# The Quandaries and Promise of Risk Management: A Scientist's Perspective on Integration of Science and Management

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THE TEXTBOOKS ON RISK MANAGEMENT ARE WRONG ... OR IMMENSELY NAÏVE.

Traditional risk analysis, such as through the use of decision trees, entails depicting (1) a set of alternative decisions or decision pathways based on a specified risk attitude of the decision-maker, (2) the response of the system of interest and associated probabilities, and (3) values (or utilities) of each outcome and expected values of each possible decision. Best decisions are then identified as those with the lowest expected cost or highest expected benefit values.

For two decades, I have worked in risk analysis on both sides of the management/research fence in a federal land-management agency in areas of wildlife and ecosystem conservation (e.g., Marcot et al. 2006). I can attest that this classical risk-management framework, as applied to public land and natural resource management, just doesn't work as portrayed in the textbooks. Here's why, and here are some practical opportunities for more successfully integrating science and management in this arena.

## The roadblocks to risk analysis and risk management

First, alternative decisions are seldom discrete, exclusive, independent, and identified *a priori*, as assumed in risk-analysis methods. Rather, decisions are often defined and made in combination, are dependent on other decisions, and are made only after initial social reactions or environmental outcomes are ascertained.

Second, what is "at risk" in risk management often means very different things to scientists and managers. Scientists might craft a risk analysis to predict the likelihood of viability of an endangered species, for example, whereas a manager might (legitimately) consider political fallout, social response, or opportunities for future funding to be what is at risk.

Third, scientists and managers are usually willing to accept different degrees and types of uncertainty. Uncertainty is one hallmark of scientific expression, but managers—like politicians, the press, the courts, and the public—often want clear, unambiguous answers. To scientists, the scientific method imposes the burden of proof of some effect (such as a management decision on a fragile ecosystem or species) on falsification of null hypotheses stated as no effect, whereas managers may impose the burden of proof on definitive evidence that there *is* such an effect. To some managers, absence of evidence is evidence of absence (or of no adverse effect from management activities), whereas under the scientific method, absence of falsification of the null hypothesis does *not* constitute evidence of no effect.

Fourth, the values (or utilities) of each outcome can be measured and interpreted in vastly different ways and often are not independent, as assumed in risk-analysis models. Utilities also typically exclude externalities and indirect pecuniary costs and effects. There are major problems in quantifying non-economic social costs and benefits in parity with economic ones, and most risk-analysis methods cannot combine unlike units of measure of utilities such as dollars and psychological satisfaction ratings.

Fifth, managers seldom articulate their decision criteria—especially prior to making a decision—perhaps, in part, out of understandable reluctance to reveal their personal values and attitude toward risk. Equally so, modelers seldom articulate the major assumptions and weaknesses of their risk-analysis models—which may similarly reflect a modeler's risk attitudes and personal values and biases—and seldom explicitly test how such assumptions affect model performance, outcomes, and interpretations.

Sixth, managers seldom disclose or even know their own risk attitudes, and seldom attempt to determine them through rigorous methods, although best or optimal decisions can vary greatly under different risk attitudes. Further, managers might not adjust their risk attitude to better match that of the public they serve, in part because the risk attitude of the public is also often unknown or is highly diverse and quite variable among interest groups.

Seventh, estimates of probabilities of outcomes for a given management decision are seldom validated by the risk modeler or corrected with monitoring data. Managers are often reluctant to incorporate monitoring as an integral element in decisions, more typically tacking monitoring tasks and objectives onto the end of a decision—and only if funding and political expediency permit.

Finally, expert knowledge compiled to parameterize a risk-assessment model can be biased, incomplete, contradictory, and just plain faulty. Most risk-analysis models entail at least some use of expert opinion. However, expert understanding, such as of ecosystems and sensitive species, often is rudimentary. Compounding of variables, propagation of error, and non-linear or chaotic behavior of systems can be nearly impossible to calculate and predict with any accuracy but can greatly affect the magnitude and direction of outcomes.

## Some ways around the roadblocks

So what are the scientists (risk modelers, risk analyzers) and managers (decision-makers) to do? Here are some suggestions for removing the roadblocks and helping scientists and managers to better communicate.

In recent years, a number of new, structured, decision-aiding tools and methods have been developed (e.g., Lynam et al. 2002) that ease some of the strict assumptions of traditional risk-analysis modeling approaches. For example, several formal methods can efficiently address multi-objective decision-making, such as multi-attribute utility theory (MAUT; Merkhofer et al. 1997), goal and analytic hierarchy process (AHP; Vargas 1990), multiple-criteria decision-making (MCDM; Mendoza and Prabhu 2000), and others. Most of these approaches are relatively simple and entail a general process of articulating objectives, identifying criteria for rating each objective, listing alternative possible decisions, quantifying performance levels for each combination of decision and objective, quantifying or weighting preferences (priorities) for each objective, ranking the alternative decisions by potential outcomes, and doing sensitivity analysis of the decisions by altering weights or criteria. The goal and analytic hierarchy procedures follow a similar approach by prioritizing objectives, estimating probabilities of various alternative decisions meeting the objectives, and filtering out decisions that have unacceptably low probabilities, given risk-attitude criteria of acceptability. Another value to such approaches is that they are able to effectively incorporate adaptive learning and monitoring information (Holz et al. 2006).

Following such rigorous decision-assessment techniques can also bring clarity to issues of mixed interpretations in regard to what is deemed to be "at risk," and of how utilities and values of decision outcomes are depicted (Ohlson and Serveiss 2007). The new methods also can deal with the problem of disparate units of measure among different utility outcomes, and can help to structure clear articulation of decision criteria, risk attitudes, and model assumptions.

Other methods have been developed to rigorously solicit and depict expert knowledge in a repeatable and defensible manner, so that expert knowledge is not viewed as arbitrary personal opinion (Newberry 1994). Such techniques date to the early 1980s, with the emergence of classic expert systems in artificial-intelligence research, in which "knowledge engineering" methods were developed to capture knowledge of an expert in some domain. Similar approaches, such as the Delphi paneling process (MacMillan and Marshall 2006), can be used to rigorously compile knowledge and opinion from a group of experts (also see Geneletti 2005). Related methods can rigorously incorporate opinions of stakeholders to help define management objectives and indicators (Lahdelma et al. 2000).

Managers are becoming more adept at dealing with risk-analysis answers stated in terms of probabilities of outcomes. Bayesian risk-modeling approaches are now popular ways to depict decision outcomes as probabilities (Steventon et al. 2006). Still, scientists can do better to educate non-scientists on the scientific method, hypothesis testing, implications of scientific and prediction uncertainties, and ramifications of various types of errors (e.g., false positives and false negatives).

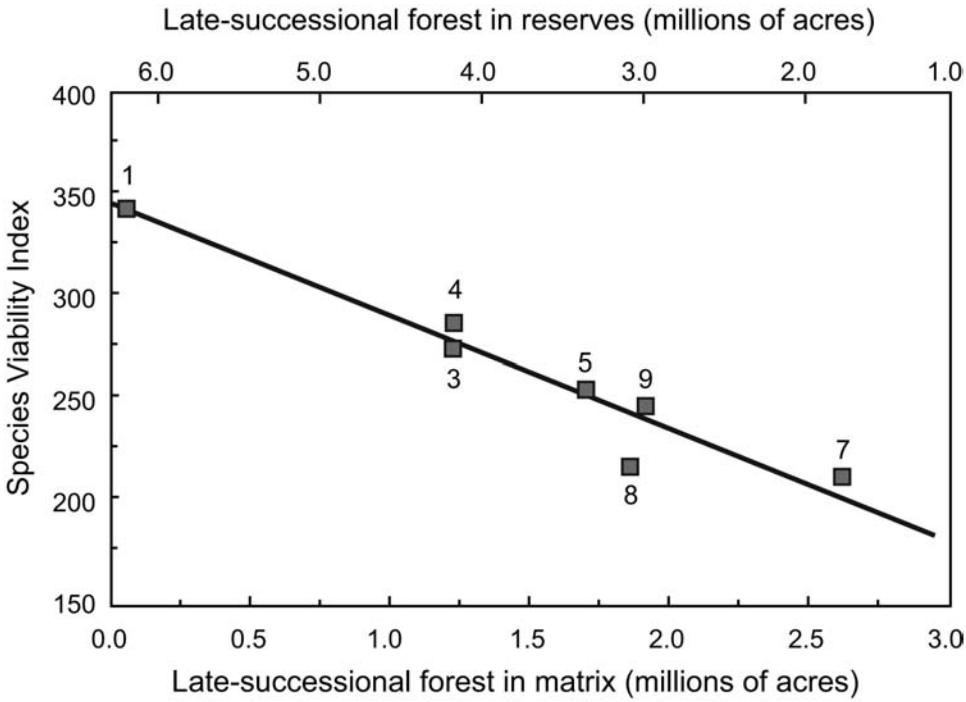
However, not much progress has been made, in the decision-analysis realm, on solving problems of covariance of variables, propagation of error, and erratic behavior of complex systems. The best approach to dealing with such messy problems is to decompose the problem set into modules or more-focused subsets of the problem using hierarchy theory (Ratzé et al. 2007), and build simpler, stepwise evaluations of the decision pathway. A complementary approach may be for the manager to consider the outcome of some similar problem already addressed, whether adequately solved or not. Other heuristic problem-solving tricks (e.g., Polya 1973) can be used to help guide difficult decisions.

Another, and perhaps the best, approach may be to consider some intractable problem from an entirely new perspective. An example might be trying to find some perfect balance between conservation of old-growth forests for northern spotted owls and exploitation of those forests for timber and other wood products. There may be no single solution that simultaneously satisfies risk attitudes of decision-makers, all public interests, legal mandates, and conservation objectives. Instead of viewing the problem as a zero-sum game with trade-offs, a more useful approach may entail breaking down the problem by geographic area, forest type, and land ownership, and then considering how to increase conservation without sacrificing other forest uses, or increase forest use without threatening conservation (Figure 1).

Finally, scientists and managers alike can make the best progress by incorporating learning into their risk analyses and risk decisions (McDaniels and Gregory 2004). Scientists can monitor changes in the system and incorporate new understanding, probabilities of outcomes, and unforeseen events into their analyses. Managers can view decisions as learning opportunities by stating them as testable hypotheses and working with researchers to phrase the tests in a scientifically correct manner.

The future is bright for applying new decision-assessment tools for aiding risk management. Perhaps the most important

Figure 1. A typical trade-off scenario depicting lower expected viability of wildlife species associated with late-successional forests (Y-axis) with increasing amount of that forest open to timber harvest in the "matrix" (lower X-axis) or with decreasing amount in reserves (upper X-axis). Shown are expected effects of seven planning alternatives (a modification of alternative 9 was eventually chosen as the basis for the Northwest Forest Plan in the Pacific Northwest, U.S.). Instead of viewing this relation as a zero-sum trade-off, however, the resourceful manager might explore how higher viability levels could be achieved from the same level of timber base (or forest reserves), such as comparing alternatives 4 and 3, and 9 and 8, which differ in their conservation guidelines. Source: FEMAT 1993.



decision to be made for true success will be for scientists and managers alike to commit to working together in a setting of honesty, openness, and mutual learning (Roux et al. 2006).

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