Chapter E.3

Contrast between Predictive and Vulnerability Approaches

Roger A. Pielke, Jr. · Thomas J. Stohlgren

While efforts to predict natural phenomena have become an important aspect of the Earth sciences, the value of such efforts, as judged especially by their capacity to improve decision making and achieve policy goals, has been questioned by a number of constructive critics. The relationship between prediction and policy making is not straightforward for many reasons. In practice, consolidative and exploratory models are often confused by both scientists and policy-makers alike, thus a central challenge facing the community is the appropriate use of such models and resulting predictions (Sarewitz and Pielke 1999).

Among the reasons for this criticism is that accurate prediction of phenomena may not be necessary to respond effectively to political or socio-economic problems created by such phenomena (for example, see Pielke et al. 1999). Indeed, phenomena or processes of direct concern to policy-makers may not be easily predictable or useful. Likewise, predictive research may reflect discipline-specific scientific perspectives that do not provide "answers" to policy problems since these may be complex mixtures of facts and values, and which are perceived differently by different policy-makers (for example, see Jamieson and Herrieck 1995).

In addition, necessary political action may be deferred in anticipation of predictive information that is not forthcoming in a time frame compatible with such action. Similarly, policy action may be delayed when scientific uncertainties associated with predictions become politically charged as in the issue of global climate change, for example (Rayner and Malone 1997).

Predictive information may also be subject to manipulation and misuse, either because the limitations and uncertainties associated with predictive models are not readily apparent or because the models are applied in a climate of political controversy and high economic stakes. In addition, emphasis on predictive sciences moves both financial and intellectual resources away from other types of research that might better help to guide decision making as, for example, incremental or adaptive approaches to environmental management that require monitoring and assessment instead of prediction (see Lee and Black 1993).

These considerations suggest that the usefulness of scientific prediction for policy making and the resolution of societal problems depends on relationships among several variables, such as the timescales under consideration, the scientific complexity of the phenomena being predicted, the political and economic context of the problem, and the availability of alternative scientific and political approaches to the problem.

In light of the likelihood of complex interplay among these variables, decision makers and scientists would benefit from criteria that would allow them to judge the potential value of scientific prediction and predictive modelling for different types of political and social problems related to Earth processes and the environment.

Pielke et al. (1999) provide the following six guidelines for the effective use of prediction in decision making.

1. Predictions must be generated primarily with the needs of the user in mind. For stakeholders to participate usefully in this process, they must work closely and persistently with the scientists to communicate their needs and problems.
2. Uncertainties must be clearly articulated (and understood) by the scientists, so that users understand their implications. Failure to understand uncertainties has contributed to poor decisions that then undermine relations among scientists and decision makers. But merely understanding the uncertainties does not mean that the predictions will be useful. If policy-makers truly understood the uncertainties associated with predictions of, for example, global climate change, they might decide that strategies for action should not depend on predictions (Rayner and Malone 1997).
3. Experience is an important factor in how decision makers understand and use predictions.
4. Although experience is important and cannot be replaced, the prediction process can be facilitated in other ways, for example by fully considering alternative approaches to prediction, such as "no-regrets" public policies, adaptation, and better planning and engineering. Indeed, alternatives to prediction must be evaluated as a part of the prediction process.

5. To ensure an open prediction process, stakeholders must question predictions. For this questioning to be effective, predictions should be as transparent as possible to the user. In particular, assumptions, model limitations, and weaknesses in input data should be forthrightly discussed. Even so, lack of experience means that many types of predictions will never be well understood by decision makers.
6. Last, predictions themselves are events that cause impacts on society. The prediction process must include mechanisms for the various stakeholders to fully consider and plan what to do after a prediction is made.

Scenarios of the future such as projections of climate change, forest production, animal migration, or disease spread are – by definition – subsets of all possible outcomes (Cohen 1996). Most projections have much in common with the typical five-day weather forecast on the nightly news:

- they are based on data from the recent past;
- they incorporate relatively few response variables (e.g. temperature and precipitation);
- they are more accurate for some response variables than others (i.e. minimum temperature versus precipitation amounts);
- no level of certainty or probability is provided or implied;
- short-term projections are typically more accurate than long-term projections; and
- their use for planning is limited to a narrowly defined set of questions (e.g. should snow ploughs be positioned near highways in anticipation of a snowstorm; Sarewitz et al. 2000).

Seasonal forecasts, such as those predicting greater or less precipitation over the next few months, are based on larger-scale phenomena such as ocean temperatures and jet stream patterns, but have additional limitations and uncertainties about the spatial and temporal accuracy of the projections (Glantz 2001).

There is more uncertainty behind long-term climate change scenarios with 30- to 100-year timeframes compared to seasonal forecasts. Long-term climate scenarios have considerably more limitations and higher levels of uncertainty due to coarse-scale spatial resolution, natural spatial and temporal variation, insufficient understanding of multiple climate forcings, longer-term biological physical feedbacks in the models, and lack of stochastic extreme events. Globally averaged results would be expected to be more reliable than local and regional results. Reliance on scenarios is reliance on predictions with all their limitations and uncertainties (Sarewitz et al. 2000).

The value of predictions for environmental decision-making therefore emerges from the complex dynamics of the prediction process, and not simply from the technical efforts that generate the prediction product (which are themselves an integral part of the prediction process).

An alternative to the scenario-prediction approach is to evaluate vulnerability based on a more comprehensive assessment of multiple stresses, multiple response variables, and their interactions. For example, natural ecosystems are often affected by multiple stresses including land-use change, loss of biodiversity, altered disturbance regimes, invasive non-indigenous species, pollution, and rapid climate change (Stohlgren 1999b). Land managers are concerned about many natural and cultural resources, local economies, and stakeholder concerns for specific resources. The interactions of the multiple stresses and response variables are important and urgent considerations. A warming climate, for example, might alter the competitive advantage of exotic annual grasses only if nitrogen from air pollution were available, grazing were limited, and forest canopies remained fairly open. The effects of decreased precipitation on aquatic biota might be more of a problem where water was over-subscribed, low flows were adversely affected by water diversion, and exotic fish inhabited the streams. Human-dominated and natural ecosystems, and their interacting components and processes, can rarely be assessed by evaluating stresses independently. It is often possible, however, to identify vulnerabilities or sensitivities in cases where prediction is impractical or impossible.

Vulnerability assessments, of course, also have limitations. Detailed information on stresses, resources, and interactions is often scant, resulting in increased uncertainty. In general, the level of uncertainty is constrained by focusing on short-term planning horizons and high priority issues at local and regional scales. However, a vulnerability assessment is easily made consistent with the needs of decision makers. It is not a new concept, and is variously referred to in the literature as "adaptive management", "vulnerability assessment", "boundedly rational decision making", and "successive incremental approximations".

An important first step in considering the implications for research and policy is to recognise the role of models and predictions for purposes of both science and action. Bankes (1993) defines two types of models, consolidative and exploratory, differentiated by their uses.

- A *consolidative model* seeks to include all relevant facts into a single package and use the resulting system as a surrogate for the actual system.

The canonical example is that of the controlled laboratory experiment (Sarewitz and Pielke 1999). Other examples, include weather forecast and engineering design models. Such models are particularly relevant to decision making because the system being modelled can be treated as being closed, i.e. one "in which all the components of the system are established independently and are known to be correct" (Oreskes et al. 1994). The creation of such a model generally follows two phases: first, model construction and evaluation and second, operational usage of a final product. Such models can be used to investigate diagnostics (i.e. "what happened?"), process ("why did it happen?"), or prediction ("what will happen?").

- An *exploratory model* – or what Bankes (1993) calls a "prosthesis for the intellect" – is one in which all components of the system being modelled are not established independently or are not known to be correct.

In such a case, the model allows for computational experiments to investigate the consequences for modelled outcomes of various assumptions, hypotheses, and uncertainties associated with the creation of and inputs to the model. These experiments can contribute to at least three important functions (Bankes 1993). First, they can shed light on the existence of unexpected properties associated with the interaction of basic assumptions and processes (e.g. complexity or surprises). Second, in cases where explanatory knowledge is lacking, exploratory models can facilitate hypothesis generation. Third, the model can be used to identify limiting, worst-case, or special scenarios under various assumptions of and uncertainty associated with the model experiment. The limiting "worst cases" generated in such a model are explorations of the boundaries of the universe of model outputs, and may or may not have significance for understandings of the real world. Frequently consolidative and exploratory models are confused in this regard. Such experiments can be motivated by observational data (e.g. econometric and hydrological models), scientific hypotheses (e.g. general circulation models), or by a desire to understand the properties of the model or class of models independent of real-world data or hypotheses.

- A shift in the culture of research is also needed. Research must be truly interdisciplinary (rather than multidisciplinary).

Assessing multiple stresses requires a broad spectrum of expertise without losing sight of the complex interactions among the sciences. Scientists must also learn to work interactively with stakeholders so that the highest priority needs are met first. To date, climate change research has been heavily focused at the global-scale and longer timeframes, as evidenced by the reliance on GCMs, projected changes in mean temperature and precipitation, and 100-year or double-CO_2 model timeframes. There is often a huge "disconnect" with local and regional stakeholders who have demanded a greater emphasis on near-future responses associated with extreme events, information on a full range of climate characteristics, and interactions from multiple environmental stresses that they deal with on a daily basis.

This suggests a rebalancing of priorities towards adaptation and vulnerability/sensitivity assessments; away from consolidative modelling and toward more exploratory efforts. Such research has the potential to contribute to a range of important societal needs.

When the prediction process is fostered by effective, participatory institutions, and when a healthy decision environment emerges from these institutions, the products of predictive science may even become less important. Earthquake prediction was once a policy priority; now it is considered technically infeasible, at least in the near future. However, in California the close, institutionalised communication among scientists, engineers, state and local officials, and the private sector has led to considerable advances in earthquake preparedness and a much decreased dependence on prediction. On the other hand, in the absence of an integrated and open decision environment, the scientific merit of predictions can be rendered politically irrelevant, as has been seen with nuclear waste disposal and acid rain. In short, if no adequate decision environment exists for dealing with an event or situation, a scientifically successful prediction may be no more useful than an unsuccessful one.

- These recommendations fly in the face of much current practice where, typically, policy-makers recognise a problem, scientists then go away and do research to predict natural behaviour associated with the problem, and predictions are finally delivered to decision makers with the expectation that they will be both useful and well used. This sequence, which isolates prediction research but makes policy dependent on it, rarely functions well in practice.

E.3.1 Societal Needs

Recently, Lins and Slack (1999) published a paper showing that in the United States in the 20th century, there have been no significant trends up or down in the highest levels of streamflow. This follows a series of papers showing that over the same period "extreme" precipitation in the United States has increased (e.g. Karl and Knight 1998a; Karl et al. 1995).

The differences in the two sets of findings have led some to suggest the existence of an apparent paradox: How can it be that on a national scale extreme rainfall is increasing while peak streamflow is not? Resolving the paradox is important for policy debate because the impacts of an enhanced hydrological cycle are an area of speculation under the Intergovernmental Panel on Climate Change (IPCC 1996).

There does exist some question as to whether comparing the two sets of findings is appropriate. Karl and Knight (1998b) note that "As yet, there does not appear to be a good phys-ical explanation as to how peak flows could show no change (other than a sampling bias), given that there has been an across-the-board increase in extreme precipitation for 1- to 7-day extreme and heavy precipitation events, mean streamflows, and total and annual precipitation."

Karl's reference to a sampling bias arises because of the differences in the areal coverage of the Lins and Slack study and those led by Karl. Lins and Slack (1999) focus on streamflow in basins that are "climate sensitive" (Slack and Landwehr 1992). Karl suggests that these basins are not uniformly distributed over the United States, leading to questions of the validity of the Lins and Slack findings on a national scale (T. Karl 1999, pers. comn.). While further research is clearly needed to understand the connections between precipitation and streamflow, a study by Pielke and Downton (2000) on the relationship of precipitation and flood damages suggests that the relationship between precipitation and flood damages provides information that is useful in developing relevant hypotheses and placing the precipitation-streamflow debate into a broader policy context (cf. Changnon 1998).

Pielke and Downton (2000) offer an analysis that helps to address the apparent paradox. They relate trends in various measures of precipitation with trends in flood damage in the United States. The study finds that the increase in precipitation (however measured) is insufficient to explain increasing flood damages or variability in flood damages. The study strongly suggests that societal factors – growth in population and wealth – are partly responsible for the observed trend in flood damages. The analysis shows that a relatively small fraction of the increase in damages can be associated with the small increasing trends in precipitation. Indeed, after adjusting damages for the change in national wealth, there is no significant trend in damages. This would tend to support the assertion by Lins and Slack (1999) that increasing precipitation is not inconsistent with an absence of upward trends in extreme streamflow. In other words, there is no paradox. As they write, "We suspect that our streamflow findings are consistent with the precipitation findings of Karl and his collaborators (1995, 1998). The reported increases in precipitation are modest, although concentrated in the higher quantiles. Moreover, the trends described for the extreme precipitation category (> 50.4 mm d^{-1}) are not necessarily sufficient to generate an increase in flooding. It would be useful to know if there are trends in 24-hour precipitation in the > 100 mm and larger categories. The term "extreme", in the context of these thresholds, may have more meaning with respect to changes in flood hydrology."

Karl et al. (1995) document that the increase in precipitation occurs mostly in spring, summer, and autumn, but not in winter. H. Lins (1999, pers. comn.) notes that peak streamflow is closely connected to winter precipitation and that "precipitation increases in summer and autumn provide runoff to rivers and streams at the very time of year when they are most able to carry the water within their banks. Thus, we see increases in the lower half of the streamflow distribution."

Furthermore, McCabe and Wolock (1997) suggest that detection of trends in runoff, a determining factor in streamflow, are more difficult to observe than trends in precipitation: "the probability of detecting trends in measured runoff (i.e. streamflow) may be very low, even if there are real underlying trends in the data such as trends caused by climate change." McCabe and Wolock focus on detection of trends in mean runoff/streamflow, so there is some question as to its applicability to peak flows. If the findings do hold at the higher levels of runoff-streamflow, then this would provide another reason why the work of Lins and Slack is not inconsistent with that of Karl et al., as it would be physically possible that the two sets of analyses are complementary.

In any case, an analysis of the damage record shows that at a national level any trends in extreme hydrological floods are not large in comparison to the growth in societal vulnerability. Even so, there is a documented relationship between precipitation and flood damages, independent of growth in national population: as precipitation increases, so does flood damage.

From these results it is possible to argue that interpretations in the policy debate of the various recent studies of precipitation and streamflow have been misleading. On the one hand, increasing "extreme" precipitation has not been the most important factor in documented increases in flood damage. On the other hand, evidence of a lack of trends in peak flows does not mean that policy-makers need not worry about increasing precipitation or future floods. Advocates pushing either line of argument in the policy arena risk misusing what the scientific record actually shows. What has thus far been largely missed in the debate is that the solutions to the flood problems in the USA lie not only in a better understanding of the hydrological and atmospheric aspects of flooding, but also in a better understanding of the societal aspects of flood damage (see Pielke and Downton 2000, for further discussion).

E.3.2 Quantifying Uncertainty Using a Bayesian Approach

As new information on vulnerability and changes in the probability distribution of extreme values become better known, risk estimates should be updated. We discuss below a procedure for handling this problem by using a Bayesian approach to incorporate uncertainty.

Going beyond the consideration of a damaging event in the definition of hazard, let us consider, for example, the quantity of interest (from Chapt. E.2) to be δI, which is defined as the amount of environmental change in the context of water resources (e.g. amount of water recharge to an aquifer; toxic metal content or silting degree of a reservoir). We are interested in the thresholds of δI beyond which there are undesirable impacts, usually understood as undesirable effects on the human well-being. In probabilistic terms the values of interest are in the tail of the corresponding probability distribution. Since δI is the result of different perturbations δA, δB, $\delta \dot{I}$ and these perturbations have an inherent uncertainty associated with each, final uncertainty of δI will be the result of a combination of uncertainties as defined by functions f_1 and f_2 given above, as well as the inherent uncertainty associated with the validity of these functions. All these considerations imply that δI is a highly-dimensional quantity dependent on several parameters which might also be unknown. In probabilistic terms δI is a random variable in a highly dimensional space.

Despite these complexities, a vulnerability assessment of a water resource would be incomplete if a measure of uncertainty is not given to the event of δI being below or above a threshold value considered as a potentially hazardous situation. The reason for this is that policymakers are always interested in expected losses and these need to be quantified in a proper way.

Bayesian statistical methods are becoming increasingly important in evaluating uncertainty related with environmental change (Adams et al. 1984; Paté-Cornell 1996; Tol and de Vos 1998; Wikle et al. 1998). Given a statistical model for a variable or a set of variables depending on a given set of parameters, the Bayesian paradigm involves three main steps:

1. Consider a prior distribution for the model parameters based on prior (as for example subjective information by experts) knowledge and before using the data. When prior information is not available noninformative (diffuse) priors could be used.
2. Obtain an expression of the joint probability distributions of the observations conditioned on the model parameters (this is known as the likelihood function in classical statistics) which implies a proposed statistical model for the variable of interest.
3. Obtain the posterior probability distribution of the model parameters by combining prior information with the likelihood function using the Bayes rule.

This last step can be quite complex since it might involve the definition of a high dimensional joint probability distribution. However, modern computational techniques such as Markov chain Monte Carlo methods (Casella and George 1992) have made possible accurate representations of the joint posterior distributions of the parameters of complex statistical models.

The advantages of a Bayesian approach rely on the possibility of updating the joint posterior distribution of the model parameters when new information becomes available (something that is needed in transient risk estimation as proposed above). A hierarchical modelling approach can also be naturally implemented with-in the Bayesian framework by using the powerful tool of conditioning on the components or parameters of a previous step of the system. This is specially useful when uncertainties related to the spatial scale of scenarios need to be resolved. By adding a downscaling layer to the analysis, under some circumstances (e.g. numerical short-term weather prediction), it is sometimes possible to deal with the uncertainty of going from a grid box to a point value to better represent sub-grid scale variability.

In order to estimate realistic thresholds of δI associated with environmental perturbations, coherence of surface variability at the relatively fine space and time scales is of particular relevance. Since this estimation should be done in probabilistic terms, calibration of atmospheric variability by simply parameterised spatio-temporal stochastic models has proven to be a very useful tool for rainfall and temperature, as discussed in Sect. C.4.1. Extension of these methods within the Bayesian paradigm (Sansó and Guenni 1999) provide tools for including the uncertainties discussed above.

A good example of how to incorporate different sources of uncertainty by using a Bayesian framework is presented by Krzysztotowicz (1999). He proposes a Bayesian forecasting system (BFS) by which the total uncertainty about a hydrological predictant (as river stage, discharge or runoff volume) is decomposed into input uncertainty (e.g. time series of precipitation amounts needed as an input to a hydrological model) and hydrological uncertainty, which considers all sources of uncertainty beyond random inputs (e.g. model, parameters, estimation and measurement errors).

Van Noortijk et al. (1997) also use a Bayesian approach to quantify different sources of uncertainty in the process of taking optimal decisions to reduce flood damage along the Meuse river in the Netherlands (near the Dutch-Belgian border). Their approach attempts to quantify the expected economic losses due to flood damage at different discharge thresholds. This methodology fits very nicely with the vulnerability perspective proposed in this part of the book.