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BEST PRACTICES IN PREDICTION FOR DECISION-MAKING: LESSONS FROM THE ATMOSPHERIC AND EARTH SCIENCES

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Abstract. Predictions that result from scientific research hold great appeal for decision-makers who are grappling with complex and controversial environmental issues, by promising to enhance their ability to determine a need for and outcomes of alternative decisions. A problem exists in that decision-makers and scientists in the public and private sectors solicit, produce, and use such predictions with little understanding of their accuracy or utility, and often without systematic evaluation or mechanisms of accountability. In order to contribute to a more effective role for ecological science in support of decision-making, this paper discusses three ''best practices'' for quantitative ecosystem modeling and prediction gleaned from research on modeling, prediction, and decision-making in the atmospheric and earth sciences. The lessons are distilled from a series of case studies and placed into the specific context of examples from ecological science.

Key words: atmospheric sciences; best practices; decision-makers; earth sciences; prediction; quantitative ecosystem modeling.

INTRODUCTION

A cautionary tale

In February 1997, forecasters predicted that the Red River of the North would see flooding larger than at any time in modern history (Pielke 1999). At Grand Forks, North Dakota, forecasters issued a prediction that the flood would crest at 49 feet (~15.1 m). On 22 April 1997, at Grand Forks, the Red River crested at 54 feet (~16.6 m), inundating the communities of Grand Forks, North Dakota and East Grand Forks, Minnesota, causing up to US$2 billion in damages. In the aftermath of the flood, local, state, and national officials pointed to inaccurate flood forecasts as a cause of the disaster. With hindsight, a more reasoned assessment indicates that by any objective measure the accuracy of the forecasts was not out of line with historical performance. Instead, both forecasters and decision-makers failed to understand the uncertainty associated with the prediction and the implications of uncertainty for decision-making. Pielke (1999) provides a comprehensive assessment of the use and misuse of forecasts in the Grand Forks flood, including a discussion of alternative outcomes.

A review of past predictions shows that the U.S. National Weather Service predictions of flood crests in Grand Forks from 1982–1996 had a mean error of 10% of the predicted crest (Pielke 1999). In 1997, this mean error would have been 4.9 feet (1.51 m) of the 49 foot (15.1 m) prediction. We can never know what decision-makers in Grand Forks would have done with a more accurate understanding of the inherent uncertainty associated with the flood outlooks. However, it is clear that mistaken perceptions of the flood forecasts contributed to decisions that were not robust with respect to the realistic range of outcomes related to the flood.

In this case, the prediction process broke down, even though potentially useful information was available. This cautionary tale illustrates that when the prediction process is evaluated according to criteria of good decisions, and not good predictions, the role of prediction and modeling in decision-making has complex and perhaps counterintuitive elements. In the case of the 1997 Grand Forks flood, a ''good'' prediction product, as measured by the criterion of accuracy, arguably contributed to bad decisions. This experience and others like it (see the case studies in Sarewitz et al. 2000) should give pause to anyone in the sciences seeking to develop models and predictions as an aid to decision-making.

Prediction in science, prediction for decision

The allure of prediction is strong. In science, many view predictive skill to be the ultimate confirmation of theory and understanding. In decision-making, predictive capabilities appear to offer the promise of control over the future. The twin goals of understanding and control have proved tempting attractions for the sciences of recent decades. Considerable public resources have been invested in programs of prediction justified by simultaneous scientific and policy objectives in ar-

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eas such as global change, earthquakes, nuclear waste disposal, asteroid impacts, flooding, weather, beach erosion, etc. Ecological science, according to some, is now ready to join this bandwagon of research programs focused on developing predictive knowledge as a guide to decision-making. For example, a recent workshop reported ''an evolving science of ecological forecasting is beginning to emerge and could have an expanding role in policy and management'' (Clark et al. 2001: 657). The report defines ecological forecasting as ''the process of predicting the state of ecosystems, ecosystem services, and natural capital, with fully specified uncertainties, . . . contingent on explicit scenarios for climate, land use, human population, technologies, and economic activity'' (Clark et al. 2001:657).

As a contribution to learning across disciplines, this paper summarizes several important lessons as ''best practices'' from experience in prediction in the earth and atmospheric sciences in support of decision-making (Sarewitz et al. 2000). Specifically, an evaluation of prediction in 10 case studies in the earth and atmospheric sciences (weather, flooding, asteroid impacts, earthquakes, beach erosion, water quality, nuclear waste disposal, hydrocarbon reserves, acid rain, and climate change) provides a set of lessons for the effective production and use of predictive knowledge. This paper proceeds by summarizing three ''best practices'': effective use of predictions results from a focus on predictions as one component in the process of decision-making, prediction for science and prediction for policy should not be conflated, and prediction products are difficult to evaluate and easy to misuse.

Three Lessons Learned

Lesson 1: Effective use of predictions results from focusing on prediction as one component in the process of decision-making

As the case of flood forecasts in Grand Forks illustrates, the successful use of predictions (i.e., making good decisions) depends upon much more than just ''good'' predictive information. The prediction process must include the participants, perspective, institutions, values, resources, and other factors that together determine the prediction enterprise and how the prediction enterprise contributes to public demands for action or tools with respect to the issues that they bring to the attention of decision-makers. Weather forecasts have value not because they are by any means perfect, but because the vast experience of users of those predictions fosters the incorporation of them into decision routines (Hooke and Pielke 2000).

Though frequently generated, policymakers frequently overlook, neglect, or are unable (for technical, institutional, or political reasons) to use potentially useful ecological predictions. For instance, cleanup and environmental mitigation of exotic zebra mussels in the Great Lakes costs US$20–100 million annually. Though an early report documented the potential spread of zebra mussels into the region (Bio-Environmental Services 1981), policymakers failed to act upon the report, not because it was inaccurate or too complex, but because decision-makers involved in the regulatory process had little experience considering such ecological forecasts (Clark et al. 2001). With the advantage of hindsight, a result was that potentially useful ecological knowledge was not integrated into decision-making (Clark et al. 2001).

Consider another example. Ecologists have known since the 1940s that fire is an integral component of many ecosystems and fire histories for many forests are well known (Millspaugh et al. 2000, Mohr et al. 2000, Veblen et al. 2000). Recent additions to federal wildland fire policy recognize that ''the role of wildland fire as an essential ecological process and natural change agent will be incorporated into the planning process,'' and that ''fire management plans and activities are based upon the best available science,'' (U.S. Department of Agriculture and U.S. Department of Interior 1995). Evolution of the traditional forest fire suppression approach in favor of a new let-it-burn approach was based on well-established knowledge about fire and fuel loads. However, as a result of the history fire suppression, fuel loads were at record levels in many forests. Thus, similar to the situation described by Peterson et al. (2003), the decision to adopt a new approach contributed to the recent spate of catastrophic forest fires, most notably the Yellowstone fires of 1988, the South Canyon Fire during 1994, and the Cerro Grande fire of 2000.

Like the Grand Forks example, these examples related to ecological science point to prediction as one component in a broader process. This broader prediction process can be thought of as three integrated subprocesses (Sarewitz et al. 2000): a research process that includes the fundamental science, observations, etc., as well as forecasters' judgments and the organizational structure which go into the production of predictions for decision-makers; a communication process that includes both the sending and receiving of information; and a choice process that includes the incorporation of predictive information in decision-making. Of course, decisions are typically contingent upon many factors other than predictions. Often, some mistakenly ascribe a linear relation to these processes, and consider them to be independent of one another. From the perspective of decision-making, these three processes are instead better thought of as components of a broader prediction process, with each of the subprocesses taking place in parallel, with significant feedback and interrelations between them. (A note on nomenclature: here, as in Sarewitz et al. (2000), we use the term ''prediction process'' to acknowledge the complexity (i.e., multiple, parallel, decision and social processes) associated with the connections of scientific prediction and policy.)

Peter Drucker has written an eloquent description of the modern organization that applies equally well to the prediction process:

> *Because the organization is composed of specialists, each with his or her own narrow knowledge area, its mission must be crystal clear. . . otherwise its members become confused. They will follow their specialty rather than applying it to the common task. They will each define ''results'' in terms of that specialty, imposing their own values on the organization.*
>
> —Drucker (1993:54)

Drucker continues with an apt metaphor:

> *The prototype of the modern organization is the symphony orchestra. Each of 250 musicians in the orchestra is a specialist, and a high-grade one. Yet by itself the tuba doesn't make music; only the orchestra can do that. The orchestra performs only because all 250 musicians have the same score. They all subordinate their specialty to a common task.*
>
> —Drucker (1993:55)

In the process of modeling and prediction in support of decision-making, success according to the criteria of any subset of the three processes does not necessarily result in benefits to society, just as the success of any one section of an orchestra does not imply good music.

Consider the following examples in light of Drucker's metaphor:

1) The case of developing skillful predictions of earthquakes in the Parkfield region of California brought together seismologists with local officials and emergency managers (Nigg 2000). A result was better communication among these groups and overall improved preparation for future earthquakes. In this case, even though the predictions themselves could not be shown to be skillful, the overall process worked because it identified alternatives to prediction of specific earthquakes (e.g., robust engineering design) that have led to decisions that are expected to reduce the impacts of any future earthquakes in this region. The key to this success was recognition of the actual predictive capacity of earthquake science.

2) The case of global climate change may be in the early stages of what was documented in the case of earthquakes (Rayner 2000). Policy-making focused on prediction has run up against numerous political and technical obstacles, meanwhile alternatives to prediction—such as no-regrets adaptation and mitigation policies (i.e., reducing societal vulnerability to extreme events and fostering national energy independence)–have become increasingly visible. The prediction process can be said to work if the goals of climate policy—to reduce the impacts of future climate changes on environment and society—are addressed, independent of whether century-scale climate forecasts prove to be accurate (Sarewitz and Pielke 2000).

3) The case of nuclear waste disposal has also evolved from one in which decision making focused first on developing skillful predictions to one in which decision-making focused instead on actions that would be robust under various alternative futures (Metlay 2000). In this case, the policy problem of storing nuclear waste for a very long time (and associated uncertainties) was addressed via decision-making (i.e., engineering), not accurate prediction over thousands of years.

4) Adaptive management encourages land managers to experiment rather than strictly adhere to fixed objectives (Lee 1999). Experimental implementation of ecological predictions coupled with detailed monitoring and adaptive responses is a model that encourages close collaboration between ecologists and land managers, and could lead to successful integration of ecological science with environmental management in a similar fashion to what has been document in other cases (cf. Brunner and Clark 1999). This illustrates the importance of adaptability and flexibility in management decision processes rather than the accuracy of predictions.

From this varied set of experiences, a lesson that can be found for decision-makers is that one is, in most cases, more likely to reduce uncertainties about the future through a focus on decision-making rather than through a focus on prediction. Key to this shift in focus is an accurate calibration by decision-makers of what prediction can and cannot do (Clark et al. 2001, 2003, Ellner and Fieberg 2003). The criteria for evaluating a prediction are thus directly related to the purposes for which it is to be used.

Lesson 2: Don't conflate prediction for science and prediction for policy

The work of most scientists falls squarely within the research-process component of the prediction process. It may seem intuitive that success in ecological research—independent of whatever happens in the other processes—would necessarily lead to predictions of great utility to policymakers, but, as discussed above, a ''good'' prediction alone is frequently inadequate to lead to good decision outcomes. And, in a field such as ecology, understanding the ''goodness'' of prediction products is fraught with difficulties due to the complexity of the systems under investigation and the lack of extensive experience with making predictions. Thus, it is important to understand how the criteria of good science may or may not fit with the criteria of good decisions. Two distinctions raised here are the differences between prediction for science and prediction for policy, and differences between policy advocacy and policy research.

Because prediction plays multiple roles within the scientific enterprise, there exist obstacles to the effective use of predictive information in decision-making (Pielke 2003). For instance, some assert that predictive capabilities are what make science ''scientific'' and are the ultimate test of knowledge, while others view prediction as simply a heuristic tool for advancing knowledge (cf., Sarewitz and Pielke 1999, Oreskes 2000, Pielke 2002). In ecology, Holling (1995) identifies ''two streams of science'' in conflict.

> *The first stream is a science of parts . . . It emerges from the traditions of experimental science, where a narrow enough focus is chosen to pose hypothesis, collect data, and design critical tests for the rejection of invalid hypotheses. The goal is to narrow uncertainty to the point where acceptance of an argument among scientific peers is essentially unanimous.*
>
> —Holling (1995:13)

The second stream is a science of the integration of parts.

> *It uses the results and technologies of the first but identifies gaps, develops alternative hypotheses and multivariate models, and evaluates the integrated consequence of each alternative by using information from planned and unplanned interventions in the whole system that occur or are implemented in nature. The premise of this second stream is that knowledge of the system we deal with is always incomplete. Surprise is inevitable.*
>
> —Holling (1995:13)

These two streams of science—the first focused on prediction as hypothesis testing and the second on characterizing irreducible uncertainties—imply dramatically different approaches to research, and by extension to the relation of research to decision-making objectives. Conflation or confusion of these approaches can lead to bad science, misuse and abuse of scientific information, and bad decisions (Bankes 1993, Sarewitz and Pielke 1999, Pielke 2003).

Consider the case of intentional species introductions for food, fuel, and fiber, which have been, for the most part, very successful according to the goals of each introduction. However, spectacular historical failures (e.g., kudzu in the southeastern United States and rabbits in Australia) resulted from a failure to fully appreciate potential ecosystem impacts. The current debate on the use of genetically modified crops is similar in that it is an attempt to evaluate the likelihood of unintended consequences of purposive human actions (Merton 1936). Developing ecological knowledge to evaluate the threat of introduction of genetically modified organisms clearly requires input from both of Hollings' ''streams'' of ecological science. For example, understanding plant hybridization potential and resulting plant fitness fall squarely within the realm of Hollings' first stream, but impacts of genetically modified corn pollen on nontarget species, such as monarch butterflies (Losey et al. 1999), cannot be predicted accurately by following this approach. Since large sources of pollen—such as an agricultural field—can transmit pollen, and corresponding genetic information, across a broad region, other approaches may be necessary to evaluate potential impacts (Hails 2000). Ultimately, successful decision making may result from clear-eyed recognition that accurate prediction of the long-term environmental and human effects of genetically modified organisms is not possible and that alternatives to prediction should be sought in the policy process.

For scientists seeking to venture more deeply into the forest of policy relevancy, it is also important to distinguish political advocacy from policy research. Political advocacy seeks to reduce the degrees of choice available to decision-makers, often focusing on one particular policy alternative. Policy research, in contrast, seeks to expand the alternatives before decision-makers to allow for greater freedom of choice (Pielke 2002). Science can be used (or misused) in support of advocacy to focus decision-maker attention on a particular policy alternative, or in support of generating a wider range of alternatives that may allow for progress to be made in situations of gridlock or intractability. Scientists often speak of ''reducing uncertainty'' in understanding while policy advocates seek to ''reduce uncertainty'' in decision outcomes. These different definitions of ''reducing uncertainty'' are often conflated in policy debate as if the former necessarily implies the latter. This would be a misinterpretation of both science and policy, as in every case a range of policy alternatives is consistent with any particular level of scientific understanding or uncertainty.

For example, within the scientific community, the debate over the relationship between biodiversity and ecosystem function is, on the surface, a debate on a very complex scientific issue (see Tilman 1996, 1997, Huston 1997, Wardle 1999). However, advocates of one policy or another promote only the scientific information that supports their own objective whether it is species preservation or easing land use restrictions. The argument is often less about science than about different philosophical approaches to ecosystem management, including the aesthetic, spiritual, and ethical value of biodiversity. In this sense, the biodiversity debate places a thin veneer of science over a thick underbody of policy and politics (Guterman 2000).

Advocates on one side or another of debates like biodiversity or climate change frequently point to scientific certainty (or consensus) as a necessary threshold for policy action. In reality, decision-making can (and does) occur at any level of uncertainty. Understanding uncertainty and the range of policy alternatives consistent with such understanding are likely more effective contributions to decision-making than seeking to narrow uncertainties in science or decision outcomes (Pielke 2001). For scientists seeking to place their work into the context of policy, it is therefore important to exercise caution in engaging in political advocacy if decision-making would instead benefit from research that expands, rather than limits decision alternatives.

Lesson 3: Prediction products are difficult to evaluate and easy to misuse

When forecasters issue a prediction there is a considerable challenge for users to understand what the prediction actually means (Sarewitz et al. 2000). For example, Murphy et al. (1980) document that, when forecasters issue a forecast of 70% chance of rain, people typically understand what ''70%'' means and what ''rain'' means but they do not know whether the forecast refers to a 70% chance of rain at each point in the forecast zone, or that 70% of the area of the zone with receive rain with 100% probability, or other possible interpretations.

Even in situations where there is no ambiguity about the predicted event, there remains a considerable challenge facing users in understanding what the prediction actually means. Take, for example, the predictions of maximum high temperature issued by the Hydrological Prediction Center (HPC) of the NOAA National Centers for Environmental Prediction. HPC forecast verification provides the mean errors in maximum temperature forecasts for predictions made three, four, five, six, and seven days in advance (available online).[4] For example, in 2000, the mean error for maximum temperature forecasts three days into the future was a little more than 4.5°F (~2.5°C). For forecasts of maximum temperature seven days into the future made in the same year, the mean error was slightly more than 6.5°F (~3.6°C). Thus, while a prediction of, say, 70°F three days hence and a prediction of 70°F seven days hence refer to the exact same event, they have very different meanings because of the different level of empirical uncertainty in the forecast. Whether or not those different meanings would be important to a particular forecast user depends upon the specific context in which the forecast is being employed (e.g., planning a picnic or buying an energy supply option). Whether the forecast is worth using would depend upon the decision context as well as other available information, such as the mean absolute error associated with using naïve prediction methods, such as climatology or persistence.

The complexity of ecological processes in the context of broader processes of decision-making makes understanding (by both scientists and decision-makers) of predictive information challenging. For example, the Cerro Grande fire disaster of 2000 began as a prescribed fire with an approved fire plan, but the fire burned more than 44 times the intended area, destroyed 235 homes, and threatened Los Alamos National Laboratory (Lonnie et al. 2000). Sources of confusion included underrating of fire complexity, misuse of the fire complexity rating system, and different fire complexity rating systems employed by different government agencies (Lonnie et al. 2000). *The New York Times* reported that ''Results from a preliminary Department of the Interior investigation laid the blame not on the precision of the data or the accuracy of the calculation but on matters of human judgment'' (Johnson 2000). Thus, even accurate information communicated using well-established systems is subject to misinterpretation.

Three important considerations in the production of ''good'' predictions in the context of the broader prediction process are accuracy, sophistication, and experience (Pielke 2003).

Accuracy.—Accuracy is important because ''on balance, accurate forecasts are more likely than inaccurate forecasts to improve the rationality of decision making'' (Ascher 1979:6). With a few exceptions, once a forecast is produced and used in decision-making, few ever look back to assess its accuracy. In ecology, understanding what constitutes forecast accuracy should itself comprise a vigorous area of research since evaluating the goodness of ecological forecasts is problematic for several reasons. First, simply comparing a prediction with an actual event does not provide enough information with which to evaluate its performance (Murphy 1997). A more sophisticated approach is needed. Thus, predictions should be evaluated in terms of their ''skill,'' defined as the improvement provided by the prediction over a naïve forecast, i.e., such as that which would be used in the absence of the prediction. Second, an ecological prediction relevant to decision-making may ''falsify'' itself if decision-makers act in response to the forecast as demonstrated by Peterson et al. (2003). Third, unlike weather forecasts for which there is an enormous body of experience, many ecological forecasts will have very few or a single case. Understanding outcomes in the context of uncertainty and chance will mean understanding accuracy itself will be highly uncertain.

Sophistication.—Decision-makers sometimes believe that a more sophisticated prediction methodology will lead to greater predictive skill, i.e., given the complexity of the world, a complex methodology should perform better. In reality, the situation is not so clear cut. An evaluation of the performance of complex models has shown that ''methodological sophistication contributes very little to the accuracy of [predictions]'' (Ascher 1981:258, see also Keepin 1986). Oreskes (2002) defines a ''complexity paradox'' as follows:

> *The more complex a model is—the more different objects and interactions it encompasses—the more open it is. . . . This might suggest that simpler models are better—and in some cases no doubt they are—but in ecosystems modeling we don't want to abandon complexity, because we believe that the systems we are modeling are in fact complex. . . . Indeed, in many cases it is the very complexity of the systems that has inspired us to model them in the first place—*

[4] URL: ⟨http://www.hpc.ncep.noaa.gov/html/hpcvrftxt.html⟩

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to try to understand the ways in which the numerous parts of the system interact. This leads to a paradox: the closer the model comes to capturing the full range of processes and parameters in the system being modeled, the more difficult it is to ascertain whether or not the model is correct. The more we strive for realism by incorporating as many as possible of all the different processes and different input parameters that we believe to be operating in the system, the more open the model becomes, and the more difficult it is for us to know if our tests of the model are meaningful.

—Oreskes (2002)

A lesson for decision-makers is that a sophisticated prediction methodology (or by extension, the resources devoted to development of predictions) does not necessarily guarantee predictive or decision success, and in some cases decision-making may benefit from simple exploratory methodologies (cf. Bankes 1993). More sophisticated models often suffer from inadequate or incomplete quantification of parameters or parameter uncertainty that has only recently been overcome (Clark et al. 2003, Ellner and Fieberg 2003). Because complex models often require significant resources (computation, human, etc.), a trade-off invariably results between producing one or a few realizations of the complex model and many runs of a simpler, less intensive version of the model. This is one area where ecologists no doubt have important lessons to share with the broader community of scientific modelers.

Experience.—In weather forecasts, society has the best understanding of prediction as a product. Consider in the United States the National Weather Service issues more than 10 million predictions every year to hundreds of millions of users. This provides a vast basis of experience on which users can learn, through trial and error, to understand the meaning of the prediction products that they receive. Of course, room for confusion exists. People can fail to understand predictions for record events for which there is no experience, as in the Grand Forks case, or even a routine event being forecast (e.g., 70% chance of rain). But experience is essential for effective decision-making, and most decision-makers have little experience using models or their products. Erev et al. provide a useful analogy:

Consider professional golfers who play as if they combine information concerning distance and direction of the target, the weight of the ball, and the speed and direction of the wind. Now assume that we ask them to play in an artificial setting in which all the information they naturally combine in the field is reduced to numbers. It seems safe to say that the numerical representation of the information will not improve the golfer's performance. The more similar are the artificial conditions we create to the conditions with which the golfers are familiar, the better will be their performance. One can assume that decision making expertise, like golf expertise, is improved by experience, but not always generalized to new conditions.

—Erev et al. (1993:92)

The importance of experience does not necessarily limit the usefulness of prediction products in decision-making, but it does underscore the importance of the decision context as a critical factor in using the output of integrative models (cf. Stewart et al. 1997, Nicholls 1999).

How the scientific community presents prediction products to decision-makers can influence how those decision-makers view science more generally. Considering the following extended example:

In Brazil, scientists are not the only social group offering predictions of El Niño; rain prophets also promote their ability to forecast seasons of rain and drought. On a statistical basis, the scientists probably produce more accurate forecasts than most of the rain prophets. However, public interactions with the two communities suggest that the overall utility of the scientific predictions for public choices may be considerably more problematic because the relationship between the scientists and the public leaves the public with no way of interpreting how much they should trust the scientists' predictions. The rain prophets may do a lousy job of predicting the climate, but people know that and so are quick to forgive them for being wrong and rarely inclined to risk much on their predictions. On the other hand, the scientific predictions are often treated insufficiently skeptically and great risks have been taken. As a consequence, when the scientific predictions are wrong they can produce a significant backlash. After such an event, the public may end up too skeptical of the scientists. Without the advantage of well-established cultural traditions and practices that enable them to determine accurately how much to trust scientists, people can easily lapse into being either overly-critical and under-critical of scientific information. Do the social networks yet exist that will enable people to take up and integrate [climate] *predictions into their choices with sufficient, but not overly much skepticism? Probably not.*

—Miller (1998:30)

This example illustrates the difficulties associated with understanding prediction simply as an information product. These difficulties can reflect back upon the scientific community and result in a loss of public or political support, if scientists are not careful to manage expectations of what role predictions might play in decision-making processes. The allure of justifying prediction in both scientific and policy terms weighs against realistic expectation setting, particularly when decision-makers look to science (with funding) to "solve" complex and politically sensitive problems.

Conclusion

Undoubtedly, meeting many current and future environmental challenges will demand the judicious integration of ecological science with needs of decision-making. The ''best practices'' discussed above illustrate a range of knowledge on the effective use of predictions and limits to predictions in decision-making from considerable experience in the earth and atmospheric sciences. All sciences could better meet their potential contributions to decision-making if the lessons of experience are incorporated into future understanding and action at the interface of science and decision-making. Institutional mechanisms, both within science and in the political process that governs science, for rewarding good, policy-relevant predictions—or even better, prediction processes—are rare, but are necessary if science is to systematically and beneficially contribute to the needs of decision-makers.

Literature Cited

Ascher, W. 1979. Forecasting: an appraisal for policymakers. Johns Hopkins University Press, Baltimore, Maryland, USA.

Ascher, W. 1981. The forecasting potential of complex models. Policy Sciences **13**:247–267.

Bankes, S. 1993. Exploratory modeling for policy analysis. Operations Research **41**:435–449.

Bio-Environmental Services. 1981. The presence and implications of foreign organisms in ship ballast waters discharged into the Great Lakes. Volumes 1 and 2. Water Pollution Control Directorate, Environmental Protection Service, Environment Canada, Ottawa, Ontario, Canada.

Brunner, R. D., and T. Clark. 1997. A practice-based approached to ecosystem management. Conservation Biology **11**:48–58.

Clark, J. S. 2003. Uncertainty and variability in demography and population growth: a hierarchical approach. Ecology **84**:1370–1381.

Clark, J. S., et al. 2001. Ecological forecasts: an emerging imperative. Science **293**:657–660.

Drucker, P. 1993. Post-capitalist society. Harper Collins, New York, New York, USA.

Ellner, S. P., and J. Fieberg. 2003. Using PVA for management despite uncertainty: effects of habitat, hatcheries, and harvest on salmon. Ecology **84**:1359–1369.

Erev, I., G. Bornstein, and T. S. Wallsten. 1993. The negative effect of probability assessments on decision quality. Organizational Behavior and Human Decision Processes **55**: 78–94.

Guterman, L. 2000. Have ecologists oversold biodiversity? Chronicle of Higher Education **47**:A24–A26.

Hails, R. S. 2000. Genetically modified plants—the debate continues. Trends in Ecology and Evolution **15**:14–17.

Holling, C. S. 1995. What barriers? What bridges? Pages 3–36 *in* L. H. Gunderson, C. S. Holling, and S. L. Light, editors. Barriers and bridges to the renewal of ecosystems and institutions. Columbia University Press, New York, New York, USA.

Hooke, W. H., and R. A. Pielke, Jr. 2000. Short-term weather prediction: an orchestra in search of a conductor. Pages 61–83 *in* D. Sarewitz, R. A. Pielke, Jr., and R. Byerly, editors. Prediction: decision making and the future of nature. Island, Washington, D.C., USA.

Huston, M. A. 1997. Hidden treatments in ecological experiments: re-evaluating the ecosystem function of biodiversity. Oecologia **110**:449–460.

Johnson, G. 2000. Chaos theory; harness fire? Mother Nature begs to differ. New York Times, 21 May 2000, Section 4, page 1.

Keepin, B. 1986. Review of global energy and carbon dioxide projections. Annual Review of Energy **11**:357–392.

Lee, K. H. 1999. Appraising adaptive management. Conservation Ecology **3**:3.

Lonnie, T. P., T. I. Thompson, J. A. Loach, T. Delfin, and C. S. Przybylek. 2000. Cerro Grande prescribed fire investigation report. National Interagency Fire Center, Boise, Idaho, USA.

Losey, J. E., L. S. Rayor, and M. E. Carter. 1999. Transgenic pollen harms monarch larvae. Nature **399**:214–214.

Merton, R. 1936. The unanticipated consequences of social action. American Sociological Review **1**:894–904.

Metlay, D. 2000. From tin roof to torn wet blanket: predicting and observing groundwater movement at a proposed nuclear waste site. Pages 199–228 *in* D. Sarewitz, R. A. Pielke, Jr., and R. Byerly, editors. Prediction: decision making and the future of nature. Island, Washington, D.C., USA.

Miller, C. 1998. Extending assessment communities to developing countries. Environment and Natural Resources Program Discussion Paper E-98–15. Kennedy School of Government, Harvard University, Cambridge, Massachusetts, USA.

Millspaugh, S. H., C. Whitlock, and P. J. Bartlein. 2000. Variations in fire frequency and climate over the past 17 000 yr in central Yellowstone National Park. Geology **28**: 211–214.

Mohr, J. A., C. Whitlock, and C. N. Skinner. 2000. Postglacial vegetation and fire history, eastern Klamath Mountains, California, USA. Holocene **10**:587–601.

Murphy, A. H. 1997. Forecast verification. Pages 19–74 *in* R. Katz and A. Murphy, editors. Economic value of weather and climate forecasts. Cambridge University Press, Cambridge, UK.

Murphy, A. H., S. Lichtenstein, B. Fischhoff, and R. L. Winkler. 1980. Misinterpretations of precipitation probability forecasts. Bulletin of the American Meteorological Society **61**:695–701.

Nicholls, N. 1999. Cognitive illusions, heuristics, and climate prediction. Bulletin of the American Meteorological Society **80**:1385–1397.

Nigg, J. 2000. Predicting earthquakes: science, pseudoscience and public policy paradox. Pages 135–156 *in* D. Sarewitz, R. A. Pielke, Jr., and R. Byerly, editors. Prediction: decision making and the future of nature. Island, Washington, D.C., USA.

Oreskes, N. 2000. Why predict? Historical perspectives on prediction in the earth sciences. Pages 23–40 *in* D. Sarewitz, R. A. Pielke, Jr., and R. Byerly, editors. Prediction: decision making and the future of nature. Island, Washington, D.C., USA.

Oreskes, N. 2003. The role of quantitative models in science. Cary Conference IX: Understanding ecosystems: the role of quantitative models in observations, synthesis, and prediction. *In press.*

Peterson, G. D., S. R. Carpenter, and W. A. Brock. 2003. Uncertainty and management of multistate ecosystems: an apparently rational route to collapse. Ecology **84**:1403–1411.

Pielke, R. A., Jr. 2001. Room for doubt. Nature **410**:151.

Pielke, R. A., Jr. 2002*a*. Policy, politics and perspective. Nature **416**:367–368.

Pielke, R. A., Jr. 2003. The role of models in prediction for decision. Cary Conference IX: understanding ecosystems: the role of quantitative models in observations, synthesis, and prediction. *In press.*

Pielke, R. A., Jr. 1999. Who decides? Forecasts and responsibilities in the 1997 Red River floods. Applied Behavioral Science Review **7**:83–101.

Rayner, S. 2000. Prediction and other approaches to climate change policy. Pages 269–296 *in* D. Sarewitz, R. A. Pielke, Jr., and R. Byerly, editors. Prediction: decision making and the future of nature. Island, Washington, D.C., USA.

Sarewitz, D., and R. A. Pielke, Jr. 1999. Prediction in science and policy. Technology in Society **21**:121–133.

Sarewitz, D., and R. A. Pielke, Jr. 2000. Breaking the global warming gridlock. The Atlantic Monthly, July 2000, pp. 55–64.

Sarewitz, D., R. A. Pielke, Jr., and R. Byerly, editors. 2000. Prediction: science, decision making, and the future of nature. Island, Washington, D.C., USA.

Stewart, T. R., P. J. Roebber, and L. F. Bosart. 1997. The importance of the task in analyzing expert judgment. Organizational Behavior and Human Decision Processes **69**: 205–219.

Tilman, D. 1996. Biodiversity: population versus ecosystem stability. Ecology **77**:350–363.

Tilman, D., J. Knops, D. Wedin, P. Reich, M. Ritchie, and E. Siemann. 1997. The influence of functional diversity and composition on ecosystem properties. Science **277**:1300–1302.

U.S. Department of Agriculture and U.S. Department of the Interior. 1995. Federal wildland fire management policy and program review. Final report. National Interagency Fire Center, Boise, Idaho, USA.

Veblen, T. T., T. Kitzberger, and J. Donnegan. 2000. Climatic and human influences on fire regimes in ponderosa pine forests in the Colorado Front Range. Ecological Applications **10**:1178–1195.

Wardle, D. A. 1999. Is ''sampling effect'' a problem for experiments investigating biodiversity–ecosystem function relationships? Oikos **87**:403–407.