteria" (recovery criteria) that define when a species is no longer at risk of extinction and can be considered for

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delisting (16 U.S.C. §1533). Actual delisting can occur presumably (but not necessarily) after the recovery criteria are met and a delisting assessment shows that the species is no longer threatened or endangered and that the five threat factors identified in the ESA (i.e., habitat destruction, overutilization, disease or predation, inadequate regulation, or other factors) have been ameliorated. While the overall intent of the ESA to protect and restore at-risk species is clear, much of the language in the law is general rather than specific [(3-5)], leaving decision-makers with the difficult task of interpreting the law and deciding exactly what is meant by phrases like "in danger of", "significant portion of", and "foreseeable future". As a result, a great deal of variation exists in the approaches used to evaluate a species' standing under the ESA, including how recovery criteria are formulated and listing and delisting decisions are made by the services [(6-8)]

One approach to evaluating whether a species should be listed or delisted under the ESA is Population Viability Analysis (PVA). PVA is a term that encompasses a wide range of quantitative techniques designed to predict the future status of a population or species [(9)]. Generally, a PVA uses information about a species' past population dynamics to project possible future scenarios through stochastic simulation modeling. One result of a PVA is an estimate of a population's risk of extinction or quasi-extinction (i.e., falling below some designated threshold) over a specified timeframe.

PVAs have an intuitive appeal with respect to ESA-related decisions since they provide an estimate of extinction risk, the very metric identified in the ESA as defining threatened and endangered species. Despite this, their use in making management decisions, especially in the context of the ESA, has been vigorously debated. Some have argued that in the context of management decisions PVAs are

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too unreliable when data are poor, require too much data to be of use in endangered species listing decisions when data are often limited, or are too imprecise to be useful [10-16]. Others have countered that their usefulness outweighs their limitations, that alternative approaches for ESA decision-making have more significant drawbacks, and that many of the perceived weaknesses of PVA can be addressed with careful application and consideration of uncertainty [17-25]. This latter view was embraced completely and authoritatively by Goodman. He suggested that a PVA model was the only approach that could use and synthesize all of the available data, which was a highly desirable, and even obligatory, property. More specifically, he advocated for use of Bayesian statistics within the PVA framework, and for the results of the Bayesian PVA to be used in a structured decision-making context.

3. GUIDING PRINCIPLES FOR ECOLOGICAL DECISION-MAKING

Goodman's advocacy for Bayesian PVA and structured decision-making was predicated on three fundamental principles for good practices in analyses used for ecological decision-making: 1) the results of the analysis should be conditioned on all available data, 2) all uncertainty should be accounted for and fully propagated into the result, and 3) the calculated results should be directly used for ecological decision-making. Goodman argued that if the first two principles were followed in the correct way, one could calculate a correct probability distribution for the state of nature given the available information and the uncertainty. It then follows that the correct probability could be used directly in structured decision-making process to arrive at a decision fully consistent with the decision-maker's values, the data, and the uncertainty. We will step through these points in detail, and discuss their specific application to endangered species listing and delisting decisions.

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3.1 Use all the data

The first guiding principle is that a scientific analysis that will be used for ecological decision-making should be conditioned on all the relevant data (not just some of it), and to the extent possible, *only* on the relevant data. In the context of species management, "relevant" means only those data that will impact the future dynamics of the species[26]. Specifically, Goodman advocated using all the data in a synthetic analysis rather than performing multiple separate analyses of different kinds of data that are separately considered for the decision, or integrated via "human integration" (i.e., people viewing the separate results and subjectively deciding what they mean in total). The non-synthetic approach is by far the most common approach to ESA listing and delisting decisions and generally requires less time and fewer resources than a fully quantitative synthesis approach. But as Goodman and others have argued, mathematical models that integrate all data reinforce an internal logic and consistency that can often be missing when separate models and ad hoc integration are used[23, 17, 27].

PVA provides precisely the type of synthetic analysis that Goodman promoted. "Using all the data" in a PVA means, as a start, including information on population size, population trend, sources of human-caused mortality, and life history information such as birth and death rates. However, it can also include data on such things as environmental forcing, variability of prey and/or natural survival rates, probability of catastrophic events, and likely future management or threat scenarios. Given the different types of data and the different temporal and spatial scales encompassed by such comprehensive inclusion of data, this principle of using all the data is rarely easy in practice. Fortunately, the increasing use of "integrated" population

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models [28-32] reflects a trend toward this type of synthetic analyses and has led to increased accessibility of techniques and tools for using a wide variety of data within a single analysis.

3.2 Include all sources of uncertainty

Using all available information may seem to have an obvious interpretation, but what may not be as obvious is that "information" includes not only what we know but also what we don't know, i.e., the "known, unknowns", as Donald Rumsfeld would say[33]. This brings us to Goodman's second guiding principle, incorporate all sources of uncertainty. An emphasis on incorporating uncertainty has been a long-running theme in conservation biology and environmental management. This is exemplified, for example, in a symposium and Special Section in the journal Conservation Biology in 2000 titled "Better Policy and Management Decisions through Explicit Analysis of Uncertainty: New Approaches from Marine Conservation". Goodman was not the only person advocating a better and more thorough handling of uncertainty in analyses, but he was an early advocate, and perhaps embraced the concept more thoroughly and emphatically than others. Although Goodman did not have a paper in the Conservation Biology special section, his influence can be seen in the number of his graduate students (or even second-generation graduate students) who did [34-37].

What does it mean to more fully incorporate uncertainty? One way to view it is through the development of applied statistical and modeling practices in ecology. This is an over-simplification, but there has been a progression in applied statistics in incorporating more uncertainty over the last few decades. Though it likely has always made statisticians cringe, there used to be many examples of ecological decision-making based solely on point estimates of parameters (e.g., the population is declining at 2.3% per year). That simplistic approach can

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be viewed as step 1 in the progress toward incorporating more uncertainty. Step 2 was to fully incorporate parameter uncertainty (e.g., the population is declining at 2.3% per year with standard error of 1.1%). Although this sounds easy and straight-forward, for complex models this was not always simple, and new statistical techniques were developed to accomplish this, such as the jackknife or bootstrap in frequentist statistics[(38, 39)], or numerical integration techniques in Bayesian statistics such as sampling importance resampling (SIR) or Markov Chain Monte Carlo (MCMC) [(40)].

Step 3 in the evolution of statistically valid approaches to uncertainty was the widespread use of more complex models in ecology, whether for abundance estimation (e.g., mark-recapture or line-transect analysis) or for population modeling. In particular, for PVA models there was clearly the need to incorporate the uncertainty that arises from stochastic processes (e.g., rather than declining at the same rate every year, the population can experience small declines in some years and larger declines in other years). Statisticians speak of uncertainty in terms of error, and stochastic processes are viewed as "process error" as opposed to "estimation error", which arises from uncertainty in the exact value of the model parameters. Treatment of these two types of error becomes important in PVA models, and their treatment can be viewed as being different in Bayesian statistics than it is in classical frequentist statistics (see Gerrodette et al. in this volume for more on this topic). Goodman was firmly in the Bayesian camp regarding the treatment of these two sources of error, and made convincing arguments for his point of view [(27, 41)].

The development of more complex and sophisticated models in ecology has mostly been a good thing, but it came at a cost, which can be viewed as Step 4. The complexity in

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newer ecological models lead to more model choices and to a greater uncertainty about which model was the "best" one (e.g., does a model with a single rate of decline fit the data better than a change-point model with two different rates of decline?). To choose, we needed a solid statistical method for deciding which model fits the data better. Although step-wise likelihood ratio tests for model selection had been around for a long time, better techniques were needed, particularly to compare non-nested models. This has led to the relatively recent move to fully embrace model uncertainty in ecological analyses, in addition to parameter uncertainty. Again, this development occurred on both sides of the statistical de-militarized zone (classical frequentist vs. Bayesian), with AIC, championed by Burnham et al. (42), gaining widespread usage for non-Bayesians, and Bayes Factors (43) and the BIC (as an approximation for the Bayes Factor) (44), gaining widespread usage by Bayesian statisticians. Each side took the model selection one step further with a subtle refinement, where rather than choosing a single model, we average our result across the best-fitting models, either through AIC or Bayesian model-averaging methods (45).

Interestingly, Goodman did not seem too keen on model selection methods. He identified model selection as a legitimate source of uncertainty, but to deal with it he advocated the use of flexible models that, when fit to data, could encompass a wide variety of realities(41). He acknowledged however, that such an approach comes at the cost of increasing parameter uncertainty (i.e., the model uncertainty is folded into the parameter uncertainty when a flexible model is used that increases the scope or number of parameters). He felt that this was an acceptable cost, and perhaps was preferable, because all uncertainty continued to be incorporated (though potentially misallocated) and could be propagated through to the

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results and did not necessitate procedures external to the primary model[41]. This point of view is at odds with much of the mainstream of recent ecological analysis methods, but perhaps speaks to his view that if you worked from first principles in a correct and thorough way, then applied a "rich enough model", you would get the correct answer, including a full characterization of uncertainty, and thus implicitly have no need for model selection.

Besides the developments in statistical methodology, there was also a related philosophical development in how we view ecological models. Perhaps the best way to view this is by looking at models that extrapolate into the future, such as PVA models. Do we assume that the world will stay the same as it is now, or do we allow for the possibility that the world may change, and with it, some of the basic assumptions that go into our models? For example, do we assume that carrying capacity in a projection model is constant, or do we allow for a future change in carrying capacity? These types of questions have become increasingly important as we struggle to deal with issues such as climate change in our models. Goodman strongly opposed using PVA simply "to replay the recent past as a stochastic simulation" [26]. He argued that the observed past is only a sample of potential environmental variability and that blind extrapolation of past trends related to human impact, as one example, may not be justified. Issues of uncertainty related to future conditions are extremely difficult to deal with, but it is in these types of uncertainties where Goodman's advocacy for the full incorporation of uncertainty strikes the starkest contrast to other approaches. He did not simply pay lip service to uncertainty as a "qualitative pejorative", but insisted that all uncertainty be quantified including the future unknown [41]. While not yet regularly employed in PVA, some researchers

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are beginning to address both subtle and severe uncertainty related to process ambiguity, rare events, or future unknowns (but not always in a Bayesian context)[23, 46-50, 31].

3.3 Apply the true probability distribution to decisions

So how does one accomplish the goal of quantifying all the uncertainty and using all the data, and how does that lead to Goodman's third principle of calculating a true probability distribution and using that distribution directly in decision-making? The short answer, in Goodman's view, is to be a Bayesian with data. Bayesian methods require the use of a probability distribution (the "prior") for the parameter that is specified *a priori* (essentially, before the data are used). According to Goodman, this prior probability distribution must contain a full characterization of the uncertainty and knowledge we have about the parameter prior to our analysis. By combining this prior that quantifies our full state of ignorance and information about the parameters with a flexible model that incorporates the uncertainty in the model structure, then bringing in the data via the likelihood function, Goodman argued that all relevant information and uncertainty can be analyzed in a single synthetic framework. Using this Bayesian approach, the mathematical combination of the prior and the data (via the likelihood) results in a posterior distribution that can be directly interpreted as a probability distribution for the parameter. Importantly, you can also directly and easily calculate a probability distribution for any function of the parameters. This is very different than what you get from a classical frequentist analysis, which results in a point estimate, and possibly, confidence intervals around the point estimate.

Numerical computation developments such as MCMC can be applied to either maximum likelihood estimation or Bayesian statistics, so to a certain extent the ability to more

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fully incorporate uncertainty has happened across all types of statistics, not just in the Bayesian paradigm. From a technical point of view, there is one significant advantage of Bayesian methods – we can use hierarchical models, such as random effects models, which is not possible in frequentist statistics without using *ad hoc* estimation methods [51]. This can be a major advantage, and this one feature has led many scientists to adopt the use of Bayesian methods. For other situations, the reasons to use Bayesian methods versus other methods is more philosophical, both in how the data are used, and in the presentation and interpretation of the results.

The difference in interpretation between a Bayesian analysis and frequentist analysis becomes substantial when a stochastic model is used, such as in a PVA. Regardless of the statistical framework, any stochastic model will yield a distribution for the probability of the event of interest simply due to the stochastic processes in the model. So even if all the PVA parameters are fixed at a single value, as in the frequentist paradigm, the result will be a distribution for the probability of extinction, i.e., there might be some probability the population goes extinct in 50 years as well as some probability the population goes extinct in 100 years. Using this type of frequentist approach, if you change the values of the fixed parameters, you will get a different distribution of extinction times. In contrast, a Bayesian analysis will give you a single distribution for the probability of extinction that integrates across all possible values of the parameters, and from which you can obtain a probability of extinction in 100 years or 50 years, or 2 years.

Your uncertainty in the Bayesian result (posterior distribution) is a seamless combination of the stochastic processes in the model as well as your uncertainty in the correct values of the parameters (process uncertainty). This can be viewed as folding two different interpretations of probability into a single distribution, where the stochastic processes of the model are truly uncertain (like the roll of a die) but the uncertainty in the values of the parameters are based just on our inability to know what their true values are. All Bayesians accept that both kinds of uncertainty can contribute to the final summary of uncertainty, and Goodman explicitly agreed with this concept of incorporating both sources of uncertainty into a predictive distribution for the quantity of interest[(41)]. However, not everyone agrees on an interpretation of what the posterior distribution means. Goodman discusses this in one paper[(26)], where he notes that one Bayesian interpretation of a probability distribution is that it represents subjective belief – this concept arises when one interprets the prior distribution as summarizing one's subjective belief about what the value of the parameter is, before the data. Goodman explicitly rejected this interpretation, and instead argued that the prior distribution should be based on empirical information, including auxiliary data relevant to your case, or even comparative data from a family of similar cases. With such data-based prior distributions, Goodman argued that the posterior distribution represented an actual probability distribution for what the value of the parameter could be, and that it was not subjective:

> *"This program of sequential application of Bayes' formula to combine different kinds of available case-specific data, and available comparative data, allows use of the mathematical machinery of Bayesian statistics, without running aground on the rocks of subjective probability."*[(26)]

This focus on making the prior distribution empirical led Goodman to perhaps think more deeply about the construction of prior distributions than others have, and it can be

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argued this was one of his main contributions to ecological risk assessment and Bayesian statistics. In fact, he devoted an entire paper to the subject titled "Taking the prior seriously: Bayesian analysis without subjective probability."[52] In that paper he discusses the details of basing a prior distribution on comparative data from other cases, and how to use hierarchical Bayesian modeling to create such priors. In another paper, he continued this theme and explicitly described how PVAs should be based on hierarchical Bayesian methods, with empirical priors established from suites of populations.[27] He also reiterated that using such methods results in the correct answer, meaning the posterior distribution for the probability of extinction represents an absolute probability of extinction, not a relative probability of extinction. To make this point clear, he notes that if one had 100 different populations for which you had calculated a 3% probability of extinction in 100 years, your expectation would be that three of the populations would actually go extinct in 100 years.[27]

These core principles Goodman was applying to ecological decisions, and PVAs in particular, directly addressed two of the core debates in the PVA literature which are related: (1) Are PVAs useful, and (2) can PVAs provide an absolute probability of extinction? PVAs often (necessarily) require one to make several assumptions about the dynamics of small populations, for which few data are available. Early on in the development and assessment of PVA models it was noted that relatively small differences in inputs could lead to large differences in the results[53], and it was argued that PVAs are potentially unreliable.[54, 10] Others noted the precision of PVAs were unlikely to be sufficient to make PVAs useful.[11, 13, 14] The interpretation of the probability of extinction as absolute versus relative has also been one of the core debates of the PVA field. In a seminal paper in the field, Beissinger and Westphal[12]

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argue PVAs are unreliable for a variety of reasons, such as difficulties in estimating variance and not capturing environmental trends and fluctuations properly. They recommended that PVAs should only be used as relative estimates of extinction risk, such as for weighing management alternatives to reduce extinction risk. In contrast, Goodman firmly believed that the sequence of conditioning on all the data, incorporating all sources of uncertainty, and forming a probability distribution for the parameter of interest was the correct way to use science to make ecological decisions.

> *"Such analyses provide the best legitimate inference that can be extracted from the available information. The inference is best in the sense that the distribution is true, and the distribution is as narrow as can be achieved with the information."*[41]

Goodman was not alone in his beliefs. It is not that scientists who believe PVAs are useful do not understand these important issues of the precision of the results, the influence of small changes in inputs, or the possible reliance on untested assumptions or inadequate data. Instead, they (and we) argue there is no better summation of what is known about extinction risk for a species than a properly done PVA, and if there is a lot of uncertainty in the answer, this is an accurate assessment of the state of our knowledge, and decision-makers need to fully take account of this, i.e., it is part of the risk. PVA advocates also point out that the alternatives, such as using proxies for extinction risk (e.g., small population size and/or declining trend) or qualitatively assessing extinction risk, are worse[55] and represent less rigorous and quantitative uses of the same data that are input into the PVA. This view is perhaps most eloquently expressed by Brook et al.[17], in response to the widely held view that in circumstances where

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data are sparse or of low quality PVAs have little useful predictive value and should be dispensed with in favor of “alternative methods”:

> *“The trouble is that none of these authors have specified why these alternatives would be superior to PVA. It is our view that even when PVAs perform poorly against some vaguely defined absolute standard, they still perform better than alternatives that are even more vague, are less able to deal with uncertainty, are considerably less transparent in their reliability, and do not use all the available information.”*[17]

It is interesting to point out that one of the best arguments in support of this view that PVAs are the correct and best tool to use for making decisions about extinction risk has come from empirical tests, where it has been shown through the use of retrospective analysis of case studies that predictions of PVAs can be reliable.[24, 56]

4. PRINCIPLES IN PRACTICE: STELLER SEA LION PVA

In 2002 Dr. Goodman was contracted by the Steller sea lion (SSL) recovery team headed by Dr. Bob Small to develop a PVA for the SSL populations, the western portion of which had declined by more than 80% and was listed as endangered under the Endangered Species Act. The recovery team was tasked with revising the original recovery plan that had been developed in 1992, and to devise new recovery criteria. The intention of the recovery team was to use the results of Goodman’s PVA to develop these revised recovery criteria.

Given the principles that Goodman espoused in his writing, it is worth examining whether he was able to put those principles into practice while developing the SSL PVA. The information we present below draws heavily from the Steller sea lion recovery plan containing

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Goodman's final PVA report as an appendix[57], but also from personal communications with Bob Small, discussions with Goodman, and Goodman's personal files. Overall we found that he applied his general principles but not always in the idealized way he had proposed.

4.1 Background

To understand Goodman's approach to developing the SSL PVA, it is helpful to have some background. Despite millions of dollars spent and years of research, no clear picture of the reasons and mechanisms for the steep declines in the western SSL population has emerged[58]. The working hypothesis is that several factors have contributed, possibly including large natural ecosystem fluctuation; competition with fisheries; direct mortality via shooting, subsistence harvest, and incidental catch; and ecosystem-level changes that may have increased predation pressures. To what degree each of these may have contributed is still far from being understood. The listing of the species under the ESA and subsequent fishing regulations have addressed (to an uncertain degree) some of the potential human impacts, but continued declines in some parts of the SSL range indicate that a full understanding of the threats and causes of the declines is still elusive. However, to model future dynamics of the SSL population, as necessary in a PVA, understanding the historic dynamics of the population and potential future threats is critical.

It was in this context that Goodman began work on the SSL PVA. Consistent with the principles outlined above, his aim was to develop a Bayesian PVA within a decision theory framework. His strategy was to take the descriptive narrative that the recovery team developed for the recovery plan, including the historic declines, the current threats, uncertainty about unexplained dynamics, and the recovery team's definition of a recovered population, and turn

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them into a synthetic quantitative model that would be logically consistent with respect to the empirical data, the policy determinations and expert opinion provided by the recovery team, and the uncertainty inherent in the system and process. Using this approach, he hoped to not only provide internal coherence between the PVA, the recovery plan narrative, and the recovery criteria, but also transparency and reduced ambiguity in the recovery plan and criteria to render them technically and legally defensible under the ESA.

4.2 PVA Model Development: Principles vs. Reality

Some of the first decisions Goodman asked the PVA subgroup of the recovery team to make were about policy elements that are not defined precisely in the ESA. First they defined in quantitative terms the extinction risk level that defined the boundary between endangered and threatened. In other words Goodman asked the subgroup to make a policy judgment that quantified the ESA's threshold of "in danger of extinction". The subgroup opted for <1% extinction risk in 100 years, a value recommended by some [59] and used in other recovery plans [25]. Second, Goodman asked the subgroup to more precisely define whether "extinction" meant absolute extinction (zero animals left), or some version of functional- or quasi-extinction. The subgroup decided to use a quasi-extinction level defined by a genetically effective population size [60] of 1,000. In this way, Goodman clearly isolated the policy questions from the modeling questions.

Once the policy questions were settled, Goodman began the process of building the PVA. Based on his personal files and descriptions of his interactions with the SSL recovery team and its PVA subgroup, Goodman spent a great deal of time and energy attempting to understand what was known and what was unknown about SSL demographics and history.

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Much work went into analyses that occurred prior to the actual development of the PVA model. For example, he clearly labored over if and how to incorporate density dependence in his model, and he used an appendix to his report to demonstrate through supplemental modeling why density dependence could be excluded from his final PVA model. Similarly, he took great pains in understanding what data were available to quantify the impact of various human-caused factors on historic SSL dynamics. This was essential for understanding and modeling the population's natural population fluctuations in the absence of these threats. Through extensive pre-model explorations, Goodman identified what he thought were the relevant data and included them in his model. Many other data related to SSL demographics exist, so clearly Goodman did not use *all* of the available data but made decisions about what data were necessary for the most defensible PVA and what data were most relevant to the question of recovery criteria.

The complexity and uncertainty surrounding the SSL decline made it a particularly vexing problem that required unique modeling approaches. Perhaps in part because of the unconventional approach, Goodman did not apply Bayesian estimation procedures and full characterizations of uncertainty to all aspects of the problem, only to the estimation of the mean and variance of the population's overall growth rate distribution. For example, Goodman attempted to elicit a range for the estimates of known sources of human-caused SSL mortality (external factors) used to adjust the net (or realized) growth rates (Fig. 1), but the PVA subgroup was unable to find data to support more than minimum estimates. Because of this lack of full quantification of uncertainty, Goodman suggested in his PVA report that the uncertainty in the full impact of external factors "must be borne in mind when interpreting the

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results" of the his model [57]. Obviously this falls short of a full quantitative rendering of all sources of uncertainty.

Goodman also used conventional vague priors for the Bayesian portion of his model. Since he did not explain his decision to do so, we are left to guess at his reasoning. Pragmatic considerations likely determined the decision, whether it was time limitations or data limitations or both. Regardless of the reason, the vague priors yielded posterior distributions carrying the maximal uncertainty present in the data and reflects a more pragmatic approach than is present in Goodman's philosophical writing.

Goodman did incorporate some level of model uncertainty in his approach to dealing with the unexplained dynamics that have impacted the western SSL population historically and how they might impact the population in the future. To deal with this aspect of uncertainty, following development of his model, Goodman conceived of three alternative hypotheses about how future SSL growth rates would operate. He asked the PVA subgroup to provide an estimate, based on expert opinion, of the probability that his PVA model assumptions were correct versus the three alternative hypotheses. If formalized into alternative PVA models, all three alternative hypotheses would result in 0% probability of extinction in 100 years under any conceivable management scenario. Thus, Goodman used the PVA subgroup's expert opinion regarding the probability of his "base" model being correct to perform a sort of model averaging. His approach was unconventional compared to other model selection approaches, but it was consistent with his principle of considering all the relevant information and uncertainty and was also consistent with the principle of using PVA and structured decision-

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making to help make explicit all the assumptions that go into a decision and the models used to aid in that decision.

Due to the Bayesian nature of the PVA analysis the joint posterior distribution on the mean and standard deviation of the population growth rate reflected the parameter uncertainty from the vague priors and the process uncertainty from the underlying growth rate estimates. The subsequent use of the joint posterior distribution in the prospective analysis aimed at estimating the SSL population's future prospects thus ensured that the parameter uncertainty was propagated through the analysis as advocated by Goodman in his philosophical writings. Likewise, the derived distribution of time to extinction embodied both parameter and process uncertainty. Given the large range in estimated natural growth rates and the vague priors, the uncertainty reflected in the joint posterior distribution was large, resulting in a wide distribution for the estimated time to extinction (Fig. 2).

When model results show a high degree of uncertainty (wide spread), as they did in this case, it is instinctual for both modelers and managers to want to reassess the model to see if the results can be narrowed to arrive at a more precise answer. Consistent with his principles, however, Goodman set the stage early in the process to ensure that such tinkering with the model to get a "better" answer would not occur. Asking the recovery team to decide upon the policy questions prior to model development was one way he did this; another was extensive communication with the recovery team throughout and following model development. Based on the data and expert opinion he elicited from the PVA subgroup and his rigorous analyses (including pre-model and post-model explorations) Goodman believed that the results from his PVA model were the most accurate estimates that could be obtained from the available data

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and that they appropriately reflected the high degree of uncertainty in both the historical dynamics of the population and its future prospects. With these "correct" PVA results in hand, Goodman spent a considerable amount of time in writing and in meetings explaining how the results could be used to arrive at recovery criteria that appropriately reflected those results. He also laid out a long-term plan for continuing to update the PVA as more data became available to potentially reduce the uncertainty in the model and reduce the estimated time to recovery.

The recovery team used Goodman's PVA results to formulate recovery criteria for the SSL western DPS, but because of the wide posterior distribution from Goodman's PVA, the timeframe for recovery was far into the future. As Goodman argued, this was the "correct" estimate of the time to recovery given the information available at the time the PVA was developed. However, since the National Marine Fisheries Service has ultimate say in what appears in the final recovery plan, prior to its final publication, the recovery criteria developed from Goodman's PVA were replaced with criteria based on what was called a "weight of evidence" approach. The final recovery criteria required lower population sizes and shorter time frames for recovery than those developed from Goodman's PVA.

5. SUMMARY AND CONCLUSIONS

Dr. Goodman championed three main principles for achieving transparent and scientifically based ecological decision making: using all available data, exhaustively quantifying uncertainties, and using a synthetic analysis to arrive at a result, complete with uncertainty, that can be used directly in the decision-making process. Mechanistically, Goodman believed that the best way to adhere to these principles in the context of species management was to use Bayesian PVA and structured decision-making. The Bayesian aspect is necessary because

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additional information and quantifications of uncertainty can be encapsulated in the prior, and the mechanisms of Bayesian analysis propagates that information and uncertainty through to the result in a statistically valid manner. The PVA portion is important because it can synthesize multiple sources of information and translate the available data and uncertainties into the common currency of extinction risk. In combination, a Bayesian PVA will result in a synthetic assessment of all information and uncertainty in the form of a legitimate probability distribution of the estimated risk of extinction, which can be used directly in a structured decision-making framework.

While we strongly support the principles Goodman laid out, we sometimes struggle with whether we can achieve the ideal that he specified. Our own experience, as well as Goodman's SSL PVA example, demonstrates that the path is not an easy one, nor are all aspects operational in all situations. For example, Goodman found it difficult, or at least too time-consuming, to fully implement empirically-based prior distributions for the SSL PVA parameters, and we suspect this may often be the case. However, using a fully Bayesian synthetic model that uses all the direct data should be obtainable in most situations.

We have also found that rigorous implementation of structured decision-making within the wildlife-management agencies can be very difficult. This difficulty stems in large part from the structure of wildlife management agencies and the separation between scientists and the upper-level managers who ultimately make the decisions. It is appropriate, in our view, to have this separation between the science and the decision-making management side. However, it can cause an issue whenever scientific methods such as PVA appear to automate the decision. From the managers' perspective, this can be seen as moving the management decision

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(inappropriately) to the science side. In reality, scientific models such as PVA, require both policy determinations (e.g., should "endangered" be defined as having an extinction risk of 5% in 100 years or 1% in 200 years or…) as well as scientific determinations (e.g., what kind of demographic model should be used and should it include density dependence). Other model inputs may also require a combination of scientific data and best guesses that will require input from both scientists and managers (e.g., to what degree will human activities impact future populations). Scientific models should therefore not be viewed purely as scientific endeavors but as collaborative efforts between decision-makers and scientists.

In Goodman's SSL PVA example, he was able to achieve buy-in from the scientific PVA sub-group, and eventually the entire SSL recovery team, through extensive communication and education about statistical fundamentals and the process and logic he used to develop his model. He also clearly outlined which aspects of the model were policy questions to be answered by the team, which aspects were expert opinion, and which aspects were purely scientific questions to be resolved by data. His work in this area provided an excellent foundation and justification for the scientific analyses that were performed as well as an example of how good communication can bring about consensus on model inputs. However, once the draft recovery plan was submitted to agency decision-makers and reviewed by others outside the recovery team, the buy-in from the recovery team held little currency. So unless the management context is relatively uncontroversial or communication and buy-in can be achieved throughout all levels of management so that the final decision-makers have input into policy relevant aspects of the model, then the rigorous application of a structured decision making process is likely not fully achievable.

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So are we to throw up our hands in despair? We do not think so. We believe that the three principles and the tools to achieve them should be used to the maximum extent practicable, with the understanding that, at times, pragmatism may have to win out (e.g., fully empirically based Bayesian priors may not be achievable), but that the principles can be followed in spirit if not always to the letter. We believe that this is what Goodman did in his SSL PVA. Following these principles will, at the least, render the science portion of the process fully transparent and documented for all stakeholders. Beyond the science, communication between scientists and managers is clearly a critical component of the process as is clarity on all sides about which aspects of model-building are policy determinations and which are scientific questions. We also believe, as Goodman did, that the road to better ecological decision-making is a long one that will require incremental progress. Perhaps Goodman's principles provide us with a picture of the ideal scenario toward which we should strive.

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FIGURES

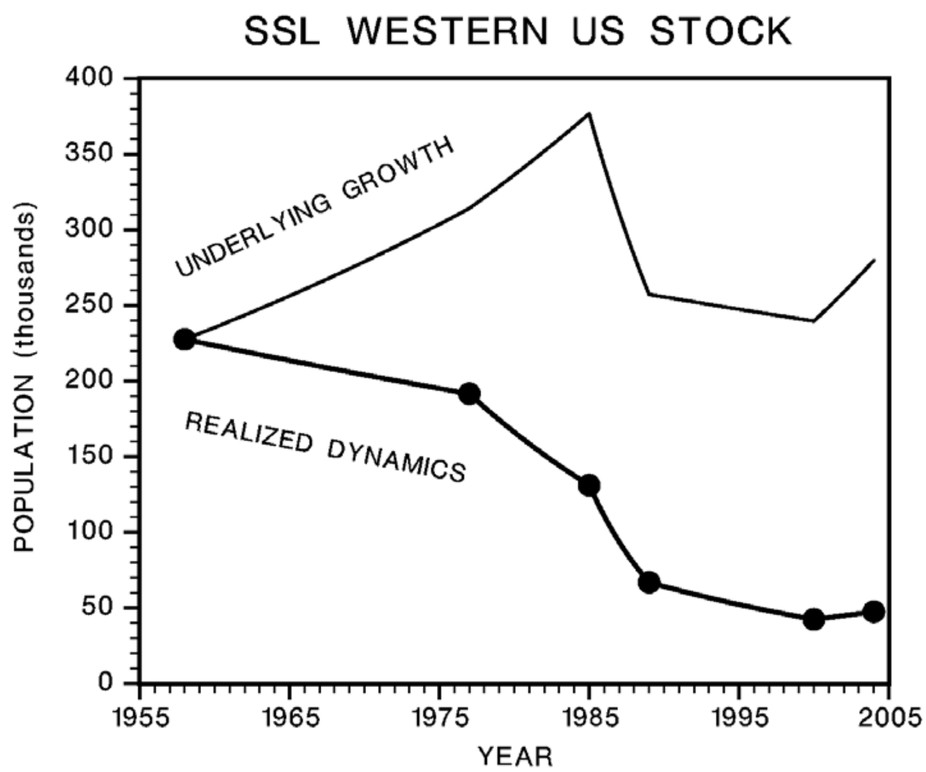

Figure 1. Figure from Dr. Goodman's PVA report in the appendix of the Steller sea lion revised recovery plan[57]. The circles represent the six Steller sea lion western DPS census estimates plotted against year. The heavy line connecting the census estimates represents the trajectory corresponding to constant exponential growth within each interval. The thin line represents a projection of a population initiated at the observed population size in 1958, and growing subsequently according to the calculated underlying growth rates for each respective period representing what would have happened, in the absence of density dependence, if, from 1958 on, the population had been released from the extraneous influences attributable to human activities as estimated by the PVA subgroup.

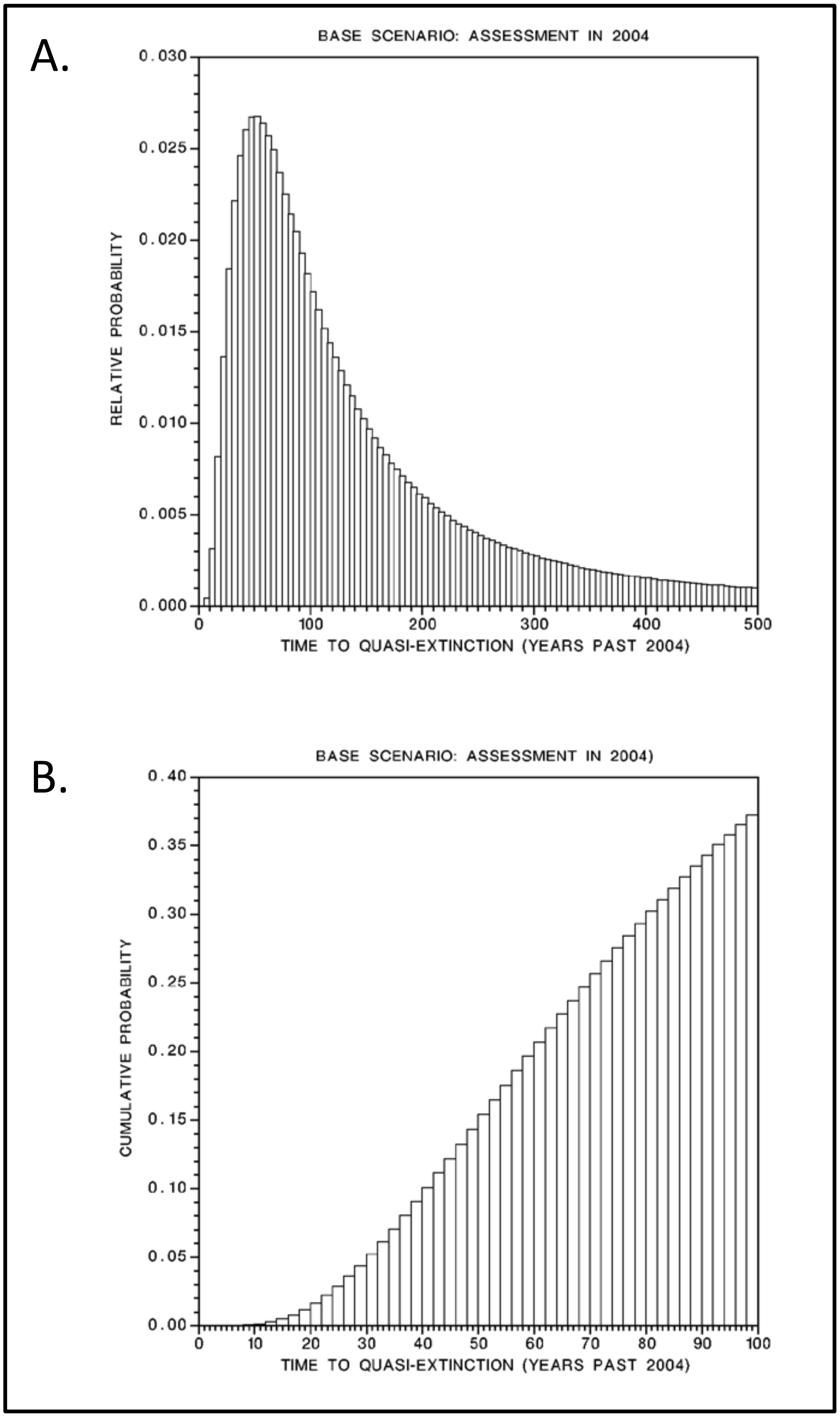

Figure 2. Figures from Dr. Goodman's PVA report in the appendix of the Steller sea lion revised recovery plan[57]. A) The results of Dr. Goodman's PVA estimating the Bayesian posterior

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distribution for the time to quasi-extinction for the Steller sea lion western DPS. B) Dr. Goodman's PVA results displayed as the cumulative probability of extinction plotted against years.

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