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"Consideration of uncertainties in environmental science and management with examples from Pacific salmon"

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Abstract

An informal review of the history of new quantitative methods in environmental science, including environmental risk assessment, shows about a 10- to 20-year lag in wide acceptance of such methods by management agencies. To reduce that lag time as innovative methods continue to emerge, environmental scientists will need to work much more intensively with communications specialists on better ways to explain risk analyses and decision-making strategies to non-technical decision makers and the public. Four key uncertainties make such communication difficult: (1) natural variability in both physical and biological processes, (2) imperfect data arising from observation error (i.e., measurement error), (3) incomplete understanding of an environmental system's structure and dynamics, and (4) outcome uncertainty (deviations between realized outcomes and management targets). These uncertainties create risks -- risks to natural populations as well as to people who use them. Examples of these four sources of uncertainty are presented here for Pacific salmon (*Oncorhynchus* spp.). One promising framework for explicitly taking such uncertainties into account was initially developed in the early 1990s by scientific advisors to the International Whaling Commission. They built stochastic models, which essentially were comprehensive formal decision analyses, to derive management procedures (i.e., sampling designs for collecting data, methods to analyze those data, and state-dependent harvest-control rules for use by managers) that were robust to all the uncertainties considered. This method of "Management Strategy Evaluation" or "Management Procedure Evaluation" is now considered the "gold standard" for conducting risk assessments and making risk-management decisions in marine fisheries.

1. Introduction -- some historical perspective

One purpose of the Daniel Goodman Memorial Symposium was to pass on to the next generation of scientists some lessons that quantitative environmental scientists like Dr. Goodman have learned from working in various environmental fields. This paper synthesizes some of those ideas, beginning with historical information about environmental science, admittedly based on my own limited experience in quantitative fisheries ecology and management.

Two key words describe Dan Goodman's work in environmental science, "quantitative" and "applied". Most young environmental scientists might think that the standard set of skills required for environmental researchers has always included quantitative expertise such as computer programming, simulation modelling, Bayesian statistics, hierarchical modelling, and geographic information systems. They might also think that research on real-world applied problems has always been widely accepted as legitimate research by those who work on non-applied "pure" or "fundamental" research topics. On both points, these young scientists would be wrong. Quantitative methods applied to real-world problems are indeed key elements of today's leading-edge environmental research (Clark and Gelfand, 2006), but this has not always been the case.

1.1 Quantitative methods

How quantitative ecology developed, and its slow progress, have implications for the future role of the much broader field of environmental science and risk analysis in societal decision making. In particular, as explained below, there is a critical need to become more creative about how we quantitative scientists communicate our esoteric and complex analyses and results to decision makers and increasingly to the public who generally have little quantitative background.

Many of these potential users of our analyses may even hold a deep suspicion of quantitative models. Today's young generation of environmental scientists and risk assessors should therefore not expect that their new methods will be readily accepted and used in management of the environment. Instead, consistent demonstration of new insights from use of those methods will be required.

Quantitative methods in ecology have not always been available, let alone common. Ecological modelling, or quantitative ecology, emerged in the late 1960s and early 1970s led by a small group of people such as George van Dyne, Ken Watt, Buzz Holling, Carl Walters, Robert MacArthur, Robert May, and Michael Hassell, to name just a few. The 1970s saw substantial research initiatives, such as the International Biological Program, for building computer simulation models of dynamics of populations and ecosystems. However, many of those models proved less valuable as representations of real systems that could be used for management decisions and more valuable as theoretical bases for generating hypotheses and setting research priorities for the future (Holling et al., 1978). As well, from the late 1960s until the early 1990s, debates frequently occurred between field ecologists and ecological modellers (and to a lesser extent, they still occur today). Among other things, field ecologists criticized modellers for ignoring important details about how populations and ecosystems functioned. In turn, modellers criticized field ecologists for not asking relevant questions with their experiments and not estimating quantities that would be useful as inputs to models. It wasn't until about the mid-1990s that simulation models in fisheries science and management were finally accepted widely as legitimate, scientifically challenging research methods that also provided useful input to management decisions.

1.2 Lag times

Scientists who work on today's real-world problems often get frustrated by how slowly their research methods and results become accepted by government or other decision makers and by the well-informed public and non-governmental organizations. They forget that long time lags are very common for accepting new ideas and methods, even among scientists. Three examples from environmental modelling illustrate this point. First, in the description above about the scientific debates between field ecologists and modellers, it took about 20 to 25 years for ecological simulation modelling to become widely recognized as a legitimate and useful method of analysis outside the small circle of quantitative ecologists. Second, ecological (i.e., environmental) risk assessment methods, which emerged in the late 1980s and early 1990s from modifications to the already accepted human-health risk assessment methods (National Research Council (NRC) of the United States, 1983) have also taken decades to evolve to an acceptable level of sophistication (Landis, 2012), but they are still not widely understood, especially by the public.

Third, in the 1990s, scientific advisors to the International Whaling Commission developed stochastic simulation models to derive management procedures that explicitly considered several key sources of uncertainty (de la Mare, 1996; Kirkwood, 1997). Here "management procedures" refers specifically to the combination of (1) sampling designs for data collection, (2) methods to analyze the data, and (3) state-dependent harvest control rules for managers. Such models were in effect risk assessment methods and formal decision analyses. They have been labeled "Management Strategy Evaluations" (MSEs) (Sainsbury, Punt & Smith, 2000), "Management Procedure Evaluations" (MPE) (Butterworth and Punt, 1999), or closed-loop simulations (Walters, 1986). It took about 10 to 15 years before numerous well-developed cases of

MSE/MPE were implemented by management agencies. Today, those cases include management of pelagic and groundfish species, mostly in North America, Europe, South Africa, and Australia (Andre Punt, University of Washington, Seattle, personal communication). Furthermore, MSEs are now considered the "gold standard" to which most people aspire for fish stock assessment and management decision making in data-rich marine fisheries. Recent MSEs aim to include all stakeholders in shaping management objectives and evaluating management options (Cox and Kronlund, 2008).

Such long time lags for acceptance of innovations also exist in the wider fields of quantitative risk assessment (estimating the magnitude of risk) and risk management (making decisions in the presence of risks). Those methods were first developed in World War II by the military and later elaborated in risk assessments of nuclear power plants in which the probabilities of disasters were very low and difficult to model (Apostolakis, 2004). In the U.S. nuclear power industry, about a 25-year lag occurred between initial development of its specific quantitative risk assessment methods and safety managers accepting the benefits of such analyses and proactively using them (Apostolakis, 2004).

Another well-known instance of lag in acceptance is the formally defined Precautionary Approach, a management response to the presence of large uncertainties. A detailed, 52-page set of guidelines for implementing that approach for capture fisheries and species introductions was first written in 1995 (FAO, 1995) at what one scientist called "... one of the most important fisheries meetings of the 20th century" (Punt, 2006). However, several key concepts of the Precautionary Approach were originally articulated in the 1982 international Convention on the Conservation of Antarctic Marine Living Resources (CCAMLR, 1982). Thus, there was a lag of 13 years between these two key documents. Subsequently, the Precautionary Approach to environmental management spread unusually rapidly in the fisheries realm and has become a cornerstone of much of aquatic management (Garcia, 2000; Punt, 2006). The general concepts of the Precautionary Approach have also been applied in many other management contexts.

A key lesson is that substantially new ideas and methods of analysis will probably continue to take a decade or more to become acceptable, especially to environmental decision makers. As elaborated upon later, better communication of technical details may shorten these lag times, but this will take a concerted effort. Methods of analysis that offer only small, incremental improvements over current methods will probably have greater acceptability in the short term, but may not offer as novel insights into solving problems as substantially new methods.

1.3 Model complexity

As computing power increased over the last few decades, many fisheries scientists tended to build ever more complex models. However, it may be more appropriate to not go beyond the data and instead follow the adage of making models "as simple as possible, but no simpler than necessary" (Morgan and Henrion, 1990). It has also been shown that more complex models do not necessarily lead to better predictive power than simpler ones (Fulton, Smith & Johnson, 2003). In this context, scientists must repeatedly ask, "Will a more complex model improve the outcomes of management decisions?" There is no simple, general response. The question needs to be answered on a case-by-case basis depending in part on the available data and understanding. As well, a Management Strategy Evaluation (MSE) is needed to evaluate management options *using a set of alternative but plausible system models* (not just "the best" single model or the one "new and improved" model) to represent uncertainties in our understanding of the system's underlying dynamic processes. Other types of uncertainty, such as those that cause deviations between management targets and actual outcomes, could mask or swamp any improvement garnered from a better system model, as was found, for example, in a MSE that included alternative models for sockeye salmon (*Oncorhynchus nerka*) populations (Dorner, Peterman & Su, 2009).

2. Uncertainties in the research and management of Pacific salmon

By the early 1990s, the importance of taking uncertainties into account became well accepted in the field of fisheries science and management. There, the existence of lengthy data sets and an already strong tradition of quantitative methods (Smith, 2012) helped stimulate development of advanced statistical estimation and stochastic (as opposed to merely deterministic) simulation models. Such stochastic models allowed for sophisticated management objectives, such as wanting to achieve "A probability of at least X of achieving outcome Y by time Z" or "A probability less than P of some adverse state occurring in the next T years" (Peters and Marmorek, 2001). The combination of advanced statistical analysis, decision analysis, and stochastic simulation became important tools in the emerging field of environmental risk assessment and risk management (Walters, 1986; Peterman, 2004; Burgman, 2005). Dan Goodman helped to both develop and apply these methods related to uncertainties and risks in real-world management contexts for many species.

Some examples of past research on Pacific salmon (*Oncorhynchus* spp.) explicitly deal with uncertainties, which are important because they create risks -- risks to salmon populations and to people who use them for sustenance or recreation. These salmon examples are likely parallel to many situations in other areas of environmental management, risk assessment, and risk management.

The most advanced models of Pacific salmon and other fish species explicitly take into account four key sources of uncertainties (Peterman, 2004):

1. Natural variability in both physical and biological processes
2. Observation error (imperfect data arising from measurement error)
3. Structural uncertainty owing to incomplete understanding of the ecosystem's structure
4. Outcome uncertainty (deviations from management targets).

The interaction among these sources of uncertainty and the management process is schematically summarized in Fig. 1.

2.1 Natural variability

Natural variability occurs in both physical and biological processes at various spatial and temporal scales. For instance, in Pacific salmon, survival rates and overall productivity (adults produced per parent spawner) vary considerably from year to year as well as across locations. This high-frequency short-term process variability occurs on top of long-term time trends and non-monotonic patterns that fisheries scientists and oceanographers refer to as low-frequency changes, decadal-scale variability, regime shifts, or autocorrelated series. In the most general sense, these long-term trends, which may be caused by climatic change or other mechanisms, are examples of non-stationarity, as defined by a change over time in mean and/or variance of some variable.

Short-term process variation can be dealt with more easily than non-stationarity. A variance term in a statistical model fit to data estimates the former, and in simulation models,

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that variance produces probability distributions of outcome indicators. In contrast, non-stationarity creates several problems. First, it makes it difficult to find relationships among variables because those relationships may shift over long periods, not just year to year (Walters 1987). Instead, in such cases, part of the observed variance will be due to a change over time in the underlying relationship. For instance, past observed correlations between sea-surface temperature (SST) and salmon productivity may not hold in the future if the indirect index of ocean productivity, SST, becomes less correlated with actual ocean productivity due to long-term changes in current patterns and upwelling driven by climate change (Mueter, Peterman & Pyper, 2002a). Second, non-stationarity creates a dilemma over how to treat long time series of data (e.g., 25-30 years). More data will usually reduce the variance in parameter estimates, but older data may not be relevant to recent years, let alone making future forecasts (Walters, 1986).

State-space models, which estimate one or more time-varying parameters, are now being used in several environmental fields as a way to deal with non-stationarity (Clark and Bjornstad, 2004). As demonstrated via a simulation analysis for Pacific salmon, a Kalman filter with a random walk error term (an example of a state-space model) can track temporally autocorrelated changes in productivity and even regime shifts (i.e., step-functions) more effectively than traditional methods for updating parameter estimates annually (Peterman, Pyper & Grout, 2000).

2.2 Imperfect data

The second major source of uncertainty relevant to Pacific salmon is observation error (i.e., measurement error). Observed data are imperfect reflections of the real situation, leading to imprecise and/or biased estimates of state variables and model parameters. To deal with observation error, it is now quite common to see equations in fisheries models that not only reflect natural variability in mortality rates or overall productivity, but also the variance in observation error, which represents how observed values deviate from true values (Walters and Martell, 2004). Bayesian methods are now frequently used to estimate those variance parameters from the available data (Walters and Martell, 2004). Extensive sensitivity analyses ("What if ...?" scenarios) can help shed light on the influence of other uncertainties for which we have little or no data, but that are relevant to making management decisions and identifying high priorities for future research. If the model is to support of some management decision, the best analyses will focus on how the rank order of possible management actions (including the state-dependent harvest control rules) changes as model assumptions are changed.

Given the importance of natural process variation and observation errors that are made when sampling populations, it is surprising that so little work has been done on taking these sources of uncertainty into account to evaluate the reliability of the International Union for Conservation of Nature's (IUCN's) widely used criteria (IUCN 2013) for categorizing extinction risk or threat status of low-abundance populations (i.e., as vulnerable, endangered, etc.). Some notable empirical (Dulvy et al., 2005; Porszt et al., 2012) as well as simulation analyses (Punt, 2000; Rice and Legacé, 2007; Holt et al., 2009; Regan et al., 2009; Wilson, Kendall & Possingham, 2011; Regan et al., 2013; Connors et al., 2014) have taken those uncertainties into account, but these are the exceptions to the norm of classifying threat status based on standard indicators and criteria (IUCN, 2013; COSEWIC, 2011). One recent example illustrates the value of such novel analyses of natural process variation and observation errors -- d'Eon-Eggertson, Dulvy & Peterman (2015) compared the reliability of 20 indicators of declining populations of sockeye salmon. Their measure of reliability reflected the combination of false negatives (concluding that a population was not at serious risk when it actually was in trouble) and false positives or false alarms (concluding that a population was at risk when it actually was not). They used a population model to simulate dynamics in the presence of observation error and temporally autocorrelated natural variability in productivity (process variation). They found that the commonly used IUCN criterion of rate of decline in the last three generations is the *least* reliable of the indicators of risk examined, and that indicators based on change from some historical baseline early in a data set were much more reliable under a wider range of conditions (d'Eon-Eggertson, Dulvy & Peterman, 2015). Furthermore, Connors et al. (2014) simulated the dynamics of a much wider range of populations to estimate the rates of false negatives and false alarms. They found higher rates of both types of errors than previously assumed. Based on such studies, it is therefore recommended that before scientists apply indicators to data to classify conservation concerns about populations, they should first determine the reliability of those indicators by conducting simulations that explicitly include two sources of uncertainty -- observation error and temporally autocorrelated natural variability in productivity (process variation).

2.3 Incomplete understanding of a system's structure

Natural variability and observation error cloud our understanding of the underlying structure of the Pacific salmon ecosystem, but other factors contribute as well. For instance, salmon systems contain complex structures of interacting variables and processes that operate at various space and time scales. Furthermore, confounded effects are common because natural and human-induced changes often occur simultaneously (e.g., changes in management regulations and climate-driven changes in seasonal timing of biological events). Such confounding makes it difficult to attribute a particular mechanism to a particular observed change, which reduces our ability to understand the underlying system.

The resulting structural uncertainty (i.e., model misspecification) is now widely recognized by fisheries scientists as being at least as important as uncertainty about parameter values (e.g., McAllister and Kirchner, 2002). Therefore, it is now routine for fisheries scientists who work on applied problems to build several alternative models that reflect different views and conduct sensitivity analyses across those structurally different models (Walters and Martell, 2004). These models may differ in only one equation (say, linear in one model and nonlinear in another), or they may have quite different community structures for predator-prey and competitive interactions (Sainsbury, 1988). Results from such alternative models can be presented to decision makers, either weighted equally or unequally, to better reflect uncertainties in projected outcomes of given management regulations than using just a single "best" model. Most preferable, though, would be to use Management Strategy Evaluation (MSE) as is done in several marine fisheries. MSE incorporates the range of alternative structural models to find the management strategies that are most robust to all uncertainties, including those related to model structure (FAO, 2008).

Uncertainty about the underlying dynamic processes can be reduced by applying advanced statistical methods such as hierarchical statistical models (Clark and Gelfand, 2006; Banerjee, Carlin & Gelfand, 2003; Royle and Dorazio, 2008; Zuur et al., 2009). Such models can, for instance, help estimate mean effects of environmental factors on productivity across multiple fish populations. However, a caution with hierarchical models is that although they improve precision of estimates of mean effects of some factor across populations of a given species, they tend to

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increase bias in population-specific parameters owing to the "shrinkage" effect that pulls the latter parameter estimates toward the mean (Gauch, 2006).

Interestingly, natural variability in salmon productivity also creates an opportunity to *increase* rather than *decrease* understanding of the ecosystem's structure. Analyses of spatial and temporal autocorrelation can identify the spatial scale and patterns of positive covariation to help point to important oceanographic processes that operate at that same, or larger spatial scale. For example, past research on pink salmon (*O. gorbushca*) found positive correlations between large numbers of pairs of time series of productivity covering numerous populations of salmon, with the largest correlations occurring between salmon populations with nearby points of ocean entry for their juveniles (Pyper et al., 2001; Pyper, Mueter & Peterman, 2005). The spatial scale of those positive correlations (~500 to 800 km) corresponded well with the spatial scale of correlations in early-summer SST measured at different locations (Mueter, Ware & Peterman, 2002), which suggested a causal mechanism linking SST with salmon productivity. The resulting hypothesis of a link between productivity of year classes and SST during the early summer of their ocean entry year as juveniles was supported by empirical analysis with hierarchical models (Mueter, Peterman & Pyper, 2002). Other oceanographic variables (e.g., upwelling, sea-surface salinity) were less likely to be drivers of salmon productivity because their spatial scale of positive covariation was not appropriate for explaining patterns of salmon productivity (Mueter, Ware & Peterman, 2002).

2.4 Outcome uncertainty

The fourth type of uncertainty is the almost inevitable deviation between management targets and actual outcomes, i.e., outcome uncertainty. This phenomenon runs through all fields of environmental management. For Pacific salmon, outcome uncertainty refers to deviations from either the target abundance of spawners or the target percent harvest rate. There are at least three causes for such deviations. First, catchability (the proportion of fish caught per unit of fishing effort) can differ from expectations because of natural variability in physical and biological processes, such as currents or water temperature changing locations of fish, which make them more or less vulnerable to fishing gear. Actual catches will thus differ from expected catches, even if the forecasted number of fishing vessels materializes. Second is non-compliance with fishing regulations by harvesters, which would generally cause catch to be too high and spawners to be too low. The third source of deviations between a target and an actual outcome is errors by managers in choosing which regulations would best meet their objectives, even if there were no structural or parameter uncertainty and perfect compliance with regulations. Such management-derived errors are generally referred to as implementation errors. The general term "outcome uncertainty" encompasses all three causes described above (Holt and Peterman, 2006).

Similar to natural variability and observation error, outcome uncertainty can be represented by a variance term in models. However, outcome uncertainty is likely to be more complex than just adding a normal or log-normal distribution error term to an equation. Deviations from targets may be state dependent and biased. For instance, Holt and Peterman (2006) found that at low salmon abundance, percentage mortality rates were higher than the target more often than below it (Fig. 2). This bias increases the chance of creating conservation problems.

2.5 Collectively accounting for these uncertainties

One way to account for all four of these sources of uncertainty is to build simulation models that explicitly include these components in equations. The technique described above of

"Management Strategy Evaluation" is an example of this method (Fig. 1). In fisheries stock assessment and management, these techniques are widely used by researchers (Peterman, 2004; Walters and Martell, 2004), although to my knowledge, the Fraser River sockeye salmon system is the only case of a Pacific salmon management agency (in contrast to agencies managing other species) using MSE to develop harvest control rules (Pestal et al., 2011).

3. Improving communication about uncertainties

These four sources of uncertainty also create a substantial challenge to effective communication about risks during discussions among scientists, managers, and the public. Scientists are good at communicating among themselves about uncertainties and risks, but we generally are much less effective at discussing such technical material with non-technical decision makers and the public. One reason for the above-described slow, 10- to 20-year acceptance of new methods and their results by management agencies and the public may be that most scientists spend more time developing and using those methods (and being rewarded for doing so) than thinking about how to improve the effectiveness at communicating the results to others. Again, if our analyses of uncertainties and risks are to have substantial impact, scientists need to get much more creative about how to transmit our results to those who can use them.

Five suggestions come to mind to improve communications. First, many more people with perhaps even just a Master's degree in some scientific field could become full-time communication specialists. Their job would be to help translate esoteric or complex methods and research results (including their uncertainties) so that non-technical decision makers and the public can better understand their meaning and implications for decisions. The United States' Sea Grant program already funds such "Fishery Extension Specialists", who are analogous to the long-standing and influential "Agricultural Extension Specialists" of the U.S. Department of Agriculture. Second, researchers could also benefit from training in communication techniques to better explain their ideas, results, and uncertainties in an understandable manner. At present, most of us are too used to talking with other scientists, rather than with people who do not have our backgrounds. Third, more internship and cooperative-education programs are needed to enable graduate students and post-doctoral fellows to work within environmental management agencies. Such positions benefit not only young scientists, but also help agency staff learn about new methods of analysis in support of decision making.

Fourth, scientists need to give decision makers and the public clearer information about difficult trade-off decisions. For instance, in fisheries where abundant and productive fish stocks are mixed during the fishing season with low-abundance, less-productive ones, managers need to see how much reduction in revenue from commercial fisheries is likely to result from restrictive fishing regulations that aim to increase the probability of meeting a conservation objective for the less productive stocks (Pestes et al., 2008). Visual presentations of such trade-offs and their inherent uncertainties using specialized interactive software such as Vismon (Booshehrian et al., 2012) can also engage managers as well as users of fish, as witnessed in salmon fisheries in western Alaska (Michael L. Jones, Michigan State University, personal communication, 2012).

Fifth, risk communication is an active field of research, but most environmental scientists and managers have not utilized its research results to effectively convey their work on uncertainties and risks to non-scientists. In particular, cognitive psychologists have shown that people are more likely to correctly interpret information about uncertainty and risk that is presented using a frequency format instead of the more common probability format. For example, a probability format ("There is a probability of 0.2 that the target population will drop below an acceptable abundance within 5 years") is more confusing to non-technical people than presenting the same information in a frequency format ("In 2 out of every 10 situations like the current one, the target population will drop below an acceptable abundance within 5 years"). Apparently the frequency format stimulates thinking about concrete sets of cases that can be visualized and counted (in contrast to the vague and confusing concept of a single-event probability) (Gigerenzer and Hoffrage 1995). Thus, even this simple change in how scientists present results about probabilities could enhance their communication with decision makers and the public. Anderson (1998, 2001) describes several uses of frequency format in other fields of environmental management.

Therefore, to make their applied quantitative research more influential for management decisions, scientists need to seriously consider and implement these and other changes to their methods of communicating results by working closely with people who have backgrounds in communication and cognitive psychology.

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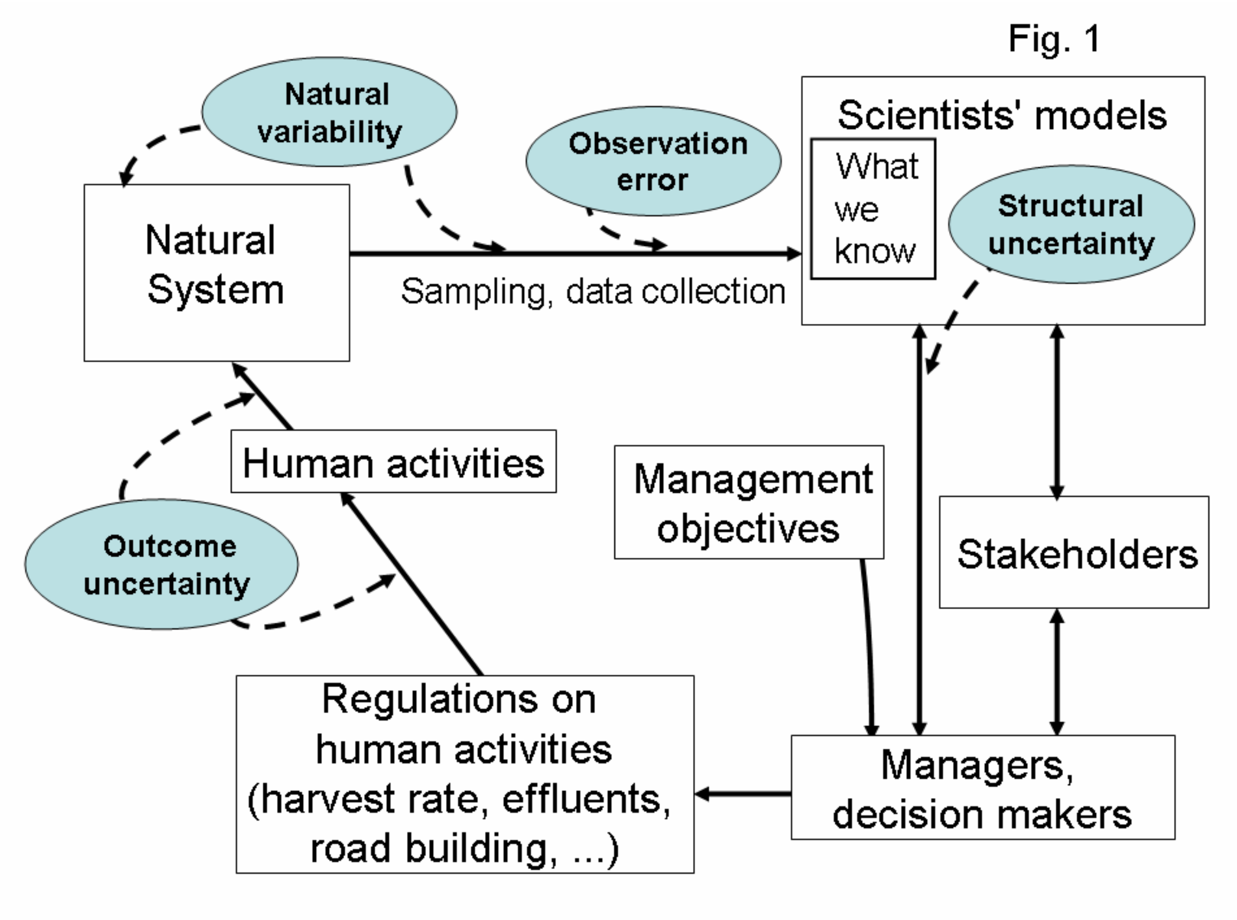

Figure 1. Components that are typically incorporated into stochastic simulation models that are used in "Management Strategy Evaluations", "Management Procedure Evaluations", and closed-loop simulations (see text). These components include natural system dynamics, procedures for data collection and analysis, modelling of the natural system, derivation of decision-making rules, and human activities, plus the four key sources of uncertainty shown in ellipses. Adapted from Peterman (2004).

Fig. 2

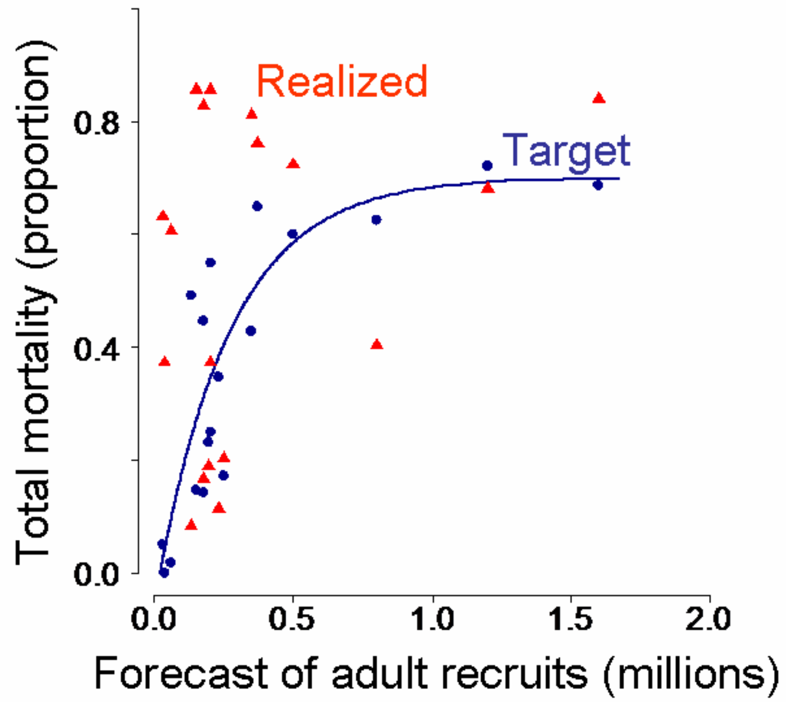

Figure 2. Annual proportions of adult Early Stuart Fraser River sockeye salmon in British Columbia harvested and dying from in-river natural mortality (the latter constituted less than 5% of the mortality in most years) as a function of forecasted abundance of adult recruits for 1986-2003. Solid line and solid circles are managers' targets; solid triangles are realized values at the end of the fishing seasons. Adapted from Holt and Peterman (2006).

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