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Theory to Practice

Useless Arithmetic: Ten Points to Ponder When Using Mathematical Models in Environmental Decision Making

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As policy makers and public administrators are acutely aware, mathematical models are simplified, generalized representations of a process or system, and their use in public administration is ubiquitous across policy domains. Perhaps nowhere, however, has their content, power, and efficacy as aids to decision making been more prevalent or potent than in the domain of environmental and natural resources (ENR) management. The move to quantify earth and biological sciences, the widespread availability of powerful desktop computers, and the dawn of predictive mathematical modeling all arrived simultaneously in the final quarter of the twentieth century.

In short order, predictive modeling of the earth's natural processes soon found widespread application (Sarewitz, Pielke, and Byerly 2000). Consider but a few examples of processes in nature that are routinely modeled and from which policy makers are presumed to make better judgments when incorporated in their ENR management decision calculi: the environmental impacts of a proposed project, atmosphere pollutant dispersal, groundwater pollutant dispersal, radionuclide waste disposal, sea-level change, weather patterns, climate changes, storm behavior, river flooding, fisheries yields, and shoreline retreat.

At the dawn of the era, it was believed that quantitative mathematical models would be a bridge to a better, more certain future in the relationship between humans and our natural environment. Not only did accurate prediction soon become an expectation of the public, but mathematical modeling came to epitomize in people's minds sophistication and state of the art in much of science and public policy. Nor were citizens alone in these judgments. Natural scientists and policy makers also assumed that quantitative mathematical models would provide a basis for predicting more absolutely the course of nature and its potential impacts.

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Society's expectations aside, however, mathematical modeling has sparked much controversy. This is not surprising for two reasons. First, the ecological, economic, and political stakes involved in the ENR challenges they are developed to address are profound. Second, uncertainties are an inherent part of the process—uncertainties that can then become fodder for controversy. These include the data gaps, assumptions, weightings, and extrapolations on which mathematical models are inevitably based. Harvard professor Shelia Jasanoff (2007) makes this case best. She argues that our society expects and even insists on certainty to a degree that it did not count on a few decades ago. But believing that certainty is attainable (as in accurately predicting the outcome of a natural process) is unrealistic and damaging to policy makers and scientists alike. Our increased reliance on science to prove absolute answers may be a product of the computer age and the widespread but often misplaced confidence that quantitative mathematical models will provide the answer. Jasanoff argues, and we concur, that humility is required: humility on the part of scientists who must know the limits of scientific knowledge, and humility on the part of planners and policy makers who must stop turning to science and mathematical models for answers and instead come up with their own solutions aided by scientific observations.

Still, the allure of mathematical modeling as a policy aid for ENR management issues remains strong, and it will continue to be so in the future. But has the optimism about mathematical modeling of ENR processes ever been realistic? Are mathematical models useful under certain circumstances and not others? How should policy makers best discern their utility, and how might

they better use them to inform their judgments? We argue that realizing high expectations for mathematical modeling in the ENR policy domain has proved, in practice, to be a bridge too far. Moreover, because reliance on some models has produced negative consequences, policy makers need to be aware of these shortcomings and communicate them to the public as they discern how much weight to give their findings in decision making.

In making these arguments, we begin by reviewing two types of ENR modeling: quantitative and qualitative. In the process, we show the paradox of quantitative modeling: While complex mathematical models strive to capture the complexity of natural systems, the more complexity they offer, the less accurate they can become. Next, and illustrating our points largely but not exclusively with examples from the mathematical modeling of beach erosion, we offer 10 lessons for policy makers to consider when interpreting and weighing the utility of recommendations derived from mathematical models. Our point is that modeling in this policy area is complex, but decidedly less complex than other applications of mathematical modeling. And though we focus on ENR modeling, our lessons are applicable to the fundamentals of modeling in a variety of policy areas. We conclude by arguing that mathematical modeling as an approach to ENR management has to be fundamentally rethought.

The (Mis)measurement of Nature: Assessing the Relative Merits of Quantitative versus Qualitative Modeling

There are two types of basic models for natural processes: quantitative and qualitative. Although both present us with a generalized perspective on a natural problem, they are not equal in terms of predictive power. The first type—quantitative models—can be used as a surrogate for nature, whereas the second—qualitative models—do the same but with less accuracy. Quantitative models are expected to provide answers of sufficient accuracy for practical societal use. The conventional wisdom is that such models may specifically answer questions related to the number of centimeters the sea level will rise in the next 100 years or predict precisely how many tons of haddock can be harvested in a sustainable catch next fishing season (surrogate for nature). In contrast, qualitative models eschew precision in favor of more general expectations grounded in experience. They are useful for answering questions such as whether the sea level will rise or fall or whether the fish available for harvest will be large or small (perspective). Such models are not intended to provide "accurate" answers, but they do provide generalized values: order of magnitude or directional predictions.

Our contention is that quantitative mathematical models are problematic and that their uncritical acceptance by policy makers may actually exacerbate society's ENR problems. A paradox leading to conceit exists in quantitative mathematical modeling. As we have noted, computers have allowed society to develop ever more complex models that track and manipulate far more variables, far more relationships, and far more data than earlier, simpler versions. Yet along with more variables, relationships, and data come more complexity, less ability to understand the model, and more room for error. Nature, we contend, is far too complex to predict in a quantitative way. Using a simple example, we don't believe that society can put a number on how high the sea level will rise in this century. We can say that models indicate that the sea level will continue to rise in the next century, that the rate is likely to accelerate, and that policy decisions should be made on that basis. In this light, the educative role for policy makers, including public managers, is important. They should train the public to expect and pay attention to this type of prediction, disabuse them of the quantitative precision in prediction in favor of trends, and garner their support for decisions that are made on this basis.

The problem runs even deeper, however. In some technical circles—for example, among the engineers who build seawalls on beaches and the hydrologists who predict groundwater movement—modeling is almost a religion. Belief in predictions is rock solid and criticism in applied modeling fields is dismissed outright, especially if the criticism comes from those who do not understand the mathematics behind the models. Model zealots seem to believe that mathematics is more important than the natural process.

James O'Malley, a fishing industry representative, expresses a common frustration of nonmodelers who deal with the impenetrable circle of modelers on a frequent basis:

> I stress that the problem [is] not mathematics per se but the place of idolatry we have given it. And it is idolatry. Like any priesthood, it has developed its own language, rituals, and mystical signs to maintain its status and to keep a befuddled congregation subservient, convinced that criticism is blasphemy. . . . Most frightening of all, our complacent acceptance of this approach shows that mathematics has become a substitute for science. It has become a defense against an appropriate humility, and a barrier to the acquisition of knowledge and understanding of our ocean environments. . . . When used improperly mathematics becomes a reason to accept absurdity. (Pilkey and Pilkey-Jarvis 2007, xiii)

But all models should not be dismissed on these grounds. Rather, it is useful to think about them as lying on a continuum running from positive to negative contributions to ENR management decision making. At one distressing end of the quantitative

modeling spectrum are coastal engineers who predict how long artificial or replenished beaches will last. It is an obviously impossible task, as one must know when the next big storms will occur in order to predict a beach's lifespan. Yet the hand of those who would model is forced because of a federal requirement to predict beach durability in a cost–benefit ratio for each beach nourishment project. In order to be allocated the money to award their projects, the U.S. Army Corps of Engineers must show a favorable cost-benefit ratio. The practice continues despite decades of predictive failures. And when these predictions fail, we are offered the excuse that beaches disappear more quickly than predicted because the big storms were characterized as unusual in strength and unexpected in timing. It is not, defenders argue, because the models were wrong. Can anyone argue with a straight face that storms are a surprise on a beach? Would we accept such excuses from engineers who build failed bridges?

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At the other, more positive end of the spectrum is the United Nation's Intergovernmental Panel on Climate Change (IPCC), which is predicting the future of global climate change and sea-level rise. The IPCC recently shared with former Vice President Al Gore the 2007 Nobel Peace Prize for its work. The quantitative models of the IPCC may be no better than the models of beach behavior. Yet these modelers agonizingly, and in great detail, list and evaluate the assumptions and model simplifications, strong and weak, behind the predictive models. Those who are skeptical of the IPCC's climate models have the criticisms laid out for them to understand and consider. There is *transparency* in the process. Moreover, although the IPCC models may be questionable in a quantitative sense, they have considerable value as qualitative indicators. For example, the models probably cannot predict how much the sea level will rise in the next century, but they can answer the qualitative question of whether the sea level will likely continue its rise.

From a scientific perspective, however, perhaps the greatest damage from relying too heavily on quantitative models is the harm done to robust science. Much-needed field and laboratory studies are not carried out because mathematical models are thought to provide a cheaper and easier way to understand the earth's natural processes. Also, as noted, there is a strong tendency for applied modelers to circle the wagons when faced with criticism. Vigorous debate and critical review of good science are often absent, victims of mathematical "certainty." In contrast, the IPCC models stand as an obvious exception to the rule. The climate modelers do not circle their wagons any more than do observational scientists.

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James Wilson, a University of Maine fishery economist, also has an opinion on how model-based science can be damaging:

> The models are not verifiable and no attempt is made to verify. The result is that we don't learn except at an extremely slow rate. Almost all the science is done in government facilities and what's not done in government facilities is done on government contract. There is no independent body capable of giving depth and breadth to an alternative view. Academic scientists including ecologists often get involved, but find that the National Marine Fisheries Service becomes an attack machine whenever there is any substantial disagreement. In short the institutions that keep science vibrant and progressive are absent. (2002, 191–92)

The extent of the damage to society that overconfidence in mathematically modeled predictions has caused ranges from the nonexistent Cold War missile gap to the loss of the Grand Banks cod fishery (Pilkey and Pilkey-Jarvis 2007; Taleb 2007). Even assuming that the models would answer the question of the fate of stored radioactive waste at Yucca Mountain, an impossible design approach was taken and the repository may never be built (unless politics trumps science, a distinct possibility). Because the math behind the models is impervious to the general public and policy makers, and even to other scientists, models are easily distorted to provide inaccurate cost estimates or overly optimistic environmental impact estimates.

Avoiding Buyer Remorse: Toward Becoming an Intelligent Consumer of Modeling

Given this spectrum of possibilities and range of modeling quality, how are policy makers to become intelligent consumers of the predictions premised on mathematical models? In this section, we offer 10 things that policy makers should know or ask about when

presented with evidence premised on quantitative mathematical modeling.

Lesson 1: The outcome of natural processes on the earth's surface cannot be absolutely predicted. Nature is far too complex to characterize with mathematics, nor can math be used to derive an exact prediction of some natural process. Consider the relatively simple task of predicting how much sand will be transported each year by surf zone waves on a given ocean beach. Elsewhere, we have listed 49 parameters that could affect the sand transport process (Pilkey and Pilkey-Jarvis 2007, 131–32). This includes wave size, type and angle of approach, sand grain size, tides, beach shape, and storm characteristics such as frequency, duration, and direction of approach. However, in the most widely used model, known as the Coastal Engineering Research Center (CERC) equation, only eight parameters are implicitly and explicitly considered. But that is not all. The relative importance of any of these parameters changes from beach to beach and from year to year on a single beach. Interactions among the parameters occur in unpredictable and unexpected sequences called "ordering complexity." The other 41 parameters not considered in the CERC model are all important sometimes and somewhere. One can never know the direction, intensity, duration, order of occurrence, and frequency with which a given parameter (such as the all important storms) will act over time. Hence, an accurate characterization in a model of annual longshore transport is impossible. But let us not forget, the same equation could be very useful to policy makers if it is used to qualitatively characterize the transported sand volume, for example, as either large or small.

Lesson 2: Examine the excuses for predictive model failures with great care and skepticism. When models fail to predict a natural process accurately, the excuses usually involve the occurrence of an extreme event, such as an unusual storm, an unexpected flood, or an unusually long time period between storms, rain, or snow. But these extreme events are, in fact, natural: They are part of the natural process whose outcome is being predicted.

An example is the failure of dams in their modeled design role of flood control because of "unexpected" large floods that require the release of water at the height of the flood to save the dam. This happened during Hurricane Fran (1996) when the Falls Lake Reservoir of Raleigh, North Carolina, was lowered in mid-flood, increasing the magnitude of the downstream disaster. Policy makers should not accept such "outlier" arguments, but rather should challenge why natural processes such as these were not factored into models, as other approximations are incorporated in them.

Lesson 3: Did the model really work? Examine claims of past "successes" with the same level of care and skepticism that "excuses" are given. While "excuses" for shortcomings in the predictions of mathematical models must be challenged, so, too, must claims of accurate predictions. Good public policy should achieve measurable objectives. These claims, in turn, should be verified through evaluation of the effectiveness of the policy, the decision, or the models. But in the case of quantitative mathematical modeling, it is common to claim success when, in reality, the model was far less than successful. Recently at Bogue Inlet, North Carolina, sand was mined to be pumped up to replenish sand that had eroded from adjacent beaches. Using sand transport models, sand movement was predicted at eight points in the inlet. Most importantly, the models predicted that the hole left by the mining would fill in. When the project was completed, virtually nothing that had been predicted came to pass, and the dredged hole remained. Tides and waves will eventually fill in the hole naturally. However, the reason this failed prediction is critical is that the sand used to fill the void will be robbed from nearby beaches, causing them to retreat at higher rates. Yet the consultant responsible for the faulty design of the project proclaimed to the media that the project had been a success and even seemed to brag about the usefulness of the models. The consultant rationalized that the nourished beach a mile or two from the inlet looked just fine, which was true enough. But the proclaimed success was a far cry from the modeled predictions.

Lesson 4: Calibration of models doesn't work either. A common approach taken by modelers to verify accuracy is to calibrate a model by using it to "predict" an event that has already happened. On the surface, "hind casting" makes sense, but in reality it doesn't work. In hind casting beach erosion, for example, one would apply a mathematical model of shoreline retreat to some time frame—say, between 1980 and 1990. The rate of shoreline retreat during those years is known, and the idea is to calibrate the model so it comes up with the known reality. The model is tweaked to accomplish this. Parameters and constants are adjusted until the correct answer is obtained. Once that is done for a defined time period, it is assumed that it will work to predict the future.

Successful model prediction of a past event, however, does not prove that a model can successfully predict the future (Oreskes, Shrader-Frechette, and Belitz 1994). Ordering complexity, described in the sand transport case, is the reason hind casting does not work. Because we cannot solve the problem of ordering complexity, successful prediction of the past may have little bearing on the success of a model in predicting the future. Said differently, the events that

drove beach erosion in one decade are not going to occur in the same order, at the same frequency, and at the same intensity in the next decade. Storms will come from different directions and will linger offshore for different time spans. Hence, the rates of beach erosion (and especially the lifespan of nourished or replenished beaches) will differ from decade to decade. And success in predicting events between 1980 and 1990 would have no bearing on the prediction of events between 1990 and 2000.

Carrying this problem one step further, the model is often applied in some fields to a second time span. If the model is again successful in predicting events, it is said to be verified. In the case of the beach erosion model, this could involve the application of the model to 1990–2000. Unfortunately, we suspect that successful verification is an uncommon event. But even when it is, policy makers need to look closely at what is considered a successful prediction for model verification. We have seen instances in which, buried deep in a report, it was clear that verifying one commonly used model for sand transport on beaches required changing the wave height for the second time span. Policy makers need to read the footnotes of any calibration report with an eye toward changes of these kinds. Replication means replication. They should also keep in mind an additional reality of calibration models: Whenever no amount of tinkering and tweaking can come up with the right answer in the process of calibration, the model is likely invalid. However, and ironically, it is only possible to falsify a model through calibration. One cannot use calibration to verify it. Be wary of any claims to the contrary.

Lesson 5: Constants in the equations may be coefficients or fudge factors. Most models use coefficients or constants in their equations, and policy makers need to consider their source. In particular, one needs to ask whether the source of these coefficients is grounded in natural processes or best guesses. Take again the example of the CERC equation, which incorporates a sediment transport coefficient. When the CERC equation is examined closely, it is clear that sediment transport coefficients have no basis in nature (Thieler et al. 2000). In fact, the CERC coefficient, which is said to vary from beach to beach, is basically used as a fudge factor. It brings values of the amount of sand carried in the surf zone into the range of "known values," thus legitimating the ultimate values generated. In the case of beach sand transport models, the coefficient (k) is multiplied by the final answer. Yet in the geologic and engineering literatures, k values range over two orders of magnitude—and there is usually no basis given for its choice. Policy makers should thus ask about the source of such coefficients to see whether they are simply pulled out of the air.

Lesson 6: Describing nature mathematically is linking a natural flexible, dynamic system with a wooden, inflexible one. All models face inherent uncertainties because human and natural systems are always more complex than can be captured in a model. Some of the inaccuracies, shortcuts, or simplifications used by models (Haff 1996) include averaging, scaling up, omission of important variables, and substitution of mathematics for actual field observations.

Annual sand transport by waves is the primary factor that determines how long an artificial beach will last. Imagine, however, the variation in wave height and direction in a surf zone over one year (or over one week). Consequently, averages are used in models. But averages do not exist in nature, and their use always reduces the modeled impact of extreme events. In the case of wave characterization, averaging takes out (or at least reduces) the importance of storms. The same problem occurs when characterizing groundwater flow, including the permeability of the rocks between point A and B, sand grain size, river floods, wind velocities, atmospheric temperatures, and fish populations.

Scaling up is another problem. Observations of beach behavior, chemical reactions, groundwater flow, and biological populations made over a period of a few months to a few years must be scaled up for model purposes into years or even centuries. Thanks to a federal court decision, the design of the Yucca Mountain radioactive waste repository now requires a certainty concerning the fate of the waste of as much as a million years. The absurdity of this required predictive time span (which is five times the span of humans on earth and 50 times the span of humans in the Americas) is a reflection of our massively misplaced confidence in predictive mathematical models.

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Fundamentally, models are mathematical simplifications of a system or process. Some variables that make a process run may be omitted, while only those that are perceived to be important are

used in the model. Often, it turns out that important variables are omitted. If an important variable in a model is poorly known, it is common practice that an optimistic value is chosen in the process of model tweaking. This can be attributable to a glass-half-full, not half-empty attitude. Or it can be an attempt to ensure a "satisfactory" answer. The story of the assumed groundwater flow at Yucca Mountain provides an example of this problem.

The assumed rate of downward groundwater movement at the proposed Yucca Mountain, Nevada, radioactive waste disposal site was very slow. As the design process evolved, the predicted rate of water movement used in the mathematical models inched ever slower. Yet when a tunnel was carved into the mountainside, tests proved that the assumed water flow rates were too low by several orders of magnitude.

This was not necessarily an act of dishonesty (although it might be characterized as an act of incompetence). Rather, it was a matter of organizational momentum (Metlay 2000). It was easy and uncomplicated to come up with a lower flow rate estimate because it made the proposed design approach all the more feasible. By contrast, proposing a higher rate encountered intense questioning and bureaucratic resistance.

Lesson 7: Models may be used as "fig leaves" for politicians, refuges for scoundrels, and ways for consultants to find the truth according to their clients' needs. As Pogo so famously put it, "We have seen the enemy and he is us." Models can be misused as fig leaves behind which policy makers hide to promote a policy or make an unpopular decision. This is what happened in the failure of the Grand Banks cod fishery in the early 1990s. Beginning with the Portuguese, the banks were fished for 500 years. The failure of the fishery off Labrador and Newfoundland, Canada, may well have been the end of the greatest fishery the world has ever known.

Twenty–twenty hindsight tells us that the accuracy of the predictive models indicating that additional fishing of these waters was manageable and ultimately sustainable was not widely accepted by fishery scientists. Their concerns were rooted in the fact that fishery models used to predict mathematically the allowable sustainable catch are hugely complex. For example, one must predict all the environmental, oceanographic, and biological factors that contribute to the success of cod at the larval and adult stages, and also to the abundance of the prey and predators (Kurlansky 1997). But politicians used the optimistic models as fig leaves to hide behind and ignored catch reports (i.e., actual field observations of cod populations) indicating that a catastrophic collapse was on its way. What politician in his or her right mind would want to join battle with, let alone shut down, an industry that employed 40,000 people at its height? When the ecological collapse foretold by the observational data finally arrived, mathematical models were partly responsible for what a task force investigating the fishery collapse described as "a famine of biblical scale—a great destruction" (Pilkey and Pilkey-Jarvis 2007, 6). Indeed, a dozen years later, the cod have not come back.

The models that the U.S. Army Corps of Engineers use fall into a category that we call "refuges for scoundrels." This agency, long known for pork-barrel projects carried out at high cost with less than outstanding results, is a heavy user of quantitative models. Regrettably, arrogance of the sort described by Mr. O'Malley (see above) is not uncommon within this modeling community. For instance, modelers will not debate the validity of the mathematical models they use to predict how long nourished beaches will last, even in the technical literature. Nor is the actual experience with artificial beaches reexamined in any systematic fashion to determine the success or failure of their models.

Almost always, the predictions of beach lifespan are highly optimistic, which is almost certainly part of the Corps of Engineers' effort to get funding from Congress. This is not surprising, as perverse incentives are built into the relationship between the agency and Congress. The Corps is set up to depend entirely on project money for its very survival. And when pressed by other stakeholders to justify any particular model, the agency typically offers what might be called a "no point in beating a dead horse" rebuttal: "We are now about to start using another generation of models which is more sophisticated and takes into account more variables." Once again, however, the vicious circle continues. The more variables in and complexity of mathematical models, the worse (i.e., the more inaccurate) the predictions are likely to be and the more potential for mischief.

The Bureau of Land Management (BLM) also has misused models to support the mining industry and to allow new mines to open. This agency does not have in-house mathematical modeling expertise, so it depends on engineering consulting firms to predict the degree of lake pollution left behind when an open pit mine is abandoned. Too often, the consultant's mathematical model predictions find that the pit lake will be close to drinking water quality in 50 years (Moran 2000). Usually this prediction is far off the mark. Because the agency is charged with promoting and not merely regulating the mining industry, the consultants simply find the truth according to their clients' needs.

We are not alone in warning policy makers to understand these perverse incentives when weighing the

mathematical models informing BLM decisions. In the last decade, the BLM has come under much criticism for its optimistic predictions of future mine pollution. But even if it insists on realistic and honest modeling from its consultants, there is no way to predict the future of a pit lake accurately. Like it or not, future predictions both for beach lifespan and mine pollution must be educated guesses at best and must be weighed by consumers accordingly.

Lesson 8: The only show in town may not be a good one. Policy makers should also fight tendencies to accept the conclusions of mathematical models simply because they are available and add legitimacy to agendas, though they have little basis in nature. The Bruun rule (Bruun 1954), for example, is the only mathematical model that predicts how much shoreline erosion will be caused by sea-level rise. The rule states that the rate of erosion is determined by the rate of sea-level rise and the slope of the beach. Not only is predicting erosion not that simple, but also the model has virtually no demonstrable basis in nature (Cooper and Pilkey 2004). The problem is that the model answers an important question that no other model does, so it is the only show in town. And because coastal managers and policy makers are so convinced that they need a number to inform and legitimize the decisions they make, the Bruun rule survives despite a storm of criticism.

The widespread use of the Bruun rule is, in part, a reflection of our society's belief that we absolutely must have an accurate figure for future erosion rates. How can we plan without an accurate number? But policy makers need to understand that there *are* alternatives to predictions premised on the illusion of precision afforded by complex models of natural processes. Most simply, we can extrapolate from present-day shoreline erosion rates. Again, precise predictions premised on the internal logic, assumptions, posited relationships among variables, and data gaps and surrogates will be impossible if one extrapolates from current data. But in the real world, we cannot predict the unpredictable anyway. Importantly, policy makers who use extrapolations of current trends to "replace" the predictions of mathematical models are likely to do better than if they rely on one type of prediction. At a minimum, the deliberations and debates among policy makers, the general public, and agency experts will be leavened appreciably.

Lesson 9: The mathematically challenged need not fear models and can learn how to talk with a modeler. One of the most dysfunctional aspects of mathematical models from a deliberative democracy perspective is the disconnect with—and disempowerment of—laypeople in decisions that affect them. Certainly, this is a tendency that is not limited to the ENR management arena (see, e.g., Sandel 1998). Indeed, as Durant, Fiorino, and O'Leary (2004) suggest, reconnecting with citizens and stakeholders is a major challenge facing policy makers and public administrators worldwide.

As natural scientists working in the ENR management arena, we contend that the modeling process must be open and citizens must question predictions. To allow this, models should be as transparent as possible. Assumptions, limitations, criticisms, and weaknesses should be forthrightly disclosed up front. As noted earlier, the IPCC provides an example to follow. The results from black-box models should never be accepted. Yet the reality in many situations is that mathematical models are closely held in the files of consultants and environmental firms and are not revealed—even to paying customers. For example, many of the Danish and Dutch mathematical models predicting the behavior of coastal engineering structures on beaches and in harbors are offered as black boxes. Our advice to policy makers is simple: Look at the variables in the equations presented to you and ask the question, "How can they be characterized?" And at a most elementary level, answer that question by applying an "embarrassment test." If a model simplification of a parameter or process is embarrassing to state out loud as a fact, then the model cannot accurately portray the process.

Consider, again, the simple longshore beach sand transport example. Modelers assume that all waves are the same wavelength, that all waves come from the same direction, that only the highest one-third of waves moves sand, and that grain size remains constant (as does the shape of the beach). A scientist who said any of these things in public would be hooted off the podium! Yet ensconced deep within a model, such absurdities are considered state of the art and distort policy deliberations accordingly when left unexamined or challenged by policy makers, laypeople, and other stakeholders.

Lesson 10: When humans interact with the natural system, accurate predictive mathematical modeling is even more impossible. The paths of those who study social science and those who emphasize the natural sciences do not often cross (Liu et al. 2007). Yet the natural processes that scientists try to predict are greatly impacted by human behavior. Everyone who has tried to predict the future of the stock market (Sherden 1998) knows the difficulty of predicting human behavior (e.g., Alan Greenspan's now famous observations about the "irrational exuberance" of investors in the 1990s). An example of this problem when it comes to natural systems is the prediction by coastal engineers of the behavior of beaches on a river delta. A dam constructed upstream cuts off the sand supply to beaches. In the process, all predictions of shoreline erosion, qualitative or quantitative, are thrown off and wrong. Oil wells are drilled on the

delta, oil extraction causes the land to sink, and the sea level rises to accelerate erosion. As a result, shoreline erosion rates rise unexpectedly.

Or consider what happened when Hurricane Floyd (1990) passed by Charleston, South Carolina, and how human behavior produced unexpected consequences for policy makers. Weather prognosticators had predicted the hurricane would make landfall over the city. It didn't, but at the time of the first evacuation order, the storm was classified as a Category 5. Many thousands of South Carolinians wisely decided to evacuate. Unfortunately, most found themselves trapped all night on jammed highways leading out of the city. Unexpectedly, the state's governor overruled emergency management officials who wanted one-way, out-of-town traffic on all lanes of the interstate (I-26) leaving the city. Heavy political fallout ensued because of public anger—not over the inaccurate hurricane alarm but because of the traffic jam. Governor Jim Hughes's inexplicable decision in a time of crisis is an example of the problem of predicting anything that involves human behavior. Emergency management officials had carefully studied and modeled hurricane evacuation long before the storm. But the models did not consider the possibility that the governor would declare that the incoming lanes should be kept open for "emergency vehicles"!

In fact, examples abound of how human behavioral reactions that are unanticipated affect the predictive validity of even the most elegant mathematical models. Model predictions of ecosystem evolution in the Great Lakes have been greatly frustrated by the introduction of invasive species carried in the ballast waters of foreign freighters. Similarly, land development patterns influence the biology of streams, and fishery population predictions are affected by changes in ocean current dynamics related to global warming. Likewise, a century of fire suppression in western U.S. forests has led to increased numbers and size of fires because of accumulated brush cover that small fires, left alone, would have naturally reduced. Finally, environmental refugees from the rising sea level in Bangladesh crowd into the remaining habitats of the Bengal tiger and threaten its existence. What policy makers need to understand from all of this is not that mathematical modelers anticipate events that are not anticipatable. Rather, policy makers must bring their own strengths as students of human behavior to the decision-making process.

Confronted with the predictions of mathematical models, they must question how well modelers' predictions assume a passive, inert, or nonstrategic set of actors. Borrowing from the policy implementation literature, one way to discern these behaviors is to engage in "backward mapping" (Elmore 1980, 1985). This backward-mapping approach to decision making involves scenario writing that anticipates behavioral reactions to circumstances created by those closest to a problem, challenge, or opportunity. Short of engaging in such a full-scale exercise, policy makers need to ask modelers what they are assuming about human behavioral reactions. To the extent that these answers fail the embarrassment test or seem inadequate or unrealistic on logical grounds, they should be wary.

A Final Word: Into a Brave New World of Qualitative Modeling?

Our argument in this article has been that mathematical models are wooden and inflexible next to the beautifully complex and dynamic nature of our earth. Quantitative models can condense large amounts of difficult data into simple representations, but they cannot give an accurate answer, predict correct scenario consequences, or accommodate all possible confounding variables, especially human behavior. As such, models offer no guarantee to policy makers that the right actions will be set into policy. Nor are the results of these realities necessarily benign for the environment; we have noted instances in which modeling predictions resulted in actual harm to the environment.

With these shortcomings in mind, we have offered 10 tips for policy makers hoping to discern where on the spectrum of utility any mathematical model presented to them fits. Our aim has not only been to demystify mathematical modeling to policy makers. We have also tried in the process to empower them to become intelligent consumers of these products. They can become so by understanding models' strengths and (more important) their limitations and by introducing an element of common sense into decision making. In doing so, our aim is to enhance deliberate democracy in the ENR management arena.

But *PAR* readers might appropriately ask, is there an alternative to quantitative modeling? We have already argued that qualitative modeling that is more grounded in observational data can help compensate for the shortcomings of mathematical models. Not only do they eschew the rarified and often intimidating realm of mathematical complexity, but they also prompt experts to engage reality-based and readily understandable trend data that may or may not support their predictions. In this vein, adaptive management, a form of trial-and-error management, may provide one path into the qualitative world (Johnson 1999).

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Using adaptive management, for example, waste could be stored at Yucca Mountain with the understanding

that it will be monitored, and the storage facilities might be modified years and even centuries down the road if needed. Or the waste could be reused in power plants. Similarly, one could estimate how long an artificial beach will last based on how long nearby artificial beaches have lasted. Or the beach could just be replenished without arguments! By the same token, limits on the harvesting of a certain species of fish could be set and varied from year to year depending on annual field observations of fish abundance. Similarly, environmental impact statements could be viewed as first estimates and monitored over time by an ombudsman agency with the power to shut down a project, mine, or factory if the environmental impact proves unacceptable.

Yet in order for alternative approaches to quantitative mathematical modeling to take their rightful place in ENR management, society will first have to make fundamental changes in its philosophy and approach to designing with nature. Policy makers will have a major educative role to play in making that change a reality. Modelers have to abandon claims of accurate prediction of many natural processes, and laypeople have to appreciate these realities and become comfortable with this step into a qualitative world. Decades of optimistic claims by scientists and engineers about the validity of modeled predictions will not be easy to turn around. The public believes that models are the state of the art and has grown to expect accuracy and to accept the "unusual storm" excuse when things do not work out. Nor will the political advantage that a lack of transparency can offer special interests and agendas in society be easy to overcome.

Nonetheless, deference to expertise is no longer axiomatic, and a variety of advocacy groups have the capacity to go toe-to-toe with experts. At a minimum, they have the capability to mount effective public relations campaigns that undermine their credibility, as the anti-nuclear and anti–genetically modified food campaigns by Greenpeace in Europe illustrate. The first step, however, is raising the consciousness of the general public to the problems and false promise of mathematical modeling. Policy makers also need to reign in its excesses by demystifying it for citizens, insisting on transparency, and appreciating how best to challenge its premises in particular cases. Readers need not share our strong preference for relegating quantitative predictive mathematical models to the historical dustbin of failed ideas to take advantage of the tools for reigning in its excesses that we have offered in this essay.

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