*Invited Paper:*

# A PRAGMATIC APPROACH TO MODELING FOR WILDLIFE MANAGEMENT

ANTHONY M. STARFIELD, Department of Ecology, Evolution & Behavior, University of Minnesota, St Paul, MN 55108, USA

*Abstract:* I contrast 2 views of modeling: the model as a representation of "truth" and the model as a problem-solving tool. Examples are given of how, in the latter case, the objective drives the design of small, simple models that focus relentlessly on the problem to be solved. A number of applications for small, focused models are offered. I stress the need for wildlife professionals to develop the skills for constructing and using such models on a regular basis; I end with ideas about how to create a modeling culture in conservation and resource management organizations.

***J. WILDL. MANAGE. 61(2):261–270***

**Key words:** decision analysis, ecosystems, management, modeling, populations, problem solving, simulation, strategy.

In a society where wildlife managers are held accountable and where decision making is subject to public scrutiny, the question is not whether to model, but rather how to model usefully and efficiently. That is the subject of this essay.

Managers make decisions. These may be one-of-a-kind decisions such as whether or not to reintroduce a species, or strategic decisions such as the design of a monitoring program, a fire control policy, or a policy for determining the number of hunting permits to issue. Good managers make good decisions, but what constitutes a good decision-making process?

A good process is one that is seen to be logical and is therefore defensible. There are at least 3 essential steps in a good decision-making process (Goodwin and Wright 1991):

1. We must know what we are trying to achieve; the first step is a lucid statement of the objective or objectives.
2. We must be able to measure how well a solution or strategy performs with respect to the stated objective. The second step is to define a set of explicit indicators or measures for evaluating the extent to which the objective has been met.
3. Finally, we need a procedure for ranking alternative options or strategies in terms of these measures.

For example, a deer management plan may have the objective (step 1) of maintaining a large and healthy deer population, in a suitable and sustainable habitat, while providing opportunities for recreational hunters. This is easy to enunciate, but how do we measure the health of the population, the suitability or sustainability of the habitat and the recreational opportunities for hunters? Until we have determined how to do this (step 2), we cannot claim to understand what our objective means. Even then our task is not complete, because one management scenario may score well on the habitat scale but not as well on the deer population scale, while another management scenario does not score as well on the habitat scale but is stronger on the population scale. This is where the third step, a procedure for ranking alternatives, comes in. Only once we have all 3 steps in place, can we claim to be making a reasoned, defensible decision.

Decisions affect the future. The explicit measures in step 2 will almost certainly relate to some future state of the system. If we have a number of alternative management scenarios, we must be able to forecast plausible outcomes for each of them. This is where modeling enters the decision process. A wildlife manager can no more make a defensible decision without a formal model than somebody in the business world can make a deal without "running the numbers."

## SEVEN MISCONCEPTIONS ABOUT MODELING

There are a number of misconceptions about modeling that act as impediments to widespread use of models in wildlife management. Here are 7 common misconceptions:

1. A model cannot be built with incomplete understanding of the behavior of a system or population.
2. It is not useful to build a model if there are gaps in the data it is likely to need (so the priority is to collect data).
3. A model cannot be used in any way or form until it has been validated or been proven to be accurate.
4. A model must be as realistic as possible, accounting for all the detailed intricacies of a biological system.
5. Modeling is a process akin to mathematics; as such it cannot be used or understood by most managers and many field biologists.
6. The primary purpose of building models is to make predictions.
7. Modeling is time-consuming and expensive; it follows that models must be designed to answer all the questions that have been thought of, or questions that may arise in the future. The more multipurpose the model, the better the value one is getting for one's investment.

These misconceptions arise from an assumption that a model is like a scientific law: it represents the "truth." A definition of a model consistent with this assumption might be "an accurate (or faithful) representation of reality."

It is more useful to think of a model as a hypothesis, an experiment or even a problem-solving tool. A good definition of a model in these terms is "a purposeful representation" (Starfield et al. 1994).

These definitions are poles apart. The measure of a good model in the first case is truth or accuracy; in the second case one cannot even talk about whether a model is good or bad without knowing its purpose, and then the sole measure of the model is how well it meets that purpose. One might even go further and argue that the measure of the model is whether it meets its purpose better than any alternative paradigm. In a decision-making context, the ultimate test of a model is not how accurate or truthful it is, but only whether one is likely to make a better decision with it than without it.

Let us revisit the list of 7 misconceptions at the beginning of this section and rectify them in the light of this pragmatic definition of modeling.

1. (A model cannot be built with incomplete understanding.) Management decisions, more frequently than not, have to be taken without a full understanding of the population or system most affected by the decisions. This is an added incentive for building a model rather than an excuse for not building one. A model, under these circumstances, represents one's current best understanding of how the system behaves within the restricted context of the decision to be taken. This is where it is useful to think of a model as a hypothesis: if the system behaves in a specified way (the assumptions), then the model reveals the consequences (Starfield and Bleloch 1991). The key here is thoroughly to be aware of the assumptions and, where there are major disagreements about them, to build several versions of the model to see the effects of alternative assumptions.
2. (It is not useful to build a model if there are missing data.) Decisions often have to be made with incomplete data. This is where it really pays to build a model, because the model can be used to see just how much difference the missing data might make. It might emerge that the choice of 1 out of 5 or 6 alternative management plans is totally insensitive to the missing data (Ralls and Starfield 1995). On the other hand, if the missing data could swing the decision one way or another, it is likely the model will offer guidance for collecting the data. For example, the modeling exercise might show that it is not the precise value of a survival rate that is needed, but only whether it is above or below a certain threshold.
3. (Validation is essential.) If truth is the measure of a model, then validation is the proof of that truth and the issue of validation is crucial. However, if a model is constructed as an experiment (albeit a thought experiment) or viewed as a hypothesis or a problem-solving tool, then the question of validation is irrelevant. The model is like a logical proposition: it only reveals the logical consequences of its assumptions (**if** this is true, **then** that follows). Instead of validating the model, we need to be concerned with the justification for the assumptions, to make sure that the model is internally consistent, and to look for evidence that we are using or interpreting the results in a sensible manner (Oreskes et al. 1994). If we are unsure

of some of our assumptions, we should model the consequences of alternative, equally plausible assumptions. Moreover, we need only be concerned about this within the context of the conclusions we wish to draw from the modeling exercise. In practice, it might suffice to argue that there is no better tool to use at this time. The model is then used cautiously, because there is no alternative, and resources should be spent on monitoring and reevaluating how the model is used.

4. (A model must be as detailed and realistic as possible.) If modeling is "truth, then it does indeed follow that a model should be as realistic as possible. If modeling is purposeful, then one wants to design the simplest, leanest model that will meet the purpose. The "truth" paradigm is open-ended because nature offers such infinite detail; there is no basis for arguing why anything at all should be neglected. Designing a model for a purpose provides the basis for restricting the model to essentials. If the purpose is to choose among 4 or 5 alternative management plans, then the differences among the plans will determine what the model needs to include and what it safely can ignore.
5. (Models are esoteric and difficult to understand.) The concept of a model as an unintelligible mathematical entity or a computational "black box" may be acceptable if that is the only way to represent a complicated truth, but it is totally alien to the paradigm of modeling as a problem-solving tool. Using a model to understand and solve problems positively requires that all who use it understand it. Understandability is therefore an important criterion for whomever designs and develops the model. A simple model that is easily understood may be preferable to a more complex but less understandable model. An important reason for building the model in the first place might be as a form of communication between scientists and managers, or managers and the public, or even between those who currently try to study and manage and those who will succeed them.
6. (We build models to make predictions.) Representations of the truth are required to make predictions. Pragmatic models are less ambitious. They may make forecasts or projections, but only for a limited purpose; they are only a means to an end. Often what one learns in the process of designing and building them, rather than the results they produce, is what matters most.
7. (Models need to be large and have multiple purposes.) The idea of a large, multipurpose model is incompatible with the idea of a model as a focused problem-solving tool. Ask a different question and chances are you will need a different model because different simplifying assumptions will hold. This will be illustrated in the next section.

Probably the most dramatic consequence of switching to a pragmatic modeling paradigm is that it leads to a shift from a few large, multipurpose models, probably developed to vague specifications by outside computer or modeling consultants, to a suite of small, single purpose models that are developed in-house to address a specific problem. Where large models are data-hungry and difficult to follow, these small models are required to be understood easily and may be built where data are sketchy or unavailable. Where large models are likely to be expensive to develop or parameterize, small models well could be built in a few days of concentrated effort. These small models should be so inexpensive to develop and use that model-building has to be the most efficient way of beginning to address a problem.

The remainder of this essay will give examples of small models, suggest where they usefully could be developed, and address the question of how to move more aggressively toward a modeling culture in wildlife management.

## PROBLEM-ORIENTED MODELS

In this section we illustrate how the design of a model depends on the objective. To do this we sketch 3 models that all relate to the management of African buffalo (*Synceros cafer*) in southern African game parks.

### Model 1

A large national park has a policy of controlling its African buffalo herds. Until recently, an extensive aerial survey was used to determine buffalo numbers and then, on the basis of the survey, decide how many to cull during the year. In an effort to reduce costs, it was suggested that with the aid of a model and data collected during the cull, it might be possible to decide how many buffalo to cull annually while censusing the buffalo only every third or fourth year. The objective of the model was, therefore, to project population numbers over a period of 3 to 4 years and to interpret data (such as age and sex structure and the reproductive status of buffalo cows) collected each year.

The buffalo have a calving period that extends over 4 or 5 months of the year and culling takes place at various times during the year. Taking this information and the objective into account led to a model that divided the population into annual cohorts for both males and females. However, the time step of the model was 1 month (in order to interpret culling data at different times of the year) and fetuses as well as newborn calves were subdivided into monthly age-classes--in the latter case because of low early calf survival. The model recognized 3 rangeland assessments (poor, medium, and good) and contained tables of fecundity rates and survival rates for each rangeland assessment.

Exercising the model led to a reevaluation of the accuracy of some of the past annual surveys, suggested that the calf-to-yearling ratio might be a useful indicator of changes in buffalo numbers, and raised the question of how one might design decision-making and culling strategies to bridge the years between surveys (Starfield and Viljoen 1993).

This is an example of a model that can be described as "small," in the sense that the dynamics are not complicated, although the actual computer program that was developed was quite sophisticated in its user interface. The model is more complicated than it might have been if one of its objectives had not been to interpret data collected during the culling operations.

## Model 2

During demonstration of the above model, a manager questioned whether there really was a need to control buffalo numbers. The argument had always been that without culling the buffalo population would explode, to the detriment of other species. The manager suggested that Model 1 be used to project the population, first with and then without culling, over a period of 50 or 100 years.

Model 1 was not designed to do this. It is not a multipurpose model. The new objective requires a new model. The new objective might be stated as "build a model to explore how buffalo numbers might change over a long period with and without culling." Most of the detail in Model 1 is irrelevant for this purpose. For instance, there is no reason to project 100 years one month at a time. Irrelevant detail in a model is distracting and interferes with communication and a sensible use of the model.

More seriously, Model 1 omits information that might be important in the long run. Because it was designed for use in a situation where buffalo numbers are controlled, it assumes they will not increase significantly; the model does not ask how the parameters might change if the density were to increase, nor is there any feedback from buffalo numbers to range condition, which is just a model input. If one is building a model to anticipate what might happen without management control, one needs to hypothesize what might, in the long run, limit the population. This has to be the key component of Model 2, but was unnecessary in the context of Model 1.

Model 2 therefore strips away all the sex and age structures in Model 1. The time step is 1 year and only 1 number, the total population, is computed for each year. Annual rainfall (in 1 of 3 categories: low, medium, or high) is used as a surrogate for range condition and 6 growth rates for the population are specified, depending on the rainfall and whether the population is above or below a density threshold (the idea being that low rainfall will have more of an adverse effect on the population if densities are high). Finally, a rule was added to the effect that in a drought (2 or more low rainfall yrs) the population would crash at high density (above the threshold) with a loss of 30 to 50 of the population. There was evidence that such crashes had occurred in the past.

This model is a thought experiment and can be developed on a spreadsheet in 1 or 2 hours. Rainfall patterns can be input from long-term records or simulated in a simple but realistic way.

The model shows the population sometimes growing, eventually crashing, sometimes recovering quickly from the crash, and sometimes remaining at relatively low numbers for long periods. As a thought experiment, it raises a number of issues and leads to some interesting conclusions. First, it changes the way managers think about their problem and expands their time horizons. Irrespective of the details, a nonequilibrium graph of population versus time, showing periods of low as well as high buffalo numbers, leads managers to rethink what might be "good" or "bad" about buffalo densities. This in turn will lead the manager to develop more sophisticated management objectives. Second, the model shows that whether culling is actually desirable or unnecessary depends on the objectives, the prevailing patterns of rainfall, and the assumed rules for population crashes. This leads to a review of what data should be collected, new ideas for research, and new ideas too for a slightly more complex model where the interaction between buffalo, vegetation and rainfall would be included explicitly.

This is a good example of how much one can learn from a model that does not have good data to support it. The model is unlikely to be accurate, but it is nevertheless a useful intellectual exercise in how to think about long-term management of a population that responds to its environment partly by short-term adjustments in its growth rate (juv mortality) and occasionally by significant die-offs.

### Model 3

A much smaller and more-intensely managed game park decided to limit its buffalo population to 200 animals, with the objective of structuring the herd to produce sustainably, a maximum number of trophy bulls. The objective of a model in this case was to determine which animals, apart from the trophy bulls, to remove to keep the herd at the limit of 200. Here we clearly need an age and sex-structured model, with a time step of 1 year. Since the herd is well below the carrying capacity of the game park, there is no need to include any density dependence or interaction between the buffalo and vegetation.

The model could be constructed as a set of constraints in a linear programming representation, allowing one to optimize the number of trophy bulls. This might be an elegant solution to the problem, but one can communicate better by simply developing the model on a spreadsheet so as to explore alternatives such as removing juvenile cows or much-older cows to keep the population constant. One could also conceivably use Model 1 to solve this problem, but, again, one would be distracted by the irrelevant details in the model and communication (and probably the credibility of the model) would suffer. It is far simpler and more effective to spend a few hours on a spreadsheet to produce a model that focuses directly on the problem (Stalmans et al. 1994).

The 3 models described above all relate to the population dynamics of buffalo in an African savanna, yet each model is different because its purpose is different. Each model was able to throw light on a problem because it was designed to address that specific problem. Each was effective in its own way, not in spite of its simplifying assumptions, but because of them.

## APPLICATIONS FOR "SMALL" FOCUSED MODELS

### Single-species Models

The African buffalo models described above fall in the category of single-species models. Single-species models are so easy to develop that they can and should be built whenever data on a species are collected. If it is worth spending the resources to collect the data, surely it is worth spending far less to build a model. One nearly always learns something from the exercise. In one instance, an age-structured rhinoceros (*Ceratotherium simum*) model, built in an hour on a spreadsheet, reinforced suspicions of inadequacies in census data that had been collected over many years, and in another instance suggested a hypothesis about sources of mortality in the population. A model is just a hypothesis of what is driving changes in a population. Comparisons between the model and data often lead to either a revision of the hypothesis or a reinterpretation of the data.

Similarly, all species-specific management actions or even ideas of what might be feasible should be tested on a model. For example, a contraceptive dart has been considered as an alternative to culling for stabilizing a large elephant (*Loxodonta africana*) population. A few hours on a spreadsheet demonstrated how many cows would have to be darted each year to stabilize the population, how quickly the population would grow if fewer cows were darted, and what changes in the age structure of the herds could be expected (Cochrane et al. 1997).

Often management, particularly in the case of problems with endangered species, is faced with a choice between a relatively small number of options, including the options of "wait and see" or "wait until more data have been collected" (Boyce, 1992). A simple model in this situation almost always will shed light on the problem, including the advantages and dangers of delaying action and what might be gained by collecting more data. The objective of the model is to choose among the limited number of options. A rational, robust choice might emerge from a model even when apparently crucial data are missing (Starfield et al. 1995).

## Modeling to Cope with Uncertainty

Suppose in a computer model we have a litter of 8 wolf pups (*Canis lupus*) and know there is, on average, no sex bias in wolf litters. There are 2 ways we can assign sexes to the pups. In the first we say half the pups are male and half are female; this is a deterministic model. In the second we use a random number generator, in effect tossing a coin 8 times; the number of "heads" determines the number of males in the litter. This is a stochastic model. The deterministic model always gives the same answer (4 M and 4 F); the stochastic model may give different answers for different replicates and from a large number of replicates can give probabilistic answers such as "the probability of all the pups in a litter of 8 being male is about 0.004".

One of the questions to be asked when designing a model is whether a deterministic or stochastic model is needed. The default answer is a deterministic model because it is so much simpler to interpret, but if chance events or the variance in the answers to a problem are important, then a stochastic model must be built.

Decision-makers prefer straight answers and like most human beings are uncomfortable with probabilistic answers and dealing with uncertainty (Tversky and Kahneman 1974). Unfortunately, uncertainty in weather, prevalence of disease, catastrophic events such as major fires, and (particularly in small populations) survival and reproduction are an integral part of wildlife management (Lemons 1996). More and more decisions involve multiple stakeholders and conflicting objectives with respect to actions where the outcomes can only be expressed in probabilistic terms. For example, there might be 3 different strategies for reintroduction of a species. Each option has a price tag. A stochastic model suggests each option has a different probability of success (defined as the projected population being above a threshold after 20 yr). The decision-makers have to weigh cost against probability of success.

A stochastic model is an indispensable part of this kind of decision process; it forces one to deal with probabilities. Since stochastic models can produce a variety of different outputs, designing the model helps wildlife professionals think through what they need to know and how to represent the probabilistic outcomes. This in turn sharpens their understanding of what they are trying to achieve: they might, for example, debate whether a low probability of an undesirable outcome is more (or perhaps less) important than a high probability of a desirable outcome. Involvement with the model provides experience of dealing with uncertainties and increases familiarity with a probabilistic way of looking at the world. Finally, it drives home the point that while the model can compute probabilities, decision-makers have the responsibility of determining the value system that will be used to interpret risks and process the model outputs. The result can be clearer thinking all round and, in the case of multiple stakeholders, a transparent process for reaching a defensible and satisfactory decision (Ralls and Starfield 1995).

## Modeling to Improve Data Collection and Monitoring

Most wildlife organizations invest a large proportion of their resources in data collection of one kind or another. Sometimes there are good statistical techniques and controls for estimating the accuracy of the data, while at other times data are collected on the basis that some data are better than no data. Like modeling, data collection should be driven by a purpose, but often after an initial justification for starting the data collection, there is no review of whether the data meet the stated purpose. Often too, data are collected for long periods of time without being analyzed or put to use.

Modeling is a tool for testing how effective it is to collect and use data in one way rather than another. For example, the goal in a wilderness area might be to hold the deer population at a fixed limit. Each year an estimate is made of deer numbers and, on the basis of that estimate, a decision is made as to how many deer to remove. How well does this management system work? Nobody really knows because nobody has knowledge of actual deer numbers. A simple, interactive model can be designed to test how well the system might work. The deer population can be simulated, introducing some stochasticity in, say, the survival rate of the youngest age class. The model can then use information about the variability in the estimation method to generate, again stochastically, a census result. This simulated census is reported to the user, who then chooses how many deer to remove. This could be repeated for 20 years. At the end of the 20 years 2 graphs show (a) what the user thought was happening to the population (the census data) and (b) what was really happening to the population (the simulated population).

In a typical situation, the actual population graph might be smooth, while the census data show peaks and valleys that cause consternation to the user. In other words, it suggests that decision-makers might be agonizing over the noise in their management system. Even if it does not do this, the exercise underscores that there are differences between perceptions and reality, often leading to questions about how to improve data collection and the way in which the data are used.

Simple simulations like this are inexpensive and can have a major effect. The point is that what is simulated is not just the data collection, but the way in which data are analyzed or used. The spirit of this approach can be applied in different ways. If they are not being used on a regular basis, long-term datasets should be exercised in model experiments, in much the same way as troops are exercised in anticipation of a crisis. No matter how carefully the dataset was designed, exercising it is the only way to be sure one is not wasting a great deal of effort.

Modeling can also be used to improve the design of data collection methods and data analysis. First one builds a model to simulate the data one is planning to collect. Then one analyzes the simulated data (in the same way one plans to analyze the real data) to see whether one actually detects the processes or patterns that were built into the model (and that one suspects exist in the real world). This often leads to a revision of the experimental design or a search for alternative ways of analyzing the data (Cale et al. 1989). The modeling exercise is a cheap precaution, and especially when one is collecting spatial data (as in a GIS), it pays to build a simple spatial model before rather than after collecting the data.

The guiding principle in this, as in the rest of this essay, is to use simple models to avoid the trap of making a large investment in money and effort without understanding how effective the investment will be. Pragmatic modeling requires models be used to design purposeful data collection instead of data availability being used to design models.

## Simple Models for Ecosystem Management

Ecosystem management is usually concerned with large spatial areas and long time periods. Obviously, there is no way to begin to understand the likely consequences of management actions on these spatial and temporal scales without modeling. It is not so obvious that simple, problem-oriented models are needed here too. Since ecosystems are undeniably complex in their dynamics, it is often assumed that ecosystem models must be similarly complex. In fact this is where a pragmatic approach really pays off; the answer to ecological complexity is to simplify it drastically (but intelligently) in the light of the objectives of the modeling exercise.

Starting with the objective of a model leads to a top-down modeling approach (capture the broad, essential aspects of the dynamics first) as opposed to a bottom-up paradigm (start with ecosystem processes). Qualitative variables (rainfall is not 2.3 cm but is categorized as low, medium, or high) can be used to simplify the modeling (Starfield et al. 1989). Further simplification is provided by frame-based modeling (Starfield et al. 1993) which recognizes functionally different states or "frames" (i.e., grassland as opposed to shrubland or forest) that may apply at different times to the same spatial region. A simple model is built for each frame, plus a set of rules that determine when changes will occur from one frame to another.

With these modeling constructs, it is feasible to have a working ecosystem model within a few days. Simple models can produce surprisingly complex results; a simple model might be all that is needed to demonstrate the advantages or disadvantages of alternative management strategies. The model might show, for example, unexpected interactions between 2 alternative management policies such as fire control and herbivore control (one policy might be ineffective without the other in promoting intermediate successional stages in a forest) or demonstrate how the effectiveness of a policy depends on the rainfall regime or soil type (Tester et al.

1997). If the simple models are too simple, they can be refined successfully, adding detail step-by-step with a clear understanding of why that detail is necessary. At any stage there is a working model that can be used to perform thought experiments and decide whether the model requires further refinement. This is in stark contrast to the bottom-up approach where the model can be used only when all the detailed components have been put together.

Even if one is convinced that in the long run a detailed process model will be essential, it makes sense to start with a grossly simplified version of the model one hopes to develop. If nothing else, this will help clarify what one is trying to achieve with the model.

## FOSTERING MANAGEMENT-ORIENTED MODELING ENVIRONMENTS

Many wildlife managers and scientists are still wary of models. One reason might be a "bad" experience with modeling in the past. They have probably had bad experiences with monitoring and fieldwork as well, but that does not mean monitoring and fieldwork should be avoided; on the contrary, the professional response is to ask how to avoid negative experiences in the future. One of the messages of this essay is that modeling should be as indispensable a part of the wildlife professional's routine as data collection and statistical analysis. The problem is that it has not been recognized as such and has not become part of their culture or their regular work schedule. In this section we make some suggestions as to how to rectify this.

The first step is awareness. Both managers and scientists need to become comfortable with pragmatic modeling. They need to understand that there are different modeling paradigms, and know when to use which paradigm, in much the same way as they already know there are different techniques for statistical analysis and have a good idea of which is appropriate when (or at least know who to consult if in doubt). Like statistics, models can lie and mislead and modeling can be abused (Wallace 1994). To be comfortable with modeling requires an understanding of what modeling can and cannot do and how to work with it within its limitations. Wildlife professionals need to know what questions to ask (such as "Does the model address the stated objectives?" or "Are the assumptions clearly spelled out and are they reasonable in the light of the objectives?") to differentiate good models from bad models. They should have some understanding of when a model could be useful and why and what kind of model is needed, and they need to be constructively skeptical, and invariably suspicious of a model that is difficult to understand. In short, they must be able to put a realistic value on modeling, neither expecting too much from it nor underestimating what it can do.

In particular, both managers and scientists also need to become comfortable with the pragmatic modeling paradigm espoused in this essay. It takes a mind-shift to accept that a model is a purposeful tool rather than a representation of reality, and it requires an act of faith to build models on the basis of insufficient data or poorly substantiated assumptions. However, it is surprising how much one can learn in these circumstances provided the objectives are clear, the modeling is developed carefully, exploring all possibilities step-by-step, and the logic is tight. Some might still be uncomfortable with the results because the parameters of the model are rough estimates or because relations are poorly understood, but it is often possible to tease out robust conclusions. These may be qualitative rather than numerical, but that does not prevent them from being useful.

Apart from reservations about modeling with poor data or understanding, one of the reasons for suspicion of modeling might be the prevailing procedures for developing and using models. In many cases a large, multipurpose model is developed by outside consultants with insufficient interactions between those paying for the model and those producing it. The assumptions and limitations might never be clarified. In fact, because the model is multipurpose, it is difficult to make appropriate assumptions and anticipate how it might be abused. The wildlife professionals eventually take delivery of software that may be user-friendly in its interface but is still a black box to them as far as its inner workings are concerned. The software is quietly neglected, partly because nobody is comfortable with it, partly because it has a plethora of data requirements without any guidance as to which inputs are more important than others, and partly because there has been no effort to integrate the model in the workplace.

In contrast, if the pragmatic approach suggested in this essay is to become commonplace, there has to be a capability, within the workplace, for developing and using, on a regular basis, a variety of small, problem-oriented models. There may, on occasion, be a need to consult a modeling expert, just as there are occasions for consulting statisticians, but the bulk of development should be in-house. The image of wildlife scientists developing their own models and interacting with managers in both their design and use is appealing; a likely benefit of a strong modeling environment will be better communication and cooperation between decision-makers and scientists.

This means making time for model development, specifying it as part of job descriptions, and giving modeling a high priority. There might be protocols to ensure that no major activity is undertaken without some simple modeling to understand the likely benefits or consequences. For modeling to become pervasive, the use of models must be institutionalized, as must a regular review process for models that are used on a regular basis.

All of this is easier said than done, but in the spirit of this essay one could begin with a few useful models on a spreadsheet and develop experience with modeling one step at a time. The only essential requirement is the will, on the part of both managers and scientists, to try it.

The goal is a decision-making environment where models are used to make projections and compare alternative options; records are kept on how the decision was taken and how the projections were used or why they were ignored; the models are used to determine the most efficient monitoring scheme for evaluating both the decision and the model itself; both the decision and the model projections are reviewed on a regular basis; and models are regularly revised or replaced in the light of what has been learned. This is an adaptive management environment with built-in procedures for learning from experience. Such an environment provides continuity in the face of changes in personnel. The models, like long-term datasets, become a part of the in-house knowledge.

There remains the problem of implementing a model on a computer. While programming might be an impediment to some, there are already a number of people with varying degrees of skill in using spreadsheets, languages such as Visual Basic, or general modeling software such as Stella (rev. by Getz 1992). A number of more specific modeling packages are also available (such as the stochastic population models described in Burgman et al. 1993) and can be useful provided one is sure the package and model are compatible. One can safely predict that software will make it easier to develop and to implement models. One can also safely predict that small, pragmatic models will become part of the everyday experience of wildlife professionals.

## LITERATURE CITED

BOYCE, M. S. 1992. Population viability analysis. Annu. Rev. Ecol. Syst. 23:481–506.

BURGMAN, M. A., S. FERSON, AND H. R. AKÇAKAYA. 1993. Risk assessment in conservation biology. Chapman and Hall, New York, N.Y. 314pp.

CALE, W. G., G. M. HENEBRY, AND J. A. YEAKLEY. 1989. Inferring process from pattern in natural communities. BioScience 39:600–605.

COCHRANE, J. F., D. MENSING, AND C. ALLEN. 1997. Can contraception help manage the Kruger National Park elephant herd? Custos 25: In Press.

GETZ, W. 1992. Reviews of Stella II: a systems simulation software package for Macintosh computers. Nat. Resour. Model. 6:221–224.

GOODWIN, P., AND G. WRIGHT. 1991. Decision analysis for management judgment. John Wiley and Sons, New York, N.Y. 308pp.

LEMONS, J., EDITOR. 1996. Scientific uncertainty and environmental problem solving. Blackwell Sci. Publ., Cambridge, Mass. 433pp.

ORESKES, N., K. SHRADER-FRECHETTE, AND K. BELITZ. 1994. Verification, validation and confirmation of numerical models in the earth sciences. Science 263:641–646.

RADOMSKI, P. J., AND T. J. GOEMAN. 1996. Decision making and modeling in freshwater sportfisheries management. Fisheries 21(12):14–21.

RALLS, K., AND A. M. STARFIELD. 1995. Choosing a management strategy: two structured decision-making methods for evaluating the predictions of stochastic simulation models. Conserv. Biol. 9:175–181.

STALMANS, M., A. VAN WYK, J. L. ANDERSON, AND A. M. STARFIELD. 1994. Boosting a buffalo bull population. Conserva 9(1):8–11.

STARFIELD, A. M., AND A. L. BLELOCH. 1991. Building models for conservation and wildlife management. Second ed. Burgess Int., Edina, Minn. 253pp.

———, AND P. VILJOEN. 1993. Wildlife management becomes computerized. Custos 21(12):35–39.

———, B. P. FARM, AND R. H. TAYLOR. 1989. A rule-based ecological model for the management of an estuarine lake. Ecol. Model. 46:107–119.

———, D. H. M. CUMMING, R. D. TAYLOR, AND M. S. QUADLING. 1993. A frame-based paradigm for dynamic ecosystem models. A I Appl. 7(2 and 3):1–13.

———, K. A. SMITH, AND A. L. BLELOCH. 1994. How to model it: problem-solving for the computer age. Burgess Int., Edina, Minn. 206pp.

———, J. D. ROTH, AND K. RALLS. 1995. "Mobbing" in Hawaiian monk seals: the value of simulation modeling in the absence of apparently crucial data. Conserv. Biol. 9:166–174.

TESTER, J. R., A. M. STARFIELD, AND L. E. FRELICH. 1997. Modeling for ecosystem management in Minnesota pine forests. Biol. Conserv. 80:313–324.

TVERSKY, A., AND D. KAHNEMAN. 1974. Judgment under uncertainty: heuristics and biases. Science 185:1124–1131.

WALLACE, W. A. 1994. Ethics in modeling. Oxford Univ. Press, Oxford, U.K. 266pp.

*Received 15 June 1996.*
*Accepted 27 December 1996.*

# STATISTICAL POWER ANALYSIS IN WILDLIFE RESEARCH

ROBERT J. STEIDL,[1] Oregon Cooperative Wildlife Research Unit, Department of Fisheries and Wildlife, 104 Nash Hall, Oregon State University, Corvallis, OR 97331-3803, USA

JOHN P. HAYES, Department of Forest Science, Oregon State University, Corvallis, OR 97331, USA and Coastal Oregon Productivity Enhancement Program, Hatfield Marine Science Center, Newport, OR 97365, USA

ERIC SCHAUBER,[2] Department of Fisheries and Wildlife, 104 Nash Hall, Oregon State University, Corvallis, OR 97331-3803, USA

*Abstract:* Statistical power analysis can be used to increase the efficiency of research efforts and to clarify research results. Power analysis is most valuable in the design or planning phases of research efforts. Such prospective (a priori) power analyses can be used to guide research design and to estimate the number of samples necessary to achieve a high probability of detecting biologically significant effects. Retrospective (a posteriori) power analysis has been advocated as a method to increase information about hypothesis tests that were not rejected. However, estimating power for tests of null hypotheses that were not rejected with the effect size observed in the study is incorrect; these power estimates will always be $\leq 0.50$ when bias adjusted and have no relation to true power. Therefore, retrospective power estimates based on the observed effect size for hypothesis tests that were not rejected are misleading; retrospective power estimates are only meaningful when based on effect sizes other than the observed effect size, such as those effect sizes hypothesized to be biologically significant. Retrospective power analysis can be used effectively to estimate the number of samples or effect size that would have been necessary for a completed study to have rejected a specific null hypothesis. Simply presenting confidence intervals can provide additional information about null hypotheses that were not rejected, including information about the size of the true effect and whether or not there is adequate evidence to "accept" a null hypothesis as true. We suggest that (1) statistical power analyses be routinely incorporated into research planning efforts to increase their efficiency, (2) confidence intervals be used in lieu of retrospective power analyses for null hypotheses that were not rejected to assess the likely size of the true effect, (3) minimum biologically significant effect sizes be used for all power analyses, and (4) if retrospective power estimates are to be reported, then the $\alpha$-level, effect sizes, and sample sizes used in calculations must also be reported.

***J. WILDL. MANAGE. 61(2):270–279***

**Key words:** confidence intervals, effect size, experimental design, hypothesis testing, power, research design, sample size, statistical inference, statistical power analysis, Type I error, Type II error.

Although the theoretical basis of statistical power was developed decades ago (Tang 1938), power analysis has only recently gained prominence in applied ecological research. Statistical power analysis has been advocated and sometimes used to improve research designs and to facilitate interpretation of statistical results in the applied sciences (Gerrodette 1987, Peterman and Bradford 1987, Peterman 1990, Solow and Steele 1990, Taylor and Gerrodette 1993, Searcy-Bernal 1994, Beier and Cunningham 1996, Hatfield et al. 1996). Failure to consider statistical power when a null hypothesis is not rejected can lead to inappropriate management recommendations (Hayes 1987).

[1] Present address: School of Renewable Natural Resources, 325 Biological Sciences East, University of Arizona, Tucson, AZ 85721, USA.

[2] Present address: Department of Ecology and Evolutionary Biology, University of Connecticut, Storrs, CT 06269, USA.