Ecological Modeling for Resource Management

Virginia H. Dale

Editor

Ecological Modeling for Resource Management

Springer
New York
Berlin
Heidelberg
Hong Kong
London
Milan
Paris
Tokyo

Virginia H. Dale
Editor

Ecological Modeling for Resource Management

With 50 Illustrations

Springer

Editor

Virginia H. Dale
Environmental Sciences Division
Oak Ridge National Laboratory
P.O. Box 2008
Oak Ridge, TN 37831-6036
USA
dalevh@ornl.gov

Library of Congress Cataloging-in-Publication Data

Ecological modeling for resource management / editor, Virginia H. Dale.
p. cm.
Includes bibliographical references (p.).
ISBN 0-387-95493-7 (hc : alk. paper)
1. Ecology—Simulation methods. 2. Applied ecology. 3. Natural resources—Management—Simulation methods. 4. Conservation of natural resources—Simulation methods. I. Dale, Virginia H.
QH 541.15.S5 E275 2002
333.95—dc21
2002070451

ISBN 0-387-95493-7 Printed on acid-free paper.

Printed in the United States of America.

9 8 7 6 5 4 3 2 1 SPIN 10877247

www.springer-ny.com

Springer-Verlag New York Berlin Heidelberg
A member of BertelsmannSpringer Science+Business Media GmbH

Participants at the workshop on “Effective Use of Ecological Modeling in Management” held in Oak Ridge, Tennessee on October 23–26, 2000, at which this book was developed.

Preface

This book was developed from a workshop on the "Effective Use of Ecological Modeling in Management," held in Oak Ridge, Tennessee, on October 23–26, 2000. The workshop was sponsored by the Department of Defense's (DoD's) Strategic Environmental Research and Development Program (SERDP), the Army Research Office, and the Engineering Research and Development Center of the Corps of Engineers as well as by the U.S. Department of Agriculture (USDA) Forest Service. It was hosted by the Department of Energy's (DOE's) Oak Ridge National Laboratory (ORNL). The organizing committee for the workshop included senior scientists from ORNL, the USDA Forest Service, and the U.S. Army Corps of Engineers (ACE). The members of the steering committee were John Barko, Paul Bradford, Bill Goran, Jeff Holland, Russell Harmon, and Mike Vasievich. They helped guide the workshop to a useful product by suggesting topics, speakers, and participants. Workshop attendees included senior ecological modelers within the Forest Service, DoD, other federal and state agencies, universities, and the private sector together with ecological-resource managers in the Forest Service, DoD, and other government and nongovernment agencies and organizations.

The book never could have come to fruition without the dedicated efforts of Fred O'Hara in editing each of the chapters and making sure that the text was complete and accurate and that standard methods of expression and design were used in the text, references, tables, and figures. His careful attention to the details and to effective communication is appreciated.

Many people helped in bringing the book to completion. Chapter authors not only contributed the bulk of the work but also assisted by reviewing manuscripts of their colleagues. In addition, chapters were reviewed by John Barko, Mark Bevelhimer, Chuck Coutant, Robert Gardner, Russell Harmon, Robert Holst, Tony King, and Robert Melton. I appreciate the support of the Environmental Sciences Division at Oak Ridge National Laboratory and, especially, of my husband and children.

VIRGINIA H. DALE
Oak Ridge, Tennessee

August 2002

Contents

Preface vii

Contributors xiii

Part 1. Introduction

1. Opportunities for Using Ecological Modeling for Resource Management 3
Virginia H. Dale

Part 2. Examples of Using Ecological Models for Resource Management

2. Modeling for Endangered-Species Recovery: Gray Wolves in the Western Great Lakes Region 23
Jean Fitts Cochrane, Robert G. Haight, and Anthony M. Starfield

3. Modeling Fish Entrainment and Impingement Impacts: Bridging Science and Policy 46
Webb Van Winkle and John Kadvany

4. Large-Scale Regional Assessments: Lessons Learned from the Southern Appalachian Assessment 70
David N. Wear

Part 3. Key Issues

• ***Barriers***

5. Overcoming Barriers to the Use of Models in Environmental Decision Making 89
Mark A. Harwell and John H. Gentile

6. Barriers to the Use of Ecological Models in Decision Making 109
Virginia H. Dale, Chris Rewerts, Webb Van Winkle, Mark A. Harwell, Mike Vasievich, and Steve Hodapp

• ***Evolving Approaches***

7. Network Theory: An Evolving Approach to Landscape Conservation 125
Timothy H. Keitt

8. Evolving Approaches and Technologies to Enhance the Role of Ecological Modeling in Decision Making 135
Eric Gustafson, John Nestler, Louis Gross, Keith M. Reynolds, Daniel Yaussy, Thomas P. Maxwell, and Virginia H. Dale

• ***Data***

9. Data and Information Issues in Modeling for Resource Management Decision Making: Communication is the Key 167
John R. Richardson and Cory W. Berish

10. Effective Ecological Modeling for Use in Management Decisions: Data Issues 180
David Hohler, Tom Ashwood, John R. Richardson, Lisa Mai Olsen, Noble Hendrix, and Alison Williams

• ***Toolkits***

11. Effective Use of Ecological Modeling in Management: The Toolkit Concept 211
Steven M. Bartell

12. Role of Computational Toolkits in Environmental Management 221
Jeffery P. Holland, Steven M. Bartell, Thomas G. Hallam, S.T. Purucker, and Christopher J.E. Welsh

• ***Investments Needed***

13. Science and Management Investments Needed to Enhance the Use of Ecological Modeling in Decision Making 249
Lev Ginzburg and H. Resit Akçakaya

14. Educational Investments in Environmental Science and Management 263
Thomas P. Maxwell, Jim Berkson, Tania Schoennagel, Karen A. Poiani, and Robert Costanza

Part 4. Finale

15. What in the World Is Worth Fighting for? Using Models for Environmental Security 289
Wendell Chris King and Virginia H. Dale

16. New Directions in Ecological Modeling for Resource Management 310
Virginia H. Dale

Index 321

Contributors

Editor

Virginia H. Dale
Environmental Sciences Division, Oak Ridge National Laboratory, P.O. Box 2008, Oax Ridge, TN 37831-6036, Phone: 865-576-8043, Fax: 865-576-8543, Email: dalevh@ornl.gov

Chapter authors

H. Resit Akçakaya
Applied Biomathematics, 100 North Country Road, Setauket, NY 11733, Phone: 631-751-4350, Fax: 631-751-3435, Email: resit@ramas.com

Tom Ashwood
Environmental Sciences Division, Oak Ridge National Laboratory, P.O. Box 2008, Oak Ridge, TN 37831-6036, Phone: 865-574-7542, Fax: 865-576-8543, Email: tla@ornl.gov

Steven M. Bartell
The Cadmus Group, Inc., 78A Mitchell Road, Oak Ridge, TN 37830, Phone: 865-425-0401, Fax: 865-425-0482, Email: smbartell@aol.com

Cory W. Berish
U.S. EPA Region 4, 61 Forsyth Street, Atlanta, GA 30303, Phone: 404-562-8276, Email: Berish.Cory@epamail.epa.gov

Jim Berkson
Department of Fisheries and Wildlife Sciences, Virginia Polytechnic Institute and State University, Blacksburg, VA 24061-0321, Phone: 540-231-5910, Fax: 540-231-7580, Email: jberkson@vt.edu

Jean Fitts Cochrane
U.S. Fish and Wildlife Service, P.O. Box 668, Grand Marais, MN 55604, Phone: 218-387-1307 Fax: 218 387-2790, Email: jean_cochrane@fws.gov

Robert Costanza
Gund Institute for Ecological Economics, University of Vermont, 590 Main St., Burlington VT 05405-1798, Phone: 802-656-2906, Fax: 802-656-8683, Email: rcostanz@zoo.uvm.edu

John H. Gentile
Harwell Gentile & Associates, LC, 98 Moss Lane, Brewster, MA 02631, Phone: 508-241-7288, E-mail: jgentile@EcologicalRisk.com

Lev Ginzburg
Applied Biomathematics, 100 North Country Road, Setauket, NY 11733, Phone: 631-751-4350, Fax: 631-751-3435, Email: lev@ramas.com

Louis Gross
The University of Tennessee, 569 Dabney Hall, Circle Drive, Knoxville, TN 37996-1610, Phone: 865-974-4295, Fax: 865-974-3067, Email: gross@tiem.utk.edu

Eric Gustafson
USDA Forest Service, North Central Research Station, Forestry Sciences Laboratory, 5985 Highway K, Rhinelander, WI 54501, Phone: 715-362-1152, Fax: 715-362-1166, Email: egustafson@fs.fed.us

Robert G. Haight
USDA Forest Service North Central Research Station, 1992 Folwell Avenue, St. Paul, MN 55108, Phone: 651-649-5178, Email: rhaight@fs.fed.us

Thomas G. Hallam
The University of Tennessee, Department of Ecology and Evolutionary Biology, 569 Dabney Hall, Knoxville, TN 37996, Phone: 865-974-3065 (EEB office), 865-974-4293 (my office), Fax: 865-974-3067, Email: hallam@tiem.utk.edu

Mark A. Harwell
Florida A&M University, Environmental Sciences Institute, Tallahassee, FL 32307-6600, Phone: 850-561-2760, Fax: 850-412-7679, Email: mharwell@EcologicalRisk.com

Noble Hendrix
School of Aquatic and Fisheries Science, University of Washington, Box 355020, Seattle, WA 98195, Phone: 206-221-5456, Email: anoble@u.washington.edu

Steve Hodapp
U.S. Army Corps of Engineers, Construction Engineering Research Lab, P.O. Box 9005, Champaign, IL 61826-9005, Phone: 217-373-7228, Fax: 217-373-7266, Email: s-hodapp@cecer.army.mil

David Hohler
USDA Forest Service, Ecosystem Management Coordination, Siuslaw National Forest, 4077 S.W. Research Way, P.O. Box 1148, Corvallis, OR 97339, Phone: 541-750-7018, Email: dhohler@fs.fed.us

Jeffery P. Holland
U.S. Army Corps of Engineers, U.S. Army Engineer Research and Development Center, 3909 Halls Ferry Road, Vicksburg, MS 39180-6199, Phone: 601-634-2644, Fax: 601-634-3193, Email: hollanj@wes.army.mil

John Kadvany
Policy and Decision Science, 1070 College Ave., Menlo Park, CA 94025, Email: kadvany@aol.com

Timothy H. Keitt
Department of Ecology and Evolution, State University of New York Stony Brook, NY 11794, Email: tkeitt@mail.utexas.edu

Wendell Chris King
Head, Department of Geography & Environmental Engineering, U.S. Military Academy, West Point, NY 10996, Phone: 845-938-2300, Fax: 845-938-3339, Email: chris.king@usma.edu

Thomas P. Maxwell
Gund Institute for Ecological Economics, University of Vermont, 590 Main St., Burlington, VT 05405-1798, Phone: 802-656-2987, Fax: 802-656-8683, Email: tmaxwell@zoo.uvm.edu

John Nestler
U.S. Army Research and Development Center, 3909 Halls Ferry Road, Vicksburg, MS 39180-6199, Phone: 601-634-3870, Fax: 601-634-3129, Email: nestlej@wes.army.mil

Lisa Mai Olsen
Environmental Sciences Division, Oak Ridge National Laboratory, P.O. Box 2008, Building 1507, MS-6407, Oak Ridge, TN 37831, Phone: 865-241-5921, Email: olsenlm@ornl.gov

Karen A. Poiani
National Landscape Ecologist, The Nature Conservancy, Department of Natural Resources, 16 Fernow Hall, Cornell University, Ithaca, NY 14853, Phone: 607-255-2834, Fax: 607-255-0349, Email: kap4@cornell.edu or kpoiani@tnc.org

S.T. Purucker
Environmental Applications Group, Center for Information Studies, The University of Tennessee, 804 Volunteer Boulevard, Knoxville, TN 37996-1610, Phone: 865-974-9553, Fax: 865-974-4967, Email: purucker@utk.edu

Chris Rewerts
Engineering Research and Development Center, U.S. Army Construction Engineering Research Laboratory, P.O. Box 9005, Champaign, IL 61826-9005, Phone: 217-352-6511, ext. 7324, Fax: 217-373-7266, Email: chris.c.rewerts@erdc.usace.army.mil

Keith M. Reynolds
USDA Forest Service, PNW Research Station, 3200 SW Jefferson Way, Corvallis, OR 97331, Phone: 541-750-7434, Fax: 603-853-2951, Email: kreynolds@fs.fed.us

John R. Richardson
U.S. EPA Region 4, 61 Forsyth Street, Atlanta, GA 30303, Phone: 404-562-8290, Fax: 404-562-0269, Email: Richardson.John@epa.gov

Tania Schoennagel
Departments of Botany and Zoology, University of Wisconsin-Madison, 220 Birge Hall, 430 Lincoln Drive, Madison, WI 53706-1381, Phone: 608-262-2791, Fax: 608-262-7509, Email: tschoenn@students.wisc.edu

Anthony M. Starfield
Department of Ecology, Evolution and Behavior, University of Minnesota, 1980 Upper Buford Circle, St. Paul, MN 55108, Email: starf001@tc.umn.edu

Webb Van Winkle
5163 North Backwater Ave, Boise, ID 83703, Phone: 208-853-0341, Email: wvanwinkle@juno.com

Mike Vasievich
NRIS-Human Dimensions Module, USDA-Forest Service, 1407 S. Harrison Road, East Lansing, MI 48823, Phone: 517-355-7740, ext. 26, Fax: 517-355-5121, Email: mvasievich@fs.fed.us, mvasie@msu.edu

David N. Wear
USDA Forest Service, Southern Research Station, Forestry Sciences Laboratory, 3041 Cornwallis Road, P.O. Box 12254, Research Triangle Park, NC 27709, Phone: 919-549-4011, Email: dwear@fs.fed.us

Christopher J.E. Welsh
Environmental Applications Group, Center for Information Studies, The University of Tennessee, 422 South Stadium Hall, Yale and Philip Fulmer Way, Knoxville, TN 37996, Phone: 865-974-1829, Fax: 865-974-4967, Email: cwelsh@utk.edu

Alison Williams
Department of Fisheries and Wildlife Sciences, Virginia Tech, 100 Cheatham Hall, Blacksburg, VA 24060, Phone: 540-231-3329, Fax: 540-231-7580, Email: alwilli2@vt.edu

Daniel Yaussy
USDA Forest Service, Northeastern Research Station, 359 Main Road, Delaware, OH 43015, Phone: 740-368-0101, Fax: 740-368-0152, Email: dyaussy@fs.fed.us

Part 1

Introduction

1
Opportunities for Using Ecological Models for Resource Management

Virginia H. Dale

1.1 Environmental Management

The roots of environmental management are diverse. One major origin is the planning arena in which decisions are made about zoning, parcel size, and adjacent land uses. Individuals involved in city and county government typically have backgrounds in planning, and some combine that expertise with an environmental perspective. Another major source of environmental management stems from an economic perspective. This viewpoint focuses on costs of obtaining resources and maximizing the benefits achieved. Renewable resources, such as timber or fish, offer an opportunity for a long-term, stable supply of goods. A third origin of environmental management is from a wildlife background. This perspective is epitomized by Aldo Leopold (1953), who called for a land ethic that is based upon the concept that humans are a part of a natural system and need to consider how their actions affect the Earth. Such an ecological point of view requires attention to the social, economic, and political arena in which environmental management occurs. To consider the opportunities and costs involved in environmental management, all of these perspectives need to be considered. An integrated approach to environmental management involves planning, sustainability, and environmental ethics and considers the social, economic, political, and environmental contexts.

The challenge of managing the environment therefore requires awareness of the diverse goals that may exist for natural resources. Some people value the environment for the economic gains it provides, such as from trees that can be harvested or grasses that can be grazed. Other people measure the worth of environmental attributes by the amount and type of recreational opportunities that they can provide. Recreational resources can be quite diverse, and their use frequently conflicts with access to or economic use of another resource. For example, a wilderness hiking experience is not compatible with the use of off-road vehicles. Land and water are also valued for their beauty. The vista of mountains, prairies, or sand dunes can provide an aesthetic experience or the inspiration for songs, art, or prose. Novelists often integrate the opportunities and conflicts of nature into their characters' development. For example, Willa Cather's descriptions of prairie life convey both the bleakness and beauty of the landscape and the hope that comes with each spring. Other people associate religious values with particular places or resources. A site may have served as an ancestral hunting ground or may house religious artifacts. Chief Seattle, leader of the Suquamish Indians, reportedly wrote to the American Government in the 1800s, "The shining water that moves in the streams and rivers is not just water, but the blood of our ancestors." Some environmental resources have scientific values, such as those watersheds that serve as long-term research sites and support a unique set of data on changes in ecological attributes. Other resources provide habitats for species, and as these species become rare, these habitats are critical to maintaining biodiversity.

Taking into account all of these values in forming environmental management decisions is difficult. Until recently, the economic value of a resource was typically given the most weight by planners. However, today environmental managers realize that all values and ecosystem services must be considered so future generations will have access to natural resources (Costanza et al. 1997).

Sustainability is often touted as a goal for environmental management. Sustainable development meets the needs of the present without compromising the ability of future generations to meet their own needs (World Commission on Environment and Development 1987). Ecological sustainability is the capability of an ecological system or process to continue over time without loss or decline. For instance, sustainable forestry practices maintain forest structure, diversity, and production without long-term decline or loss over a region. Sustainable water use provides for the water needs of a human community without reducing water quality or quantity to levels that might compromise ecological processes. Resource use can be sustained locally over the long term with the help of external subsidies from other areas, but this practice can result in degradation of the larger system. Thus, sustainability needs to be viewed from a broad perspective in both time and space. Sustainability is widely regarded as economically and ecologically desirable; in the ultimate sense, it is the only viable long-term pattern of human interaction with the environment.

Having "sustainment of a system" as the goal of environmental management is logical and even noble. A major challenge is the quantitative or qualitative characterization of this goal or even of the intermediate steps toward it. In a number of international arenas, this topic has been broached with no definable goal(s) that can be applied universally, although advances have been made [e.g., Costanza et al. (1997); Stork et al. (1997); Cairns et al. (1993); Angermeier and Karr (1994); Lindenmayer et al. (2000)]. In most instances, human society cannot go back to past levels of interactions with the environment because it cannot be attained (e.g., a nonrenewable natural resource may no longer be available). In other situations, even when restoration is possible, the financial resources might not be available, or the economic or social stability of the area might be threatened by the change.

It is also necessary to recognize that every resource is not available in any one place. Therefore, some governments have instituted laws to protect water and air quality or endangered species and their habitats. These regulations typically apply to land owned by the government or to federally funded actions. As such, federal agencies are often the leaders in developing tools for sustainable-management practices. Often, however, the piecemeal protection of individual resources is not sufficient to retain a unique and valuable suite of conditions. Thus, areas may be preserved with the intent of sustaining natural resources, yet critical gaps in protection may exist. For example, some of the territory required for long-term sustainability of a species (like breeding grounds or winter forage sites) may be in jeopardy of degradation or change.

Furthermore, in most countries, private lands cover a much larger area than public lands (Figure 1.1), and few regulations of environmental management practices apply to private property. Typically, landowners base their management on cultural traditions. Yet social, economic, or geographic realities may restrict options for land use and management so that past practices are no longer relevant. For example, as nations are split into new countries, historic lines of commerce may be lost, requiring development of new ways to relate to the land. This disruption is what happened to the lands of the Masai in Africa whose traditional territories were divided up into new countries.

Private landowners typically look to the practices of their neighbors, government agencies, or nongovernmental organizations (NGOs) for

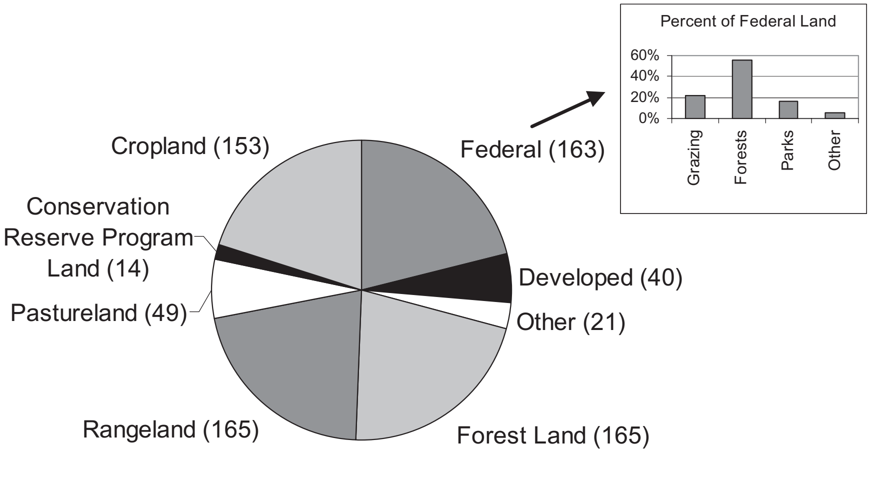

FIGURE 1.1. Area (in millions of hectares) of United States federal and nonfederal holdings by land use (USDA 2000).

guidelines and advice on how to appropriately manage natural resources. Yet, the agencies are often so busy that they cannot respond to an owner's request in a timely fashion. For example, in the state of Tennessee, there are more than 300,000 parcels of forest land larger than 15 acres and only 33 state foresters to assist with the management of these lands. The lack of environmental managers is quite bleak in developing nations. Individual landowners frequently would like to manage their resources in an ecologically appropriate way, but lack the information or tools to do so. Thus, resource owners often turn to other approaches to seek advice on how best to manage their resources. One of the most effective ways to educate landowners about sustainable land-use practices is to establish demonstration projects. For example, in the Brazilian state of Rondônia, the government has established farmers who grow a mix of crops and use native products in a way that can provide long-term support. However, looking at other examples of environmental management is not always applicable, because each situation is unique in its environmental conditions, socioeconomic and political constraints, and opportunities for resource extraction and use.

Ecological models offer a means to quantify definitions of sustainability and to project the function, composition, and structure of sustainable systems over space and time. Developing a model requires explicit statement of the goals, inputs, and outputs of concern. The time frame and spatial boundaries and influences must be chosen. In other words, the management context and implications must be explicitly discussed and set forth. The act of determining parameter values and boundary conditions of models is valuable to the decision-making process. Models also need to be able to integrate information from several disciplines to address the specific constraints, conditions, and opportunities noted above. These tools need to address key resource management concerns, to be usable within the cultural traditions and economic and time constraints of the resource manager, and to be made known and available to potential users. Integrating models into decision making requires developing flexible tools for environmental management and making them available and understandable to landowners and resource managers. For such applications, ecological models need to be designed up front to meet these diverse needs. However, applicable and usable models are not always available to resource managers and, as a result, are not used in many instances in which they could make a significant contribution to the decision-making process. Therefore, this book is devoted to an exploration of the development and application of ecological models for resource management.

One purpose of this book is to bring to the environmental manager's attention the diversity of models that can be used in management activities. Some ecological models require technical data and instruments, such as remote sensing data or sophisticated computers. Some models build upon previous information that has been acquired from ecological, historical, social, economic, or anthropological analyses. This volume will introduce the reader to a variety of ecological models that have been successfully applied to environmental planning. Demonstrations of the uses of some of these models show the benefits that can be obtained from these types of tools. The remainder of this chapter explores the different types of models of environmental resources and sets forth the organization of the book.

1.2 Models

Models are tools that represent essential features of a system so that relationships can be analyzed within established boundary conditions. Modeling may be used to simulate natural conditions and scenarios of resource use. Analyses of models can be used to examine potential impacts of a decision. Ecological models are a tool for environmental managers to enhance understanding of both the complexities and the uniqueness of a given situation and its response to management or change. Models allow managers to summarize information on the environment, determine where gaps exist, extrapolate across the gaps, and simulate various scenarios to evaluate outcomes of environmental management decisions.

1.2.1 Types of Models

There are at least three types of models: heuristic, physical, and mathematical (Dale and O'Neill 1998). Heuristic models tend to be relatively simple but capture key relationships of the system. They can be depicted as pictures, diagrams, words, or mathematical relationships. Sometimes scientists call these "back of the envelope" models because they can be explained in a small amount of space. Such models are appealing in that they are relatively easy to understand. However, their simplicity may mean that some of the important interactions in the system are not fully characterized.

Physical models are scaled-down versions of the real world, typically constructed in three dimensions, and are sometimes used to show changes over time (the fourth dimension). Examples are microcosms, wind tunnels (used to examine aerodynamic properties of airplanes, cars, and seeds), and aquariums (used in studies of fish population dynamics). One interesting example is the use of model streams built of fiberglass in which certain chemicals can be added or the size, shape, and density of substrate materials controlled. Stream water is circulated in these models, and the growth or behavior of fish or invertebrates is observed. The model streams are designed for monitoring their interior at a height of 1 m rather than ground level of natural streams, which makes the experiments easier to observe.

Mathematical models describe relationships via numerical formulations. The chosen equations should appropriately reflect the constraints of the question at hand. The assumptions, form, and outcomes of the model need to be realistic for the situation and clearly communicated to the user. Based upon his experience in using models in courtroom situations, Swartzman (1996) points out several elements of a mathematical model that allow effective communication with decision makers.

- The model must make common sense. For example, a Leslie matrix model (Leslie 1945) is commonly used to analyze population dynamics but can project infinite growth. To avoid this unbelievable possibility being discussed in the courtroom, Swartzman (1996) introduced a density-dependent fecundity term into the model.
- A model must be simple enough for the judges, lawyers, and jury members to understand.
- Jargon must be avoided.
- The model and its projections must be clearly described; simple illustrative graphics are helpful.

These lessons are general enough to be applicable to mathematical models that might be applied to environmental decisions. The act of modeling is often called an art because there are many ways to express observed relationships using mathematics, and it takes experience, expertise, and creativity to appropriately capture complex interactions. Because of the wider use and range of applicability of mathematical models, they are the focus of this volume.

1.2.2 General Characteristics of Models

Models are a valuable tool for increasing understanding about environmental interactions. They are quantitative and, when run in a deterministic mode, are repeatable. They are able to integrate known information from a number of different sources. They can also be adjusted to a desired spatial and temporal resolution (e.g., a particular locality). However, the sophistication of numerical models often leads to a false sense of confidence and may inhibit people from questioning the results. In addition, the use of such models may be costly, time consuming, or require special expertise. Models need to be validated by comparing projections to field data or historical conditions, but such a comparison is not always done and may be infeasible in some cases. Backcasting and comparing model results to historical conditions sometimes offers a useful way to validate a model.

The ability to simulate conditions without disturbing the situation makes models particularly useful. Although the high variability of natural settings can confound the interpretation of model results, much of the variability can be controlled in their use, which enhances the potential for model experiments and the testing of hypotheses.

Ecological models can be applied to a broad range of spatial and temporal scales. The specific environmental management issue focuses the scale of the question and also the type of model to be used. Environmental managers often deal with a single ownership, although it is recognized that actions of adjacent owners must be considered (White et al. 1997) and that natural boundaries are important.

Temporal scales of ecological models are highly variable. Some models focus on processes that occur on the order of seconds to minutes while others consider changes on the time scale of decades, centuries, or millennia. Because most environmental management decisions are considered over years to decades, this book focuses on models that run over that time period. However, some ecological impacts are not apparent for many decades or even centuries, which makes it useful to consider models that can forecast results for a longer period. In any case, the time scale of a model needs to relate to the time scale of the management questions and their implications.

Many ecological models exist, and they deal with all media (land, water, and air) and associated biota. This volume applies to a diversity of environmental situations, but space is available to mention only a small number of these models. The application of models is also discussed in several volumes [e.g., Emlen (1989); Barnthouse (1992); Botkin (1992); Stalnaker (1993); Jorgensen et al. (1996); McKelvey and Hull (1996); Jackson et al. (2000); Akçakaya (2000); Akçakaya and Sjögren-Gulve (2000); Caswell (2001)]. These sources should be consulted for further information and insights. Modeling textbooks [e.g., Swartzman and Kaluzny (1987); Jeffers (1988); Bossel (1994); Haefner (1996)] provide introductory explanations of many aspects of ecological modeling. The textbooks are particularly helpful because of their extensive examples. At present, no one place exists where environmental managers can access the diversity of models that are available to address the ecological aspects of environmental management questions. The purpose of this book is to introduce the ways in which ecological models can be used for decision making and to explore ways to enhance their use.

1.3 The Roots of Modeling for Environmental Management

1.3.1 The Beginnings of Ecological Modeling

The roots of ecological modeling for environmental management lie in attempts to explain human population dynamics. The earliest explorations of geometric progression provide a way to explain human population growth (Hutchinson 1978). Recognition that an exponential growth of people up to the sixteenth century would lead to an unrealistic estimate of the people on the Earth in the future required rethinking the use of an uncontrolled exponential growth curve.

Verhulst (1838) discovered that the leveling of population growth could be represented by "the logistic equation." The term "logistic" has a rare meaning of "calculation by arithmetic," which may explain the use of the term. Data from animal populations showed that exponential growth was not often observed but that an "S" curve of population growth was more typical (i.e., it could be calculated from the data). But the logistic equation was not adopted in the analysis of population growth until studies with laboratory animals confirmed that a saturation point was typically attained. Lotka (1924) expanded upon Verhulst's work with the logistic equation to come up with the formula that is still in use today.

Volterra (1926) expanded the use of the logistic equation to describe the populations of competing species and developed the first published case of an ecological model being used for resource management. His model results were applied to explain changes in the proportion of fish in the Mediterranean Sea that resulted from the suspension of commercial fisheries during the war years of 1915 to 1918. Gause subsequently (1934) provided experimental confirmation of these interactions.

A decade later, Nicholson and Bailey (1935) used finite difference models to examine parasitism and predation (critical agricultural problems). Difference models rely on discrete time steps rather than the continuous time steps of differential equations. Therefore, difference equations are closer to the data collected at regular intervals by biologists measuring population changes. However, the mathematical properties of differential equations are more easily solved by analytical techniques so they quickly become more widely accepted. Today, both types of approaches can be implemented in computer models.

Building upon earlier applications, Hutchinson (1954) constructed mathematical models of population regulation to argue for the importance of feedback loops, which are integral to resource management. His insistence on a rigorous approach to ecology led several of his students to invoke mathematical techniques. Robert MacArthur added a quantitative analysis to the field of community ecology in the development of the concept of competitive exclusion (MacArthur 1958), which led him to the hypothesis that competition determines relationships of species occupying the same area (MacArthur 1960).

At about the same time Leslie (1945, 1948) developed a matrix approach to examine changes in life stages over time, and that technique eventually became a common tool in resource management. While working at the Bureau of Animal Population at Oxford, Leslie used matrix algebra to express age-specific relationships (Leslie 1945), explore logistic population growth and predator–prey relations (Leslie 1948), and consider time lags (Leslie 1959). Lefkovitch (1965) built upon Leslie's ideas but classified individuals by development stage rather than age. This stage approach was also used by Usher (1966) to classify trees. However, these matrix approaches were not adopted by the broad ecological community for about 25 years.

Part of the lag in the application of these ideas was the large amount of computation required.

1.3.2 Development of Computers

The development and application of ecological models are tied to the development of computers. Computer availability and flexibility enhanced the usability of models. For example, Caswell (2001) notes that the lack of computational speed hampered the adoption of the matrix models introduced by Bernardelli (1941), Lewis (1942), and Leslie (1945). Instead of those approaches, life-table methods developed at about the same time (Birch 1948; Leslie and Park 1949) were more accessible and could perform most analyses offered by matrix models without the use of computers.

The history behind the development of computers goes back for several centuries. The abacus is an ancient manual arithmetic device first used by the Chinese to add, subtract, multiply, and divide and to calculate square roots and cube roots. It consists of a frame with moveable counters. The first mechanical calculating machine was invented in the 1600s. During the 1830s, the English mathematician Charles Babbage developed the idea of a mechanical digital computer, but the existing technology was not advanced enough to provide the precision parts needed, and Babbage was not able to secure funding to develop the device.

In 1930, Vannevar Bush, an American electrical engineer, built the first reliable analog computer. Many improvements were made during the next decades, but it was John Van Neumann's idea that programs could be coded as numbers and stored in a computer's memory that hailed the next major advance. This idea was used in developing the first stored-program digital computer built in 1949.

The invention of the transistor in 1947 and related solid-state devices in the 1950s and 1960s helped produce faster and more reliable computers. The first computers represented numerical data by analogous physical magnitudes or electrical signals, whereas later models used binary digits. The move from analog to digital computers increased the speed of computations. Subsequent miniaturization of computers was based on electronic advances in the 1960s and 1970s and led to the wider dissemination of computers. The development of personal computers, the Internet, and mass-storage devices led to a proliferation of hardware and software capabilities that are now basic to many ecological models used for resource management. Today, computers are available and related to almost all aspects of business, communication, and education. In fact, children's games examine population dynamics in a mathematically sophisticated manner. A continuing challenge, however, is to include the most up-to-date ecological understanding and required complexity in models and to get those models into the hands of resource managers.

1.3.3 Systems Ecology

The field of systems ecology developed a way to use computers to address the complexity inherent in ecosystems. The technique also allowed for mathematical representation of the flow of nutrients, water, and energy, which were recognized to be a part of natural systems as the concept of ecosystems began to take hold (Odum 1983). Systems ecology recognizes the interconnectedness of ecology, and putting the ecological paradigm into a computer model allows for quantification of these connections. Feedbacks and lags can be considered. Both linear and nonlinear relationships can be modeled. Thus, a systems perspective provides for a more holistic analysis of ecological systems.

With the expansion of computing, there has been an explosion in the development and use of ecological models. Today, computers are available to many resource managers and decision makers, and many types of mathematical models contribute to understanding of environmental management issues. Models are often available to describe ecological interactions or to assess the implications of resource use. Yet deficiencies still persist in the use by managers of mathematical models to understand or to project ecological interactions and effects of resource use. Simply put, ecological models are not used as often as they could be. This book explores why this is the case and seeks to remedy the situation.

1.4 Using Model Projections for Environmental Decision Making

This book focuses on ecological models that are useful for environmental managers, models that are concerned with the ecological aspects of the values mentioned above. The models provide a way for managers to make decisions about resources while incorporating an ecological perspective. Models help to organize and track information in a way that would not be possible otherwise.

Mathematical models are particularly useful in cases where field or laboratory data are not available, complete, appropriate, or directly applicable to the decision being made. In these cases, results from models often provide a valuable perspective on alternative decisions. Such model results may be needed to complement existing information or to relate extant data to conditions at hand. However, even when extensive data are available, the complexity of the situation may require a model for interpreting interactions or expanding results to larger spatial scales, longer time scales, or higher levels of biological organization.

Effectively used, model results do not so much mimic data from the real world as reveal our current understanding of the environment (Dale and Van Winkle 1998). They can provide information regarding what the real world might and could do, but not necessarily what it *will* do. Some sort of validation is useful to determine if the model produces realistic projections.

Model results *always* contain uncertainties because they are based on (1) current understanding of interactions and (2) field and laboratory studies. That is why we call model results *projections* (i.e., estimates of future possibilities) rather than *predictions*, something that is declared in advance (Dale and Van Winkle 1998). Great caution is required in basing decisions solely on model results. Models produce approximations to real situations and are only as good as the assumptions upon which they are based. Because these assumptions are typically specific to each situation, caution must be used in applying a model developed for one circumstance to another case. The appropriate application of a model has time implications as well. Thus, a corollary to a dictum often adopted by modelers that "Reality Is a Special Case" is that "Reality (t) ≠ Reality (t + 1)" (Dale and Van Winkle 1998). Until information is available to validate a model for the situation at hand, model results should be considered with caution; they are the logical extensions of existing data produced via a process that assimilates and applies current understanding.

Current understandings of complex environmental systems, as reflected in models, will rarely be adequate alone to provide simple answers to environmental questions. The caution required in interpreting model calculations is illustrated by an example documented by Christensen et al. (1981) and Barnthouse et al. (1984). Under the scrutiny of legal proceedings, two computer simulation models were developed to determine the potential impacts of several power plants on fish populations. One model, emphasizing a particular theory of population dynamics, concluded that there would be little impact and that changes in the fish population could be explained by natural factors. The second model, relying on a different understanding of how fish populations interact with their environment, concluded that significant impacts would occur. Both models were subjected to intense scrutiny, but the difference in conclusions remained. Such cases notwithstanding, model projections often remain our best source of information for extrapolating limited theory and field and laboratory data to the real-world decision arena.

Although some would argue that models should be used as a crystal ball to gaze into the future, we think such use of models is an inappropriate goal. Models should not be believed more than any other scientific hypothesis (Dale and Van Winkle 1998). "Belief" suggests a faith or trust based on incomplete information. Instead, models should be used to improve understanding or insight about the ecological relationships and management implications. When the process of modeling inappropriately emphasizes belief rather than understanding, the failure of a model to predict a specific reality reflects, in part, unrealistic expectations.

The discussion and examples in this book build upon experiences in applied ecology, where industries or agencies are looking for models to help environmental managers, regulators, and lawyers make decisions and resolve conflicts. Often, incomplete information must be accepted, and decisions must be made with the best available information. In cases where the scientific evidence is incomplete or contradictory, decisions are often made without scientific input [e.g., as Wiens (1996) found in the aftermath of the *Exxon Valdez* oil spill].

This absence of full information does not imply that there is no scientific value in developing models in ecology. The process of a group of scientists collaborating and sharing their expertise to develop a simulation model can be a worthwhile scientific accomplishment, even if a working computer code is not completed (as occasionally occurs). Development of a simulation model is an integrative, interactive, and iterative process. Simulation modeling is a powerful process for the synthesis of data, theories, and opinions over scales of space, time, and biological organization. It also is a process for creating new insights and questions for new experimental studies. New insights and questions often emerge even when models in some sense "fail" to meet the expectations of their developers (Aber 1997). Nevertheless, the ultimate purpose for many models is to use them in decision making.

1.5 Organization of Book

The goal of the book is to identify the necessary science and technology investments and approaches that are required to increase the usefulness of ecological modeling for management decisions. The primary focus is to characterize and address the gaps between the state of the art in ecological modeling and the state of the practice in using the outcomes of models as decision aids for management deliberations. The assumptions underlying this volume are that (1) ecological modeling offers value to those engaged in the management of public and private lands, (2) the current use of models and model results falls short of this potential value, and (3) further investment will improve the value of ecological models for management use.

The material in this book is designed to be appropriate for a diverse audience who want to learn about how models can be useful for environmental management. Students interested in environmental management will find this book appropriate for critical evaluation of literature and an introduction into the diversity of types of models available for environmental management. Managers themselves will find this a useful resource for evaluating the types of tools that are available and for placing the tools they use into a broader context. Finally, scientists involved in developing new methods for environmental management will find this book to be a useful reference for determining the context of their inquiries and for elucidating questions important to address in environmental management.

This introduction chapter lays out the need for models to address environmental management issues. It also discusses how human values and patterns of resource use influence the need for tools to make appropriate decisions on how to use the resources. It provides an overview of the history of modeling for resource management and sets the stage for the diversity of models and approaches that are discussed in the subsequent chapters.

The next three chapters present examples of successful applications of models in very different fields:

- Models of endangered species, with wolf as a case study
- Ecological modeling as a component of an ecological-risk-assessment process with impacts of entrainment and impingement on fish populations as an example
- Large-scale regional assessments as a class of models that uses a variety of approaches ranging from geographic information system (GIS) to landscape to economic models to examine the impacts of decisions, with the case study focusing on the Southern Appalachian Assessment

Each of these "success stories" addresses some common questions. How does the modeling effort appear to be a success? What aspects make this a success and what aspects do not? Together, these examples provide a description of diverse ways that models can contribute to environmental management.

The following section of the book presents five sets of paired chapters. The first chapter in each set presents future challenges in the use of models for environmental management, and the second chapter discusses ways to meet the challenges. Although there is some overlap between the questions and issues for each pair of chapters, this framework provides information that is useful for the environmental managers as well as for those who develop models. The five topics are:

- *Barriers to the use of models in decision making*—Questions here include: What enhances or retards effective communication between modelers and decision makers? The pair of chapters evaluates opportunities and constraints in technology, bureaucracy, language, and cultures of science versus management. The chapters consider the type of information in models and what sort of model outputs communicate information most pertinent to decision makers.
- *Evolving approaches and technologies that will enhance the role of ecological modeling in decision making*—How can models take advantage of evolving technology to enhance the effective use of ecological modeling in management? The pair of chapters discusses the stream of information from data collection to models and then to managers and how technology can be used to enhance flow. They consider the spatial and temporal scales at which data needs are addressed and how data col-

lection influences the type of questions that can be addressed. They provide an impetus for the development of certain kinds of technologies.

- *Data issues*—This topic considers how information is collected and what kind of information (at what scale of temporal or spatial resolution) is needed to go into models, what type of information is output from models, how it is communicated to decision makers, how the decision makers use the information, and what type of information is important to them. These chapters discuss the flow of information all the way from the field situation to how it is used by managers. They also evaluate the ways in which uncertainties and variation are considered at various stages in the process. The topic has some overlap with the toolkit discussion, for toolkits are one way in which models can improve the flow of information.
- *The toolkit concept*—This pair of chapters considers how a set of modeling tools might be pooled to facilitate the use of ecological models for management. It discusses such concepts as how modules are built and combined, how visualization tools can aid understanding and expression, and what kind of information should go into a toolkit. It also evaluates how models are combined in a meaningful way, for the toolkit approach has implications for the types of science questions that can be addressed.
- *Science and management investments needed to enhance the use of ecological modeling and decision making*—Where is science investment needed to enhance the use of ecological modeling in management? This pair of chapters evaluates the current state of the science and what kinds of scientific questions are important to address in a modeling framework in order for models to be more useful for management. It also addresses how the current and future availability of tools could change the sort of science that is possible to be addressed in ecological modeling. It considers science investment in terms of experiments, data collection, tools, and what questions need to be addressed.

The last section of the book deals with the future use of models for environmental management. In one chapter, models are discussed as a key component in providing environmental security for the United States and the world. The final chapter examines the challenges for the future and what the next steps may be in model development. It also reviews some of the questions that existing models are not able to address and other limitations of current models.

Together, these chapters provide an understanding of the need, basis, and history of ecological models used for resource management and discuss how different models can contribute to a better understanding of the effects of ecological interactions on environmental use and management. It is our hope that this discussion of the modeling process will increase the use of models in environmental management and facilitate the discussions between analysts and decision makers. The ultimate goal, of course, is that wiser decisions are made that will help to maintain the sustainability of ecological resources.

Acknowledgments. Russell Harmon, Robert Holst, and Webb Van Winkle provided insightful comments on an earlier draft of this chapter. The effort was supported by a contract from the Strategic Environmental Research and Development Program (SERDP) to Oak Ridge National Laboratory, which is managed by UT-Battelle, LLC, for the U.S. Department of Energy under contract DE-AC05-00OR22725.

References

Aber, J. 1997. Why don't we believe the models? Bulletin of the Ecological Society of America **78**:232–233.

Akçakaya, H.R. 2000. Population viability analyses with demographically and spatially structured models. Ecological Bulletin **48**:23–38.

Akçakaya, H.R. and P. Sjögren-Gulve. 2000. Population viability analysis in conservation planning: An overview. Ecological Bulletin **48**:9–21.

Angermeier, P. and J. Karr. 1994. Biological integrity versus biological diversity as policy directives: Protecting biotic resources. BioScience **44**:690–697.

Barnthouse, L.W. 1992. The role of models in ecological risk assessment: A 1990's perspective. Environmental Toxicology and Chemistry **11**:1751–1760.

Barnthouse, L.W., J. Boreman, S.W. Christensen, C.P. Goodyear, W. Van Winkle, and D.S. Vaughan. 1984. Population biology in the courtroom: The Hudson River controversy. BioScience **34**:14–19.

Bernardelli, H. 1941. Population waves. Journal of Burma Research Society **31**: 1–18.

Birch, L.C. 1948. The intrinsic rate of natural increase of an insect population. Journal of Animal Ecology **17**:15–26.

Bossel, H. 1994. Modeling and Simulation. A.K. Peters, Wellesley, Massachusetts, USA.

Botkin, D.B. 1992. Forest Dynamics: An Ecological Model. Oxford University Press, Oxford, UK.

Cairns, J., P.V. McCormick, and B.R. Niederlehner. 1993. A proposed framework for developing indicators of ecosystem health. Hydrobiologia **236**:1–44.

Caswell, H. 2001. Matrix Population Models: Construction Analysis and Interpretation. Sinauer Associates, Inc., Sunderland, Massachusetts, USA.

Christensen, S.W., W. Van Winkle, L.W. Barnthouse, and D.S. Vaughan. 1981. Science and the law: Confluence and conflict on the Hudson River. Environmental Impact Assessment Review **2**:63–88.

Costanza, R., et al. 1997. The value of the world's ecosystem services and natural capital. Nature **387**:253–260.

Dale, V.H. and R.V. O'Neill. 1998. Tools to characterize the environmental setting. Pages 62–90 *in* V.H. Dale and M.R. English, editors. Tools to Aid Environmental Decision Making. Springer-Verlag, New York, New York, USA.

Dale, V.H. and W. Van Winkle. 1998. Models provide understanding, not belief. Bulletin of the Ecological Society of America **79**:169–170.

Emlen, J.M. 1989. Terrestrial population models for ecological risk assessment: A state-of-the-art review. Environmental Toxicology and Chemistry **8**:831–842.
Gaus, G.F. 1934. The Struggle for Existence. Williams & Wilkins, Baltimore, Maryland, USA.
Haefner, J.W. 1996. Modeling Biological Systems: Principles and Applications. Chapman and Hall, New York, New York, USA.
Hutchinson, G.E. 1954. Theoretical notes on oscillatory populations. Journal of Wildlife Management **18**:107–109.
Hutchinson, G.E. 1978. An Introduction to Population Ecology. Yale University Press, New Haven, Connecticut, USA.
Jackson, L.J., A.S. Trebitz, and K.J. Cottingham. 2000. An introduction to the practice of ecological modeling. BioScience **50**:694–706.
Jeffers, J.N.R. 1988. Practitioner's Handbook on the Modelling of Dynamic Change in Ecosystems. John Wiley & Sons, New York, New York, USA.
Jorgensen, S.E., B. Halling-Sorensen, and S.N. Nielsen. 1996. Handbook of Environmental and Ecological Modeling. Lewis Publishers, Boca Raton, Florida, USA.
Lefkovitch, L.P. 1965. The study of population growth in organisms grouped by stages. Biometrics **21**:1–18.
Leopold, A. 1953. The Land Ethic. Round River, Oxford University Press, Oxford, UK.
Leslie, P.H. 1945. On the use of matrices in certain population mathematics. Biometrika **33**:183–212.
Leslie, P.H. 1948. Some further notes on the use of matrices in population mathematics. Biometrika **35**:213–245.
Leslie, P.H. 1959. The properties of a certain lag type of population growth and the influence of an external random factor on a number of such populations. Physiological Zoology **32**:151–159.
Leslie, P.H. and T. Park. 1949. The intrinsic rate of natural increase of *Tribolium castaneum* Herbst. Ecology **30**:469–477.
Lewis, E.G. 1942. On the generation and growth of a population. Sankhyā **6**:93–96.
Lindenmayer, D.B., C.R. Margules, and D.B. Botkin. 2000. Indicators of biodiversity for ecological sustainable forest management. Conservation Biology **14**:941–950.
Lotka, A.J. 1924. Elements of Physical Biology. Williams & Wilkins, Baltimore, Maryland, USA. (Reprinted in 1956 by Dover Publications of New York, New York, USA, as Elements of Mathematical Biology.)
MacArthur, R.H. 1958. Population ecology of some warblers of northeastern coniferous forests. Ecology **39**:599–619.
MacArthur, R.H. 1960. On the relative abundance of species. American Naturalist 94:25–34.
McKelvey, R., and V. Hull, editors. 1996. Special issue: Ecological resource modelling. Ecological Modelling **92**.
Nicholson, A.J. and V.A. Bailey. 1935. The balance of animal populations. Proceedings of the Zoological Society of London **1**:551–598.
Odum, E.P. 1983. Basic Ecology. Saunders College Publishing, New York, New York, USA.
Stalnaker, C.B. 1993. Fish habitat evaluation models in environmental assessments. Pages 140–162 *in* S.G. Hildebrand and J.B. Cannon, editors. Environmental Analysis: The NEPA Experience. Lewis Publishers, Boca Raton, Florida, USA.

Stork, N.E., T.J.B. Boyle, V. Dale, H. Eeley, B. Finegan, M. Lawes, N. Manokaran, R. Prabhu, and J. Soberon. 1997. Criteria and Indicators for Assessing Sustainability of Forest Management: Conservation of Biodiversity. Center for International Forestry Research Working Paper No. 17. Bogor, Indonesia.

Swartzman, G. 1996. Resource modelling moves into the courtroom. Ecological Modelling **92**:277–288.

Swartzman, G.L. and S.P. Kaluzny. 1987. Ecological Simulation Primer. Macmillan Publishing Company, New York, New York, USA.

U.S. Department of Agriculture (USDA). 2000. 1997 National Resources Inventory, Revised December 2000. USDA Natural Resources Conservation Service, Washington, District of Columbia, USA.

Usher, M.B. 1966. A matrix approach to management of renewal resources, with special reference to selection forests. Journal of Applied Ecology **3**:355–367.

Verhulst, P.F. 1838. Notice sur la loi que la population suit dans son accroissement. Correspendances Mathématiques et Physiques **10**:113–121.

Volterra, V. 1926. Variazioni e fluttuazioni del numero d'individui in specie animali conviventi. Mem. Acad. Lincei **2**:31–113. (Translation in an appendix to R.N. Chapman. 1931. Animal Ecology. McGraw-Hill, New York, New York, USA.)

Wiens, J. 1996. Oil, seabirds, and science: The effects of the Exxon Valdez oil spill. BioScience **46**:587–597.

White, D., P.G. Minotti, M.J. Barczak, J.C. Sifneos, K.E. Freemark, M.V. Santelmann, C.F. Steinitz, A.R. Kiester, and E.M. Preston. 1997. Assessing risks to biodiversity from future landscape change. Conservation Biology **11**:349–360.

World Commission on Environment and Development. 1987. Our Common Future. Oxford University Press, Oxford, UK.

Part 2

Examples of Using Ecological Models for Resource Management

2
Modeling for Endangered-Species Recovery: Gray Wolves in the Western Great Lakes Region

Jean Fitts Cochrane, Robert G. Haight, and
Anthony M. Starfield

2.1 Introduction

The Federal Endangered Species Act is intended to conserve endangered and threatened species and their habitats and to improve the species' status so that they no longer need protection under the Act. In the process of planning the recovery of threatened or endangered species, the U.S. Fish and Wildlife Service increasingly uses demographic models to predict population growth and risk of extinction, investigate the factors responsible for species endangerment, and examine the relative effectiveness of alternative management options for species recovery. Demographic models range from simple matrix models for estimating population change (Getz and Haight 1989) to complex, spatially explicit, individual-based models of population dynamics (Dunning et al. 1995). Such models require at a minimum an understanding of the age, stage, and social structure of the population and estimates of reproductive success and survivorship for different life stages. The purpose of this chapter is to describe an example of the construction of a demographic model with application to questions associated with the recovery and management of the endangered gray wolf (*Canis lupus*)population in the western Great Lakes region of the United States.

The most common use of demographic models in recovery planning is the prediction of long-term, range-wide extinction risks, a process called population viability analysis (PVA) [see Boyce (1992a) and Beissinger and Westphal (1998) for review]. An endangered-species recovery plan contains criteria for recovery (i.e., delisting) and reclassification (i.e., change from endangered to threatened status) that specify goals for the size, distribution, and other attributes of the population. The results of a PVA inform recovery planners who set the population goals. For example, Kelly et al. (1999) and Ellis et al. (1999) describe applications of commercial PVA software in recovery planning for the endangered red wolf (*Canis rufus*) and Florida panther (*Felis concolor coryi*) in the southern United States. In other cases, such as the endangered piping plover (*Charadrius melodus*)

(U.S. Department of the Interior 1996), custom models have been built to predict population trends and to help establish recovery targets.

Demographic models have also been developed to address specific questions about the management of an endangered species that arise during the implementation of the recovery plan. These questions usually relate to potential threats, such as habitat destruction or any other natural or man-made factor that might affect the continued existence of the species. For example, Lamberson et al. (1994) analyzed the impacts of habitat patch size and spacing on population viability and thereby helped direct the design of forest reserves for the endangered Northern spotted owl (*Strix occidentalis caurina*).

The modeling projects in this chapter address specific management questions that were raised during the recovery of the gray wolf. The questions involved predicting the impacts of human-caused mortality, changing regional environmental conditions, and disturbance on the persistence of small wolf populations. In addition, the questions involved predicting the relative performance of different strategies for controlling wolf populations. Our approach involved constructing a relatively simple population model that was consistent with the current level of understanding of wolf dynamics and was customized to address specific management questions. Our model included the basic processes of wolf demography (birth, survival, and dispersal) and the social structure of a wolf population. We used the model to simulate population impacts of changes in demographic parameters, and we used model predictions to infer how changes in management activities and environmental processes might affect wolf populations. While we used the same basic population model for all the projects, we modified the model and developed distinct simulation experiments to address each question separately. Our approach differs from other gray wolf modeling projects, such as long-term PVA using commercial software [e.g., Rolley et al. (1999); Kelly et al. (1999); Ewins et al. (2000)] and analytical wolf-prey models [e.g., Walters et al. (1981); Boyce (1992b)], which do not address the population effects of wolf social structure.

2.2 Wolf Biology and Recovery Status

Wolves live in packs and defend exclusive territories (Mech 1970). Generally, packs are family groups consisting of one dominant breeding pair and their offspring (Mech 1970). In the western Great Lakes region, midwinter pack size averages 4 to 8 wolves, about half of which are pups (Fuller 1989). Because of territoriality, regional population density and reproductive rate depend on the number and size of territories. Wolves are not habitat specific, instead they can live wherever they find enough to eat (primarily ungulates), provided killing by humans or disease is not excessive (Fuller 1995; Mech 1995). Population turnover rates are naturally high, with six pups born per pack and more than half of pack members lost to mortality and dispersal each year (Mech 1970; Cochrane 2000). A dispersing wolf may pair with one of the opposite sex and colonize a vacant territory or may join another pack and replace a missing breeding member (Mech 1970; Rothman and Mech 1979). A wolf population can cover thousands of square kilometers with several independent but interacting packs. In the western Great Lakes region (Minnesota, Wisconsin, and Michigan), midwinter pack territories average 150 to 180 km^2 (Fuller et al. 1992). Range expansion is facilitated by great variation in dispersal behavior: some wolves establish territories and mate near their natal territories, whereas others move long distances (Gese and Mech 1991).

Although gray wolves once lived throughout the Lake States, European settlers nearly eliminated wolves through intensive, unregulated exploitation. By 1960, wolves were limited to the wilderness of northeastern Minnesota, contiguous to a large Canadian wolf population, and Isle Royale in Lake Superior (Mech 1970). Following protection under the U.S. Endangered Species Act in 1973, wolf numbers and range in the Great Lakes region increased. Yet in the core wilderness range within the Superior National Forest, Minnesota, precipitous local extirpation of white-tailed deer (*Odocoileus virginianus*) caused a sharp decline in wolf numbers in the 1970s until the remaining wolves switched to hunting less numerous moose (*Alces alces*) (Mech 1986). The wolf decline was thought to be spreading westward into Voyageurs National Park in the mid-1980s (Gogan et al. 2000). Thus, while wolves were generally faring well by the 1980s, their long-term persistence was still not certain throughout the western Great Lakes region.

After determining that most wolf mortality near Voyageurs Park was caused by humans, either accidentally or by deliberate illegal killing, biologists raised concerns about recreational disturbance impacts on the park's wolves. Interagency consultation with the U.S. Fish and Wildlife Service on park development proposals in 1992 led to stipulations for a cumulative effects model to assess the long-term fate of wolves in the park (Cochrane 2000). At the same time, wolves had moved into the largely forested region of northern Wisconsin, but their fate was uncertain because they had colonized isolated areas with relatively low road densities within a human-dominated landscape. To meet recovery goals in Wisconsin and Michigan's Upper Peninsula, wolves would have to be able to survive in nonwilderness conditions. Modeling was seen as a useful approach to explore wolf viability in human-dominated landscapes (Haight et al. 1998).

By the late 1990s, the picture for wolves was much more favorable, with their range covering most of northern Minnesota, northern Wisconsin, and upper Michigan (Figure 2.1). In 2000, the population in Minnesota exceeded 2400 wolves (W.E. Berg and S. Benson, Minnesota Department of Natural Resources, personal communication, 2000), and the populations

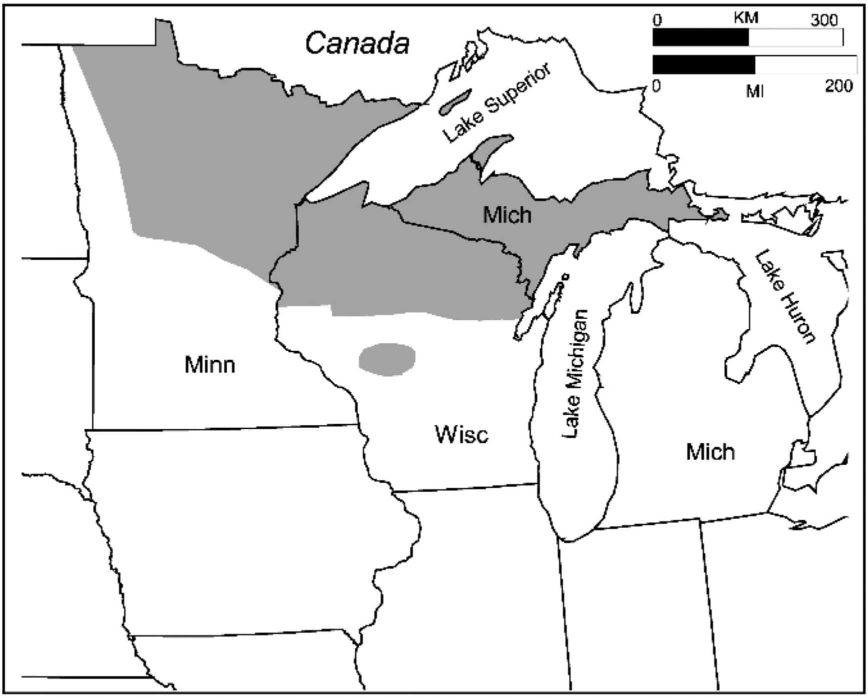

FIGURE 2.1. Shaded areas show the approximate range of gray wolves in Minnesota, Wisconsin, and Michigan in the year 2000.

in Wisconsin and Michigan each exceeded 200 wolves (U.S. Department of the Interior 2000). The great increases in wolf numbers and range raised new issues about controlling negative impacts from wolves, including depredation on livestock and pets, which could be explored through modeling (Haight and Mech 1997).

Because of the growth and recovery of wolf populations in the Lake States, the U.S. Fish and Wildlife Service has proposed reclassifying the gray wolf from endangered to threatened in the western Great Lakes region. Full removal of this population from the federal list of endangered and threatened species is expected to follow within a few years. When the gray wolf is delisted, responsibility for wolf management will be transferred from the federal government to the states. To facilitate federal delisting and to guide state governments as they prepare to assume wolf management responsibilities, state agencies developed management plans with the primary goal of ensuring the long-term survival of the wolf while addressing concerns about wolf range expansion into agricultural areas and animal damage control. The modeling projects we describe addressed specific questions about managing wolves during the recovery process.

2.3 Case Studies

During the period of wolf recovery in the 1990s, we worked with decision makers and biologists to define and address five wolf management questions, in this order:

1. What conditions support or hinder the persistence of disjunct wolf populations in human-dominated landscapes (e.g., newly colonized habitats in Wisconsin)?
2. What are the cumulative effects of regional environmental conditions and human-caused mortality on wolf population size in a small park (e.g., Voyageurs National Park)?
3. How much disturbance does it take to cause reductions in a small wolf population?
4. Is vasectomy a practical alternative for controlling or reducing the size of a disjunct wolf population?
5. What wolf removal strategies are most effective and efficient for reducing wolf depredation on livestock?

Our management questions involved predicting the impacts of human-caused mortality, regional environmental conditions, and disturbance on the persistence of wolf populations. In addition, the management questions involved predicting the relative performance of different strategies for controlling wolf population size and depredation. We decided not to model these environmental processes and control strategies directly. Rather, we made a demographic model of wolf population dynamics and made assumptions about how these environmental processes and control strategies affected the birth, survival, and dispersal of wolves. Then, we used the model to investigate the population impacts of changes in these demographic parameters. Finally, we interpreted the model results as inferences of the population impacts of the environmental processes and control strategies.

We constructed the wolf population model to represent key elements of wolf demography and social organization. Because wolves live in packs and defend territories, we decided to represent a wolf population as a collection of packs and to model the demography of each pack. Within a pack, only one female breeds each year, and mortality rates are age dependent. Furthermore, we were interested in the population impacts of human activities that affected breeding. Thus, we decided to use a stage-structured model that kept track of the age, sex, and breeding status of wolves in each pack. Juvenile and adult wolves disperse from natal packs in search of mates and territories. Because of the great variation in dispersal behavior, we decided to use a random dispersal process and did not represent territories as specific shapes on an actual landscape.

In the sections below, we first describe the structure and parameters of the wolf population model and then describe its application to the management questions.

2.3.1 A Gray Wolf Population Model

We developed a demographic, stage-structured, stochastic simulation model of wolf dynamics. The model was designed to simulate a wolf population living in a human-dominated landscape with abundant, well-distributed prey. The landscape was bounded by the assumption that it could support a maximum of 64 pack territories. Each territory was classified based on the dominant land use (e.g., agriculture or wilderness). The number of territories and the land-use classifications varied with the objectives of the application.

To simulate wolf life history, we created a stage-class model for the dynamics of each pack. The model used stochastic difference equations with a 1-year time step to simulate the mortality, dispersal, and birth of wolves and the fate of dispersing wolves. Detailed lists of model assumptions and demographic parameter values are given in specific applications in Haight and Mech (1997), Haight et al. (1998), and Cochrane (2000). For illustration, we describe the parameter values used to predict the performance of alternative wolf removal strategies for population size control (see Section 2.3.6). These parameter values represent 5- to 10-year averages of observations in north central Minnesota (Fuller 1989) and Wisconsin (Wydeven et al. 1995).

Each pack was characterized by the number of wolves of each sex in each of four stages, which were defined based on age and breeding status. Three age classes for nonbreeding wolves were pup (0 to 12 months), yearling (12 to 24 months), and adult (>24 months). The fourth stage was defined for the breeding pair, each of which must be at least 12 months old by the first of May. Because breeding was assumed to take place in March, the minimum breeding age was 22 months.

The annual cycle of events (Figure 2.2) began in autumn with the tally of population attributes, including population size and the number of packs. The first demographic event was mortality in autumn and winter, which represented losses from natural and human (accidental and illegal) causes. The number of wolves that died in each life-history stage was a binomial random variable with a mean that depended on wolf age. Pups were subject to a 65% mortality rate, while yearlings and adults had a 32% mortality rate. In other applications, the age-dependent mortality rates varied from pack to pack, depending on the land-use class (e.g., adult mortality rates were lower in packs in wilderness areas compared with packs in agricultural areas because there was less human-caused mortality).

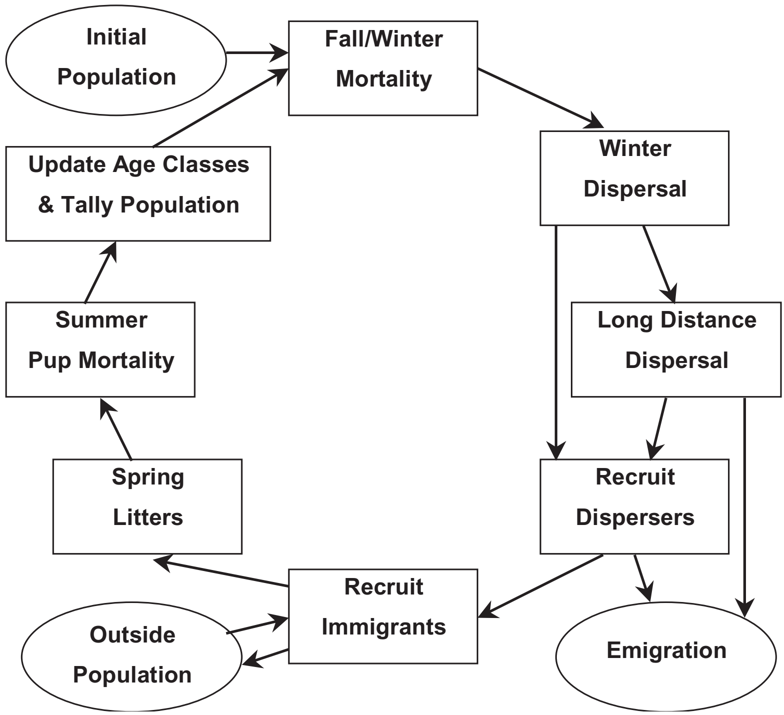

FIGURE 2.2. Annual sequence of events in the gray wolf population model.

Dispersal took place in late winter and depended on the survival of the breeding pair. If the breeding pair died, remaining pack members dispersed. If one or both breeders were present, the number of dispersers from each age class was a binomial random variable. Dispersal probabilities for pups, yearlings, and nonbreeding adults were 25, 50, and 90%, respectively, so that most nonbreeding wolves dispersed before reaching 4 years old (Gese and Mech 1991). We assumed that 20% of the dispersing wolves were long-distance dispersers that immediately emigrated from the area and thus were lost from the population, based on studies demonstrating this type of rapid, long-distance dispersal behavior in Minnesota wolves (Gese and Mech 1991).

Each remaining disperser searched the area for a suitable site, which was defined as a vacant site or a site with an available mate. Wolves could only settle into territories by mating or becoming a territory-holding, available breeder. To account for immigration from a population outside the area, we assumed that six outside wolves joined this pool of dispersing wolves in the search for suitable sites. Each dispersing wolf and immigrant was assumed to sample six territories at random with replacement [see Lande (1987) and Lamberson et al. (1994) for other applications of this kind of search model]. The implication of this assumption was that spatial coordinates and shapes of pack territories were not included. The probability of finding a suitable site was one minus the probability of failing to find a suitable site within six trials:

$$P = 1 - [(1 - S)/T]^{\wedge} N$$

where P is the probability of success, S is the number of suitable sites, T is the total number of sites, and N is the number of trials.

A uniformly distributed random number was drawn for each dispersing wolf and compared with the probability of success. A successful wolf was randomly assigned to a site with an available mate, and if no mate was available, to a vacant site. An unsuccessful wolf was assumed to be lost from the population (e.g., the wolf died or emigrated). Thus, whether or not dispersing wolves settled into a territory and remained in the population depended on the number of suitable sites.

A new litter of pups was born in spring if a breeding pair was present. Litter size was chosen from a discrete probability distribution with a mean of 6.5 pups and a range of 0 to 10 pups (Fuller 1989). The sex of each pup was a Bernoulli trial with equal probability. If there was only one member of the breeding pair present, the wolf held its territory but did not produce a litter. Nonbreeding pack members could not mate without first dispersing from their natal pack. Recent evidence suggested that parent–offspring or sibling mating rarely, if ever, occurs (Smith et al. 1997).

Summer pup mortality was modeled as a binomial random variable with a mean depending on the modeled scenario, such as incidence of disease or prey biomass available. Instead of defining a separate process for the summer mortality of older wolves, we assumed that any older wolves that died in the summer were accounted for in the winter mortality process, which was based on annual mortality rates.

Following birth and summer pup mortality, the age distribution of each pack was updated, and population statistics were tallied, representing a typical autumn population census. The number of wolves by life stage of each pack was used as the basis of the next annual cycle.

Using the demographic parameters described above, we tested the model by comparing the growth rate of a simulated colonizing population with the actual recolonization of wolves in northern Wisconsin. The Wisconsin population grew from an estimated 34 wolves in 1990 to 248 wolves in 2000, an average annual growth rate of 22% (U.S. Department of the Interior 2000). The simulated population started with 40 wolves in 4 packs and grew to 244 wolves in 38 packs in 10 years, an average annual growth rate of 20%.

We also checked the model's prediction of the relationship between population growth and mortality (Haight et al. 1998). The rates of population growth and mortality observed over 5 to 10 years have been compiled from wolf population studies throughout North America (Fuller 1989) and show a strong negative correlation. Using a colonizing population of 40 wolves in 4 packs, we simulated the 5-year population growth under different adult mortality rates (10 to 50%). The rates of population growth were negatively correlated with mortality and suggested that population size stabilized with a mortality rate of about 35%, similar to the conclusion of Fuller (1989) based on field studies. Additional model tests and sensitivity analyses are reported in Cochrane (2000).

The software for the wolf simulation model was written by and is available from the two senior authors. Versions of the source code were written in FORTRAN and Visual BASIC. The applications were performed on an IBM300PL and other personal computers. We have used this type of model for other social carnivores, including the San Joaquin kit fox (*Vulpes macrotis mutica*) in California (Haight et al. 2002) and the African lion (*Panthera leo*) (Starfield et al. 1981). Population models with similar territorial and dispersal mechanisms were used for northern spotted owl (*Strix occidentalis caurina*) recovery planning (Lande 1987; Lamberson et al. 1994).

2.3.2 Persistence of Wolves in Human-Dominated Landscapes

Following protection under the Endangered Species Act in 1973, wolves from northeastern Minnesota recolonized most of northern Minnesota and parts of northern Wisconsin and northern Michigan (see Figure 2.1). The landscape in this range was not wilderness but a mosaic of forest, agricultural, and developed land under a variety of public and private ownerships (Mladenoff et al. 1995). Logging and agriculture had created extensive areas of young forest that supported large populations of white-tailed deer, the preferred prey of wolves in this region. Colonizing wolves first settled in forested areas with few roads and little human settlement. Later, wolves settled in forested areas with higher road and human population densities (Fuller et al. 1992). The wolf populations in Wisconsin and Michigan were separated from the larger source population in northern Minnesota by large areas of less-favorable habitat and Lake Superior. Further, much of the wolf mortality was human caused, whether intentional, accidental, or indirectly caused through the transmission of disease from domestic dogs (Fuller et al. 1992).

Because the management objectives of state agencies included protection of colonizing wolf populations, the agencies wanted to predict the fates of small, disjunct populations under alternative assumptions about human-caused mortality. To address this question, Haight et al. (1998) used the wolf model to simulate a hypothetical disjunct wolf population. The model assumed a maximum of 16 wolf territories divided into core and peripheral ranges. The average annual mortality rate in the core range was 20%, whereas the mortality rate in the peripheral range was higher (40%) because of human-caused deaths. Haight et al. (1998) conducted a set of simulation experiments in which they varied the proportion of the 16 territories in core and peripheral ranges and observed the 50-year occupancy of that range by wolf packs. In the sensitivity analysis, they repeated this set of experiments under different assumptions about pup and dispersal mortality and immigration.

These sets of simulations supported a favorable outlook for the survival of small, disjunct wolf populations like those in northern Wisconsin and Michigan. The results showed that the level of occupancy increased as the number of core sites and immigrants increased. With pup and dispersal mortality rates that were consistent with disease-free and legally protected populations, the model predicted that wolves would saturate a cluster of 16 territories with as few as two core, low-mortality sites, regardless of immigration rates. When pup and dispersal mortality rates were high, as few as two immigrants per year helped maintain site occupancy in clusters with four or more core sites.

These simulation results were consistent with observations of disjunct wolf populations in the United States and Canada (Fritts and Carbyn 1995). For example, during the past 60 years, a population of 40 to 120 wolves has lived in and around Canada's Riding Mountain National Park (3,000 km^2). The park is surrounded by agricultural land, and the nearest wolf population is 45 km away. The population survived even though many of the packs were vulnerable to human exploitation along the park boundary. Based on empirical evidence and simulation results, Haight et al. (1998) concluded that wolves can survive and thrive in networks of disjunct populations, provided that they are linked by dispersal, human persecution is not excessive, and prey are abundant. Further, they concluded that, with continued protection from deliberate killing, wolf range will expand in human-dominated landscapes where prey are abundant. These predictions were incorporated into wolf recovery and management plans written by state agencies. The results also raised questions about the need for population control, especially where wolf presence conflicts with other valued land uses.

2.3.3 External Threats to Gray Wolves at Voyageurs National Park

Voyageurs National Park is a small (882 km^2) reserve of boreal and mixed-deciduous forests and numerous lakes in the heart of wolf range on Minnesota's Canadian border. In the 1990s, park biologists were concerned that high levels of human-caused mortality among wolves immediately surrounding the park could combine with changing prey densities and disease incidence to reduce or even threaten park wolves. Following interagency consultations to evaluate the impacts of proposed park recreation development, park biologists commissioned use of a cumulative effect model to address their concerns. Rather than build the comprehensive, habitat-based model envisioned by park biologists, Cochrane (2000) used the demographic wolf population model to predict the relative effects of four environmental factors (prey availability, human-caused mortality, immigration, and disease mortality) on the persistence of wolves in the park.

To predict the relative impacts, Cochrane (2000) employed a full-factorial experimental design with the four environmental factors at five levels each. The wolf population in the model was assumed to occupy a maximum of 15 territories, 3 inside the park and 12 surrounding the park. The response variable was the likelihood that wolf population size inside the park fell below specified thresholds in any year before the 30-year time horizon. Ten response variables were measured with population sizes from 0 to 18 wolves in increments of 2. The level for each primary environmental factor was specified in terms of the levels of one or more demographic parameters in the simulation model. The level of prey availability affected mean litter size and the rates of dispersal and winter mortality; human-caused mortality affected the rate of winter mortality in territories outside the park; and disease mortality affected the rate of summer pup mortality. The levels of immigration were 0 to 24 immigrants per year in increments of 6.

The results of this factorial analysis (Figure 2.3) suggested that disease mortality is the most important factor affecting whether or not the park wolf population would remain near its initial population size. Immigration had the most impact on the likelihood that the wolf population in the park would fall below a threshold of seven wolves. Human-caused mortality in wolf territories outside the park had little effect on the number of wolves in the park, except when the population was already very small under extreme conditions of no immigration, very low prey biomass, and high disease mortality. While changes in the demographic parameters associated with alternative levels of prey availability had little effect on wolf population size, prey availability had stronger effects in experiments where prey determined territory spacing or sizes (results not shown). Thus, prey availability within foreseeable ranges had an effect on total wolf numbers (through the number of territories that can "fit" within the small park) but very little relationship with the likelihood of extirpation. It was easier to maintain breeding pairs rather than a large population in the park, and these breeding pairs were highly resilient to extirpation because of the readily available pool of replacement breeders.

The results of this factorial analysis helped ameliorate concerns about human-caused mortality of wolves outside the park while focusing new attention on the spread of disease from dogs to wolves. In addition, the model results indicated which environmental conditions would likely enhance the security of the population. Those environmental conditions, which supported the population's reproductive capacity more than a constant, large population size, could be monitored in lieu of intensive wolf population sampling or trend interpretation.

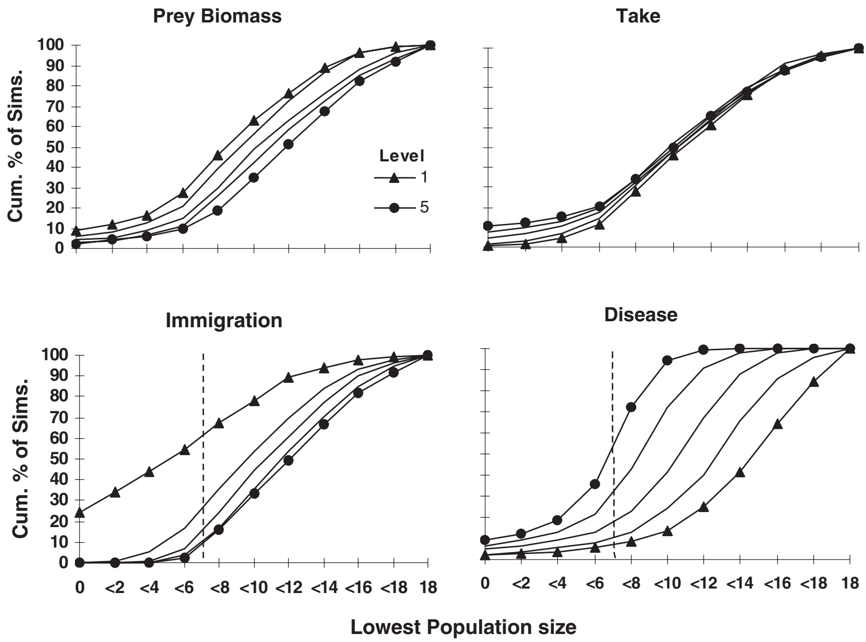

FIGURE 2.3. Proportions of simulations that fell below different wolf-population-size thresholds in Voyageurs Park out to a 30-year horizon. Each graph shows outcomes associated with one cumulative impact factor at five different levels from the lowest (Level 1) to the highest (Level 5) level tested. "Take" refers to human-caused mortality. The initial population included 18 wolves in the park.

2.3.4 Disturbance Effects on Gray Wolves inside Voyageurs National Park

In addition to human-caused mortality of wolves outside Voyageurs National Park, biologists were concerned about the impact of humans on the behavior of wolves inside the park. For example, when disturbed by humans, wolves sometimes move pups to alternative den sites and temporarily ignore prey. While examples of these responses to humans have been observed in protected areas, their frequency and impact on wolf demography at this park are not known. Cochrane (2000) used the wolf population model to investigate how altered behavior of individual wolves or packs, expressed as temporary changes in the demographic parameters in the population model, might affect the persistence of wolves in the park. The purpose was to provide park biologists with guidance on the magnitude and frequency of disturbance events that could affect wolf population size.

To predict the relative impacts of different types of disturbances, Cochrane (2000) simulated a wolf population that was assumed to occupy a maximum of 15 territories, 3 inside the park and 12 surrounding the park. The demographic parameters represented current regional conditions for prey biomass, human-caused mortality, wolf disease, and immigration.

Cochrane (2000) defined 125 disturbance scenarios based on type of disturbance event and frequency of occurrence within the park. The five types of disturbance events were loss of one, two, and three wolves; loss of an entire litter; and displacement of an entire pack from its territory. The 25 frequency classes had average intervals between events from 1 to 100 years. Each disturbance scenario was simulated 1000 times, and the response variables were the average size of the wolf population in the park after 30 years and the likelihood of falling below population-size thresholds, as in the previous study.

The disturbance events had little effect on population size when the number of years between events averaged 6 years or more (Figure 2.4). When disturbances occurred with an average return interval of less than 6 years, scenarios involving losses of litters resulted in the smallest wolf populations. The results in Figure 2.4 can be used to inform the development of management guidelines for controlling disturbance events. For example, to obtain a population of at least 24 wolves after 30 years, a litter of pups cannot be lost more often than once every 6 years. The results in Figure 2.4 are projections of average responses to simulated disturbance events under current conditions, and we explained to park managers that they should not expect to see such a specific or precise impact, given the diverse factors affecting park wolves at any time.

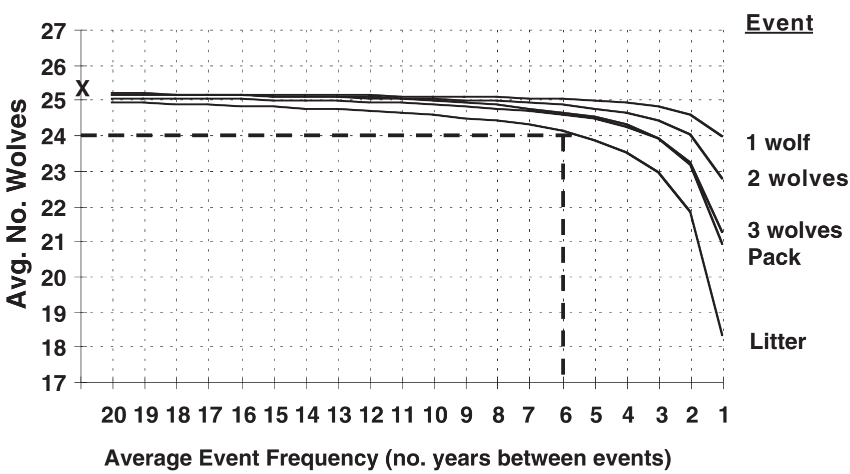

FIGURE 2.4. Predicted relationships between the average number of wolves in Voyageurs Park after 30 years and the frequency of disturbance events. The five types of disturbance events were loss of one, two, and three wolves; loss of an entire litter; and displacement of an entire pack from its territory.

These modeling results must be linked to field research to resolve what human activities cause the kinds and frequencies of disturbance that we considered. Generally, if the primary management goal is maintaining wolf numbers, then management actions should focus on protecting the integrity of territories for sustainable use by breeding pairs rather than protecting individual animals from human harassment. This quantitative analysis did not address alternative and largely implicit goals of protecting wolves from any behavioral changes caused by human disturbance or displacement within a natural ecosystem (e.g., Forbes and Theberge 1996).

2.3.5 Vasectomy for Wolf Control

In the late 1990s, recovering wolf populations in Minnesota, Wisconsin, and Michigan prompted state management agencies to consider strategies to control wolf population growth. Population control may be necessary where wolves colonize areas close to human settlement and conflict with other valued land uses. Because killing wolves to control population size is not acceptable to many people, vasectomy was proposed as a nonlethal control strategy that might have wider public acceptance.

Vasectomy involves sterilizing a male wolf in the field with chemical sclerosing agents to harden and block the sperm tract without affecting hormones. The primary reason that vasectomy might be practical for controlling wolves is that single pairs of adult wolves occupy large territories (150 to 180 km^2 in the western Great Lakes region) and thus control the number of offspring over a large area for 5 years or more. Pairs that fail to produce young because of vasectomies or natural reasons may continue to hold territories for years (Hayes 1995; Mech et al. 1996). Thus, by sterilizing the breeding male in a territory, theoretically a manager could restrict the number of wolves in that large area for years.

To evaluate and compare wolf control strategies, Haight and Mech (1997) used the wolf population model to predict the effects of both vasectomy and removal on the trends of a small, disjunct population. The hypothetical population occupied a landscape composed of a maximum of 16 wolf territories equally divided between core (20% annual mortality rate) and peripheral (35% annual mortality rate) ranges. The wolf management strategies included periodic sterilization of all breeding males, sterilization of fertile males caught in a random-trapping design, and various wolf removal designs. Of particular interest was the effect of immigration from neighboring unmanaged populations on the performance of the strategies in the managed population.

Simulations suggested that the effects of wolf vasectomy in a small, disjunct population are strongly related to the level of annual immigration. With low immigration, periodic sterilization reduced pup production and resulted in lower rates of territory recolonization. Consequently, average pack size, number of packs, and population size were significantly less than those for an untreated population. With high immigration, periodic sterilization reduced pup production, but not territory recolonization and, therefore, resulted in only moderate reductions in population size relative to the untreated population. While periodic wolf removal produced the same population size trends as sterilization, more than twice as many wolves had to be removed than sterilized.

While sterilizing free-ranging wolves for population control has never been attempted, the simulation results of Haight and Mech (1997) suggested that for small, disjunct wolf populations, such as those that inhabit much of Wisconsin, Michigan, and central Minnesota, vasectomy may be a practical, cost-effective method of controlling wolf numbers. The method would require handling fewer wolves than would lethal trapping, although sterilizing captured wolves would require more highly trained workers.

Whether vasectomy would be effective or practical in larger populations is unknown. The simulation results of Haight and Mech (1997) suggested that, when turnover in breeding tenure is high, vasectomy is less effective. However, lethal methods would also be less effective in such populations. Thus, experimentally comparing sterilization and lethal control appears to be worth trying even in larger populations.

2.3.6 Wolf Removal Strategies for Animal Damage Control

Wolf management planners in Minnesota, Wisconsin, and Michigan must develop strategies that balance competing demands for wolf protection and animal damage control. As wolf populations in these states increased in the 1990s, wolf range expanded into areas with farms and livestock, and wolf depredations on livestock and domestic animals increased. For example, from 1979 to 1988, an average of 26 Minnesota farms were affected, and 32 wolves were destroyed annually; from 1989 to 1998, an average of 66 farms were affected, and 126 wolves were destroyed each year (Mech 1998). As a result, many farmers and rural residents expressed concern about expanded wolf range and increased animal damage, calling for population controls or sport harvest seasons. At the same time, wolf protection advocates argued that depredation control should continue as a government program but without a general harvest or limitations on wolf range and population expansion.

Given these conflicting demands for wolf management in agricultural regions, we used the wolf population model to evaluate and compare the performance of three types of wolf removal strategies that were considered by state management agencies as candidates to balance those demands. The removal strategies included reactive management, in which wolves were removed from territories following recent depredation; preemptive management, in which wolves were removed from territories in which depredation had occurred in 1 or more of the previous 5 years; and population control, in which wolves were removed from all territories overlapping livestock production areas regardless of the depredation history. We simulated a hypothetical 64-pack wolf population living in a landscape composed of equal proportions of farm and wild areas. The simulations were used to predict the relative performance of the three strategies taken alone and in combination. The model predicted the number of wolf depredations on livestock and the number of wolves removed out to a 20-year horizon.

The most significant result was that, compared with no action, each removal strategy alone cut depredation in half (Figure 2.5). Depredations were reduced because each strategy focused on wolf removal in territories overlapping farms. As a result, many farm territories were free of wolves during the spring and summer, when depredation occurs. While wolf removal focused on farm territories, wolves were not removed from wild areas within the simulated region. As a result, the population was never in danger of extirpation. The number of removals varied greatly among strategies and depended on the timing of removals. Under preemptive management, wolves were trapped and removed in winter before pups were born. As a result, preemptive management removed far fewer wolves than reactive removals or population control in which wolves were trapped and removed after pups were born (see Figure 2.5). Further reductions in depredation were obtained by using two removal strategies each year, which increased the number of farm territories that were free of wolves. If the cost of wolf removal is proportional to the number of wolves removed, the simulation results suggest that preemptive removal of wolves from farm

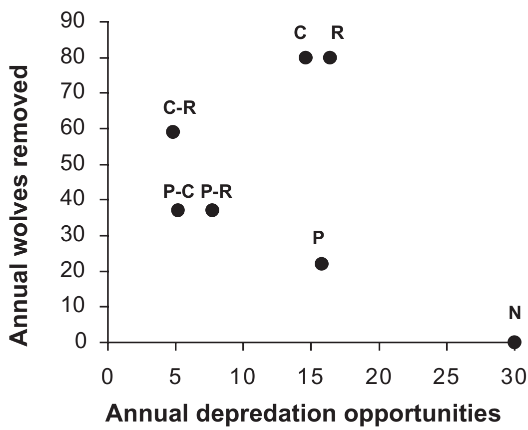

FIGURE 2.5. Predictions of the annual number of wolves removed and the number of depredation opportunities for preemptive (P), reactive (R), population control (C), and no-action (N) strategies. The number of depredation opportunities is the number of wolf packs with territories that overlap farms.

territories in winter is a more cost-effective way to reduce depredations than reactive or population control strategies.

2.4 Lessons Learned

In planning the recovery of an endangered species, models are typically used to estimate the likelihood of extinction and to set minimum viable population sizes for recovery targets. However, as demonstrated by our applications to wolf recovery, models can also be used to address various management questions that arise during the implementation of the recovery plan. In our studies, the management questions involved predicting the potential impacts of human-caused mortality, regional environmental conditions (external threats), and disturbance on the persistence of wolf populations. In addition, the management questions involved predicting the relative performance of different strategies for controlling wolf population size and depredation. As a result of these applications, we learned a number of lessons about management-oriented modeling (Table 2.1). Many of these lessons are consistent with pragmatic guidelines that have been proposed for interdisciplinary modeling projects (Starfield 1997; Nicolson et al. 2002).

A measure of a modeling project's success is the degree to which the results are considered in the development of resource management policy. We found that working in teams that included both expert biologists and managers (Rule No. 1) and carefully defining the management questions (Rule No. 2) was absolutely necessary to fulfill this measure of success. When we involved expert biologists and managers in each phase of model construction and evaluation, the simulation results comparing management strategies and predicting relative effects of environmental factors were credible and informative. Furthermore, by carefully delimiting the management questions, we could better decide and defend which details of wolf demography and behavior were important to include in the model (Rule No. 7).

Our partners understood that the purpose of our modeling exercises was to predict the relative effects of alternative management strategies or different environmental scenarios. Framing our simulation results in relative terms helped our teams gain insights about the management problems, which was more useful and reliable than attempting to predict population attributes precisely under uncertain future conditions (Rule No. 3). Thorough sensitivity analyses were then used to determine how robust the rankings of performance or effects were to changes in uncertain parameters of wolf demography (Rule No. 11). This approach is consistent with an emerging consensus among people involved in endangered-species management that demographic models should be used cautiously in population viability analysis because of concerns about the accuracy of predictions

TABLE 2.1. Heuristics of pragmatic modeling to support management planning.

Rules	Caveats
1. Work as a team with modelers, biologists, and managers	Requires full commitment and good communication skills Continually reaffirm common understanding of objectives and methods
2. The problem must be well defined *first*	Begin from a system or big-picture perspective rather than from the components
3. The purpose of pragmatic modeling is to gain insights and improve management decisions, not to produce precise predictions or absolute answers	Stochastic modeling is well suited to strategic planning (such as setting priorities for regional endangered-species recovery) but is not a panacea for site- and case-specific risk assessments under high uncertainty
4. The project and models must be flexible and adaptable	Be able to change directions (including redirecting funding)
5. Use rapid prototyping and iterative modeling with reevaluation of objectives and process	Rapid turnover of preliminary results to management engages managers in the project and promotes continual focus on modeling relevance and iterative refinement of the objectives and approach Be willing to throw out models that are not working and start over
6. Models must be transparent or easily understood and manipulated	Be careful in using others' models
7. Avoid filling models with extraneous details; err toward simplicity and transparency	Details or variations can always be added if they become important to the objectives
8. Balance what is clearly known with what must be hypothesized	Avoid concentrating on what is already known while ignoring elements that are relevant to the objectives but poorly understood
9. Chose the model scale carefully to match objectives	Generally, scales cannot be blended; if need be, build more than one model at different scales
10. If a simple model does not meet the objectives, consider using a suite of models (each with a well-defined objective)	All-purpose or comprehensive models do not work Modeling experiments built around scenarios can reduce complexity while exploring a wide range of conditions and parameter values
11. Sensitivity analysis is essential	Be explicit about the assumptions and guesses that inevitably must be made to develop a model (virtual-world) representation of the real world Sensitivity analysis tests these assumptions and provides essential perspective

(Beissinger and Westphal 1998). Rather than taking predictions of extinction risk or population size at face value to make a decision, demographic models of population viability are better used to compare the effects of different management options with the goal of setting priorities.

We found it very useful to have a basic model that could be readily adapted to alternative management questions (Rule No. 6), but only because the scale and important factors were similar enough among our projects that it was appropriate to use the same model structure (Rules Nos. 7 and 9). All our projects were concerned with small wolf populations where stochasticity and social population structure influence population densities. Each of our wolf projects asked such distinct questions, however, that different experiments, model adaptations, and output were required.

Our ability to address different management questions was enhanced by developing case-specific versions of our computer code, not a finished package that could be used in multiple ways (Rules Nos. 6 and 10). Our attempt to create a user-friendly version of our model did not work because the model kept changing to meet case-specific needs. The user shell rapidly became obsolete and was not worth the investment. The development of a simpler, educational version of the model may be useful, but this should be a separate project with its own objectives (Rule No. 2).

We contend it would not have been useful to have a "standing" model or box to be pulled out and plugged in to answer these management questions. For the kind of management questions we explored, it was better to keep a modeler involved and working hand-in-hand with biologists and managers than to try to write a model that staff without programming ability could use. We repeatedly revised elements of our modeling experiments beyond the basic model structure. For example in the cumulative effect experiments for Voyageurs Park (see Section 2.3.3), we tested different algorithms for compensation between discrete mortality sources, linked disease to different population segments, considered alternatives with and without density responses in four demographic rates, and so on. In addition, in some of our projects we were able to quickly address questions about model and experimental structures as they arose by producing preliminary results from model prototypes or iterative versions of the model (Rule No. 5). Building a single, general model retaining all these options would have been terrifically cumbersome, more time consuming, and error prone.

Even with our "simple" model, the experiments were at times sufficiently complex to be overwhelming, especially if all assumptions were challenged and tested. We recommend that when modeling exercises bog down in details or complexity or the next step becomes unclear, the modeler should step back and look for ways to simplify the situation and get the next phase started somehow. In other words, cut through the details to keep focusing on what is important (Rule No. 7). Using an iterative or top-down modeling approach (Starfield and Bleloch 1986) was helpful, starting with the most important management issues and environmental factors (Rule No. 2). For example, in the cumulative effect model, we did not include the mechanisms or human actions that drive the demographic variables in the model (Rule No. 7; see also Figure 2.2). Hypothetical scenarios focusing on a limited set of presumed, key factors were a useful way to limit complexity while still exploring a full range of parameter values. Our results indicated that only some of the innumerable environmental and anthropogenic conditions that could be linked to the key factors of wolf population trends merit more detailed investigation.

The Voyageurs Park cumulative effect projects would have benefitted from even greater interaction between park staff and modelers (Rules Nos. 1 and 2). Numerous conditions resulted in initially vague project objectives and priorities: a project mandated by an agency outside the park, a long lead time between project instigation and modeling, staff turnover, and political pressures on park management. Further, we proposed a novel approach to cumulative effect analysis to a staff with limited experience with either modeling or wolves. In retrospect, it would have been helpful to develop some initial analyses or model exercises to connect the new managers to the project and establish more clear objectives for the project from the start.

One of the barriers we experienced with managers was their expectation that the model would "solve their problem" or at least convince constituents that managers were doing the right thing (Rule No. 3). Strategic modeling helps management by revealing the relative importance of different factors and the conditions under which the population is most vulnerable and secure. It may also help identify thresholds for rapidly increasing risk that suggest management criteria. However, modeling does not relieve managers from establishing clear objectives under diverse political pressures or making judgments under uncertainty. Stochastic modeling can provide important insights, but does not tell managers whether or not to prohibit specific human actions or even which management approach is "best" under conflicting societal demands. We had to help managers understand that stochastic population modeling is experimental, not prescriptive. Further, modeling is a process not a product, an interactive, adaptive activity that evolves with the management objectives.

2.5 Conclusions

We illustrated a pragmatic approach to modeling that involved working with expert biologists and managers to construct a simple population model that addressed specific management-oriented questions. The model included the basic processes of wolf demography and social structures necessary to make accurate predictions. Simple simulation experiments were used to determine the population impacts of changes in demographic parameters, and the results of the experiments were used to infer how changes in management activities and environmental processes might affect wolf populations. This approach to modeling will help address new questions about how wolves are managed in the western Great Lakes region as the population continues to recover and is removed from the Federal Endangered Species List. This modeling approach should also contribute to the recovery and management of other endangered species.

Acknowledgments. Funds for our gray wolf modeling projects were provided by the National Park Service, the University of Minnesota Graduate School, the University of Minnesota Conservation Biology Graduate Program, and the North Central Research Station of the USDA Forest Service. We appreciate greatly the contributions of Dave Mech to our work.

References

Beissinger, S.R. and M.I. Westphal. 1998. On the use of demographic models of population viability in endangered species management. Journal of Wildlife Management **62**:821–841.

Boyce, M.S. 1992a. Population viability analysis. Annual Review of Ecology and Systematics **23**:481–506.

Boyce, M.S. 1992b. Wolf recovery for Yellowstone National Park: A simulation model. Pages 123–138 *in* D.R. McCullough and D.H. Barrett, editors. Wildlife 2001: Populations. Elsevier Applied Science, New York, New York, USA.

Cochrane, J.F. 2000. Gray wolves in a small park: Analyzing cumulative effects through simulation. Ph.D. dissertation. University of Minnesota, Minneapolis–St. Paul, Minnesota, USA.

Dunning, J.B., B.J. Danielson, B.R. Noon, T.L. Root, R.H. Lamberson, and E. Stevens. 1995. Spatially explicit population models: Current forms and future uses. Ecological Applications **5**:3–11.

Ellis, S., R.C. Lacy, S. Kennedy-Stoskopf, D.E. Wildt, J. Shillcox, O. Byers, and U.S. Seal. 1999. Florida Panther Population and Habitat Viability Assessment and Genetics Workshop Report. IUCN/SSC Conservation Breeding Specialist Group, Apple Valley, Minnesota, USA.

Ewins, P., M. de Almeida, P. Miller, and O. Byers. 2000. Population and Habitat Viability Assessment Workshop for the Wolves of Algonquin Park: Final Report. IUCN/SSC Conservation Breeding Specialist Group, Apple Valley, Minnesota, USA.

Fritts, S.H. and L.N. Carbyn. 1995. Population viability, nature reserves, and the outlook for gray wolf conservation in North America. Restoration Ecology **3**:26–38.

Forbes, G.J. and J.B. Theberge. 1996. Cross-boundary management of Algonquin Park wolves. Conservation Biology **10**:1091–1097.

Fuller, T.K. 1989. Population Dynamics of Wolves in North-Central Minnesota. Wildlife Monograph 105. The Wildlife Society, Bethesda, Maryland, USA.

Fuller, T.K. 1995. Guidelines for Gray Wolf Management in the Northern Great Lakes Region. Technical Publication No. 271. International Wolf Center, Ely, Minnesota, USA.

Fuller, T.K., W.E. Berg, G.L. Radde, M.S. Lenarz, and G.B. Joselyn. 1992. A history and current estimate of wolf distribution and numbers in Minnesota. Wildlife Society Bulletin **20**:42–55.

Gese, E.M. and L.D. Mech. 1991. Dispersal of wolves (*Canis lupus*) in northeastern Minnesota, 1969–1989. Canadian Journal of Zoology **69**:2946–2955.

Getz, W.M. and R.G. Haight. 1989. Population Harvesting: Demographic Models of Fish, Forest and Animal Resources. Monographs in Population Biology 27. Princeton University Press, Princeton, New Jersey, USA.

Gogan, P.J.P., E.M. Olexa, N. Thomas, D. Kuehn, and K.M. Podruzny. 2000. Ecological Status of Gray Wolves in and Adjacent to Voyageurs National Park, Minnesota. Draft technical report. U.S. Geological Survey, Northern Rocky Mountain Science Center, Bozeman, Montana, USA.

Haight, R.G. and L.D. Mech. 1997. Computer simulation of vasectomy for wolf control. Journal of Wildlife Management **61**:1023–1031.

Haight, R.G., D.J. Mladenoff, and A.P. Wydeven. 1998. Modeling disjunct gray wolf populations in semi-wild landscapes. Conservation Biology **12**:879–888.

Haight, R.G., B. Cypher, P.A. Kelly, S. Phillips, H. Possingham, K. Ralls, A.M. Starfield, P.J. White, and D. Williams. 2002. Optimizing habitat protection using demographic models of population viability. Conservation Biology **16** (in press).

Hayes, R.D. 1995. Numerical and functional responses of wolves, and regulation of moose in the Yukon. M.S. thesis. Simon Fraser University, Vancouver, British Columbia, Canada.

Kelly, B.T., P.S. Miller, and U.S. Seal, editors. 1999. Population and habitat viability assessment workshop for the red wolf (*Canis rufus*). IUCN/SSC Conservation Breeding Specialist Group, Apple Valley, Minnesota, USA.

Lamberson, R.H., B.R. Noon, C. Voss, and K.S. McKelvey. 1994. Reserve design for territorial species: The effects of patch size and spacing on the viability of the northern spotted owl. Conservation Biology **8**:185–195.

Lande, R. 1987. Extinction thresholds in demographic models of territorial populations. American Naturalist **130**:624–635.

Mech, L.D. 1970. The Wolf: The Ecology and Behavior of an Endangered Species. The Natural History Press, Garden City, New York, USA.

Mech, L.D. 1986. Wolf Population in the Central Superior National Forest, 1967–1985. U.S. Department of Agriculture (USDA) Forest Service Research Paper NC-270. USDA Forest Service, North Central Forest Experiment Station, St. Paul, Minnesota, USA.

Mech, L.D. 1995. The challenge and opportunity of recovering wolf populations. Conservation Biology **9**:270–278.

Mech, L.D. 1998. Estimated costs of maintaining a recovered wolf population in agricultural regions of Minnesota. Wildlife Society Bulletin **26**:817–822.

Mech, L.D., S.H. Fritts, and M.E. Nelson. 1996. Wolf management in the 21st century, from public input to sterilization. Journal of Wildlife Research **1**:195–198.

Mladenoff, D.J., T.A. Sickley, R.G. Haight, and A.P. Wydeven. 1995. A regional landscape analysis and prediction of favorable gray wolf habitat in the northern Great Lakes region. Conservation Biology **9**:279–294.

Nicolson, C.R., A.M. Starfield, G.P. Kofinas, and J.A. Kruse. 2002. Ten heuristics for interdisciplinary modeling projects. Ecosystems **5**:376–384.

Rolley, R.E., A.P. Wydeven, R.N. Schultz, R.T. Thiel, and B.E. Kohn. 1999. Wolf viability analysis. Appendix B. Pages 39–44 *in* Draft Wisconsin Wolf Management Plan. Wisconsin Department of Natural Resources, Madison, Wisconsin, USA.

Rothman, R.J. and L.D. Mech. 1979. Scent-marking in lone wolves and newly formed pairs. Animal Behavior **27**:750–760.

Smith, D., T. Meier, E. Geffen, L.D. Mech, J.W. Burch, L.G. Adams, and R.K. Wayne. 1997. Is inbreeding common in wolf packs? Behavioral Ecology **8**:384–391.

Starfield, A.M. 1997. A pragmatic approach to modeling for wildlife management. Journal of Wildlife Management **61**:261–270.

Starfield, A.M. and A.L. Bleloch. 1986. Building models for conservation and wildlife management. Macmillan Publishing Company, New York, New York, USA.

Starfield, A.M., P.R. Furniss, and G.L. Smuts. 1981. A model of lion population dynamics as a function of social behavior. Pages 121–134 *in* C.W. Fowler and T.D. Smith, editors. Dynamics of Large Mammal Populations. Springer-Verlag, New York, New York, USA.

U.S. Department of the Interior, Fish and Wildlife Service. 1996. Piping Plover Recovery plan. U.S. Department of the Interior, Fish and Wildlife Service, Hadley, Massachusetts, USA.

U.S. Department of the Interior, Fish and Wildlife Service. 2000. Wolf Recovery in the Western Great Lakes States. Fact sheet. U.S. Department of the Interior, Fish and Wildlife Service, Region 3, Minneapolis–St. Paul, Minnesota, USA.

Walters, C.J., M. Stocker, and G.C. Haber. 1981. Simulation and optimization models for a wolf-ungulate system. Pages 317–337 *in* C.W. Fowler and T.D. Smith, editors. Dynamics of Large Mammal Populations. Springer-Verlag, New York, New York, USA.

Wydeven, A.P., R.N. Schultz, and R.P. Thiel. 1995. Gray wolf (*Canis lupus*) population monitoring in Wisconsin, 1979–1991. Pages 147–156 *in* L.N. Carbyn, S.H. Fritts, and D.R. Seip, editors. Ecology and Conservation of Wolves in a Changing World. Canadian Circumpolar Institute, Edmonton, Alberta, Canada.

3 Modeling Fish Entrainment and Impingement Impacts: Bridging Science and Policy

Webb Van Winkle and John Kadvany

3.1 Introduction

Impingement and entrainment at cooling-water intake systems (CWIS) are two sources of potential mortality for fish. Impingement occurs when fish are trapped or pinned by the force of the intake flow against the intake screens at the entrance of a facility's CWIS. Mortality can be high, but numerous technologies have been developed to successfully reduce at a reasonable cost both the number of fish impinged and the mortality of those fish that are impinged (Taft 2000). Entrainment occurs when fish eggs and larvae are taken into a facility's CWIS, pass through its heat exchanger, and are pumped back to the water body with the discharge from the facility. Mortality can approach 100% for sensitive species and life stages. However, for many species, mortality for those eggs and larvae entrained can be reduced when facilities are operated to reduce exposure of entrained organisms to potentially lethal high temperature, to large changes in temperature, and to toxic chemicals (Dey et al. 2000; Mayhew et al. 2000). Substantially reducing the number of eggs and larvae entrained, however, is difficult to achieve at a reasonable cost for power plants with once-through cooling systems. This cost difference between mitigation technologies for entrainment as compared to impingement, in combination with the uncertain ecological impact created by entrainment, has led to a good deal of the difficulty and controversy surrounding the regulations associated with Section 316(b) of the Clean Water Act of 1972.

The entire 316(b) text from the 1972 Clean Water Act is remarkably brief: "Any standard established pursuant to section 301 [regulating effluent limitations] or section 306 [describing effluent performance standards] of this Act and applicable to a point source shall require that the location, design, construction, and capacity of cooling water intake structures reflect the best technology available for minimizing adverse environmental impact" (USEPA 2000). The key terms "best technology available" (BTA), "minimizing," and "adverse environmental impact" (AEI) are not further defined. Without a characterization of AEI, it is not known what to "minimize." As discussed below, either a general definition can be provided, or a process can be suggested to define the site-specific AEI. In either case, modeling plays a central role in linking scientific knowledge to a value-laden decision-making framework. A theme of this paper is to identify numerous choices possible in building this science–policy bridge.

The U.S. Environmental Protection Agency (EPA) published 316(b) assessment guidelines in 1977 that were remanded in court because of procedural issues. Nonetheless, state regulators essentially followed the unofficial guidelines into the 1990s, with several hundred assessments of entrainment and impingement performed during the 1970s and 1980s. In the absence of EPA regulations clearly defining AEI, BTA, or an assessment process, state and federal permitting authorities produced their own definitions on a case-by-case basis, relying on past decisions, administrative findings, scientific advances, and site-specific considerations. Several recent papers trace the history of 316(b) assessments (Anderson and Gotting 2001; Dey et al. 2000; May and van Rossum 1995; Nagle and Morgan 2000).

Renewed interest in 316(b) assessments has been triggered by a 1995 consent decree that establishes a timetable for EPA to propose and take final action with respect to addressing impacts from existing and new CWISs. The EPA recently proposed a draft tiered regulatory approach for its 316(b) rule making (Nagle and Morgan 2000). Tier 1 requires performing a screening analysis to determine the potential for impacts from entrainment and impingement. Tier 2 requires a characterization of uses and biological status of the source water body to determine the potential for AEI from entrainment and impingement. Tier 3 requires studies to quantify impacts from entrainment and impingement and to determine the appropriate BTA. Modeling of impacts from entrainment and impingement likely would be a component of 316(b) assessments only for those CWISs requiring Tier 3 evaluations. This paper applies to facilities with such CWISs.

The potential impacts of 316(b) regulatory controls on economics, electricity reliability, and the environment are far from trivial (Veil 2000). Consequently, there is renewed interest in the science underlying assessments of entrainment and impingement, including constructive roles that can be played by modeling. This chapter presents a forward-looking strategy about the central role of modeling in decision making involving impact assessments on fish. An example success story is summarized in Sidebar 3.1. Other modeling successes are detailed in Barnthouse (2000) and Lorda et al. (2000).

Modeling is considered here in the broader context of value-laden decision making. "Value" refers here to specific management goals, management objectives, endpoints, measures, and decision criteria. (See Sidebar 3.2 for definitions and examples.) We describe two roles for modeling, and

Sidebar 3.1
More complex and realistic was not more effective

In the mid-1960s, concerns surfaced regarding entrainment and impingement of young-of-the-year (age-0) striped bass by electric-power-generating facilities on the Hudson River. These concerns stimulated the development of increasingly complex models to evaluate the impacts of these facilities. Christensen and Englert (1988) reviewed the history and compared the 11 models that were developed over a 15-year period [also see Barnthouse et al. (1984); Barnthouse et al. (1988); Barnthouse (2000); Swartzman et al. (1977)].

The earliest simplistic formulas, based on empirical data, proved inadequate because of conceptual shortcomings, incomplete development, and lack of data. By 1972, complex transport models based on biological and hydrodynamic principles had been developed and applied by scientists representing both the utilities and the government. Disagreements about the acceptability of these models spurred the development of even more complex models. The entrainment models stimulated the collection of substantial amounts of field data to define the spatial distributions and entrainment survival of early life stages. As the difficulties of accounting for the movement of early life stages based on hydrodynamic principles became more evident and as more field data became available, simpler empirical modeling approaches became practical and defensible. Both empirical and hydrodynamic modeling approaches were applied during the EPA's hearings on the Hudson River power case (1977 to 1980).

The main lessons learned from the experience with modeling of entrainment and impingement are that complex, mechanistic models are not necessarily better than simpler, empirical models for young fish (Christensen and Englert 1988). The hearing process became paralyzed by the complexity of the models and intractable scientific issues relating to long-term predictions and density dependence. However, the modeling activities clearly identified the need for certain types of data, which stimulated the collection of such data, albeit at considerable cost. As the field data became available, empirical modeling became increasingly attractive. While empirical models required these data, they required a minimum number of assumptions, were easy to explain and defend, and could be inexpensively run for different fish species and CWIS scenarios. They were particularly useful in the settlement egotiation process during 1979 and 1980. Refinements of these empirical models continue to be tools that are used in current repermitting activities of these Hudson River power plants (D.J. Dunning, New York Power Authority, White Plains, New York, personal communication, December 2000).

suggest broad questions to consider prior to model selection, including both technical and decision-making issues that should be addressed by all the parties involved in a 316(b). We use a tree of aquatic-impact-assessment measures and corresponding methods to summarize modeling approaches, with the suggestion that modeling choices be made to balance scientific standards and policy-making needs. We recommend EPA's ecological-risk-assessment framework as an approach for effectively guiding 316(b) assessments and the role for modeling. Finally, we consider the challenges of agreeing on management objectives, endpoints, measures, and risk criteria, and we make five recommendations for 316(b) that provide a useful perspective for the role of modeling.

Sidebar 3.2
Hierarchy of terms needed for environmental decision making

The EPA's framework for ecological risk assessment (USEPA 1998, 2001) uses a hierarchy of five terms that we have adhered to throughout this chapter. Whether or not this framework is used, specifying the equivalent of these five terms is a critical step in any decision-making process. A *management goal* is a general statement of the desired condition or direction of preference for the entity to be protected. It is often developed independently of any specific risk assessment, such as part of federal or state legislation [e.g., 316(b) regulations and guidelines]. A *management objective* is a specific statement about something one desires to achieve that includes an ecological entity targeted for protection and a direction of preference. It is commonly derived from a management goal on an assessment-specific basis. An *assessment endpoint* (or just *endpoint* in this paper) is an explicit expression of what is to be protected. It is defined by an ecological entity and the entity's attributes, ideally including spatial and temporal extent.

The EPA defines three classes of *measures*. Collectively, these measures are used to describe an endpoint or factors affecting risk to that endpoint. *Measures of exposure* characterize the existence and movement of a stressor in the environment and its contact or cooccurrence with the endpoint. *Measures of effect* describe a change in an attribute of an endpoint, or its surrogate, in response to a stressor to which it is exposed. *Measures of ecosystem and receptor characteristics* describe factors that influence the behavior and location of ecological entities, the distribution of a stressor, and life-history characteristics of the endpoint that may affect exposure to, or effect of, the stressor. Measures generally have unambiguous operational definitions and are accessible to credible measurement and monitoring or prediction. Selecting measures and estimating their values are the scientists' primary input to risk assessment.

A *risk* (or *decision*) *criterion* (or *threshold*, *target*, or *benchmark*) is defined as the level or value for a measure above which (or below which, depending on the measure) is thought to result in an unacceptable level of risk (or protection). The choice of measures and associated decision criteria is always a value-laden technical judgment (Barnthouse 1992; Shrader-Frechette and McCoy 1993).

Potential examples in the context of 316(b) assessments help make this hierarchy of five terms more meaningful.

- *Management goal*—To preserve aquatic organisms and the ecosystems they inhabit in waters used by CWISs
- *Management objective*—To preserve representative fish species in waters used by CWISs
- *Endpoint*—Individual fish, cohort or year-class, population of representative fish species
- *Measure (and associated decision criterion)*
    - *Exposure*: Daily intake flow (e.g., 2 million gallons per day), proportion of water withdrawn for cooling purposes (e.g., 25%), intake approach velocity (e.g., 0.5 ft/sec)
    - *Effect*: Equivalent adult loss (e.g., 500 fish), fractional loss (e.g., 5%), population decline (e.g., 5% per year)
    - *Ecosystem and receptor characteristic*: Waterbody type; life-history characteristics of the representative fish species

3.2 Two Roles for Modeling in 316(b) Assessments

The modeling process can play two roles in assessments of the effects of entrainment and impingement on fish. The first role is the meat and potatoes of modeling: hypothetical what-if scenarios. Examples of obvious what-if scenarios are

- Comparing alternative levels of mortality resulting from entrainment and impingement
- Evaluating alternative protection, mitigation, and enhancement (PM&E) measures

Here the motivation is to characterize the potential impacts of mortality resulting from entrainment and impingement per se and the potential benefits of different PM&E measures.

Three additional what-if scenarios provide examples of issues where modeling can play a constructive role by placing potential population-level effects of mortality resulting from entrainment and impingement in a broader ecological perspective. The first involves comparing the mortality from entrainment and impingement of early life stages with the fishing mortality of older fish. This comparison can demonstrate that the population-level consequences of increased mortality of early life stages (that experience high natural mortality) are likely to be substantially less than the consequences of comparable levels of increased mortality of older fish (that experience low natural mortality). The second example involves comparing the dynamics of fish species with different demographic characteristics. That comparison can illustrate that not all fish species are demographically equal. Consequently, it is likely that they will not respond in the same manner to incremental mortality of early life-history stages (i.e., those life stages most commonly experiencing mortality from entrainment and impingement). The third example involves comparing the consequences of negative and positive extreme events (e.g., droughts and floods) and can demonstrate that such events may result in either missing or dominant year classes. Such perturbations to the age structure of a fish population can influence its dynamics, making it more difficult for scientists to interpret past trends or to predict consequences of mortality from entrainment and impingement.

The second role for modeling, using the modeling process to communicate with and educate decision makers and stakeholders, can be part of the regulatory decision-making process itself. In the context of permitting electric-power-generation facilities under Section 316(b), the decision-making process involves the values and objectives of all stakeholders, only some of which deal directly with entrainment and impingement of fish. This broader decision-making framework can be viewed as involving (1) information collection, analysis, and model development and application; (2) development of decision models or criteria; and (3) decision making (Figure 3.1) (Clemen 1991). As the decision stakes and complexity of an assessment increase, each of these three activities becomes more intense and challenging. Whether consciously or not, most 316(b) decisions involve all these activities. The process is iterative. As more is learned about a water body, decision options are discovered or limited (e.g., whether mitigation measures, such as stocking or protecting wetlands, are allowed or whether a protective technology actually works). In the course of the process, facility owners, regulators, and stakeholders establish negotiation positions (e.g., the maximum amount to invest in impingement or entrainment protection before mitigation is considered and how to cost mitigation measures). Communication between key individuals in the first column of Figure 3.1 (typically scientists) and key individuals in the third column (typically nonscientists) is important.

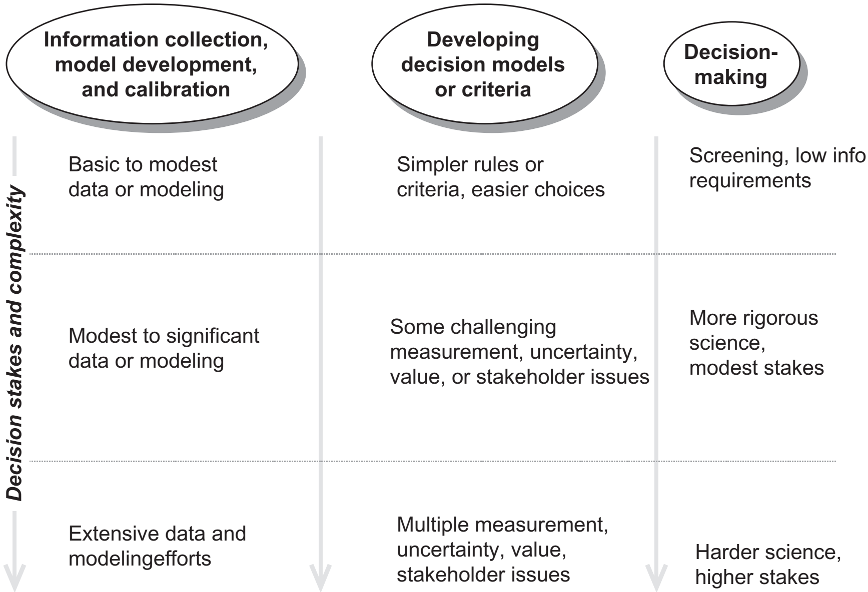

FIGURE 3.1. Resource management decisions involve three major activities that vary as the decision stakes and complexity of the assessment increase.

The resulting modeling challenge is to effectively estimate and communicate to decision makers and stakeholders the risks and uncertainties associated with using models to estimate effects on measures associated with specific endpoints. Those measures may include, as an example, some combination of population-level effects, effects on commercial and recreational fisheries, and effects on entire ecosystems. Each of these categories of effects, however, must be framed in terms of specific endpoints and associated measures useful for decision makers and stakeholders. For any given 316(b) assessment, the choice of a tractable set of species, of endpoints and associated measures, of models and methods of analysis, and of how to present and interpret results all involve value-laden judgments similar to those made for human-health outcomes. Such choices are unavoidable in risk assessments. These choices are the bridge connecting scientific understanding with value-laden policy perspectives. Because of the relative lack of experience in characterizing and valuing ecological outcomes, 316(b) decisions cannot fall back on an accepted and narrowly defined set of risk management protocols. Furthermore, the scientific understanding of the ecological world is inherently complex, dynamic, and uncertain.

Thus, a major responsibility of the modeling task is to help decision makers and stakeholders identify which endpoints and associated measures can be estimated and with what uncertainty and to provide the best estimates possible (including uncertainty) of potential changes in these measures, given time and other resource constraints. Public policy decisions often must make do with satisfactory models, not necessarily those that are scientifically optimal. Hence, decision-making constraints and context, such as the resources available and the alternative CWIS choices being considered, should guide model development and use.

3.3 Difficult Questions That Must Be Confronted

Each time the need arises for an assessment of the impacts of entrainment and impingement, the same question surfaces: What modeling approach (or specific model) should be used? We recommend that this question *not* be answered until the following more difficult questions have been confronted and addressed by all the parties involved.

1. What is at stake in terms of alternative CWIS decisions? Answering this question involves evaluating the values and objectives of all parties. Estimating relative decline in single populations, broader ecological changes, or recreational or commercial-fisheries impacts may each require different modeling approaches. Values matter because, if an outcome is highly valued, additional or more accurate information may become more relevant, regardless of the magnitude of physical or biological change. Further, decision making implies comparing solutions rather than problems, so it is appropriate to ask, "By how much do alternative decisions change the impact(s)?" Although some minimal baseline knowledge is always needed, modeling for decision making requires only the information needed to compare decision options, not to produce the most realistic model. Finally, some model outcomes may require considerable judgment for interpretation, such as potential shifts in the trophic structure of a fish community.

The modeler has to provide the necessary information to distinguish between decision options, including the selection of appropriate endpoints and associated measures and decision criteria that reflect the values of the various parties (Keeney 1992). While, in principle, endpoints and associated measures and criteria are distinct from value judgments, in practice some value judgments are implicit in their selection. We recommend the use of EPA's framework for ecological risk assessment (USEPA 1998) as discussed below, although this framework still implies a rigid and unrealistic separation between technical assessments and the values and objectives of the various parties.

2. What are the specific questions to be addressed in the assessment? Risk of population extinction? Risk of decline in population size? Absolute numerical losses? Comparison of mortality from entrainment and impingement and mortality from fishing? Given that AEI has yet to be defined big EPA and given the site-specific differences in water bodies and fish species, the choice of endpoints and associated measures and decision criteria is fundamental. Some decision makers and stakeholders lack sufficient understanding of biological science to make sound choices. Hence, modelers and other scientists need to help them define the objectives and select the modeling approach, including the species selected for study and useful endpoints and associated measures and decision criteria. This type of open-ended and constructive process requires trust that scientists, regulators, and stakeholders are jointly striving to avoid or at least minimize predictable bias.

3. What modeling approach will most likely be accepted? For any given 316(b) assessment, several modeling approaches of differing complexity and designed to estimate different measures associated with the same endpoint may prove helpful (i.e., the weight-of-evidence approach). As an example, when the endpoint is fish populations, the minimum level of complexity, beyond estimates of the number killed by entrainment and impingement, might be the number of equivalent adults lost. [Equivalent adults lost represents an extrapolation of the number of fish killed by entrainment and/or impingement at younger life stages (e.g., eggs, larvae, and juveniles) to the number of these fish that would otherwise have survived to be adults (EPRI 1999).] Estimating a value for this measure involves a model that is relatively easy for all parties to understand and that can be used as a screening tool (EPRI 1999; EPRI in press). At the other extreme of complexity, a probabilistic forecast of risk of population decline that is made with a stochastic population-simulation model (e.g., Lohner et al. 2000) is an attractive measure because it more directly addresses the management objective of sustainability of fish populations. However, even the simplest stochastic simulation models represent a relatively high level of sophistication for many regulatory decisions, making the science–policy bridge all the more important. The level of complexity is almost limitless with the stochastic individual-based modeling approach, where the effects on individual fish of daily changes in temperature, flow, water velocity, food availability, competition, predation, ambient pollution, extreme weather events, and anthropogenic impacts (such as fishing) can be modeled explicitly to estimate population effects (Van Winkle et al. 1993).

As model complexity increases, understandability generally decreases. In addition, most 316(b) decisions will not be helped by increasing levels of model complexity that do not more clearly differentiate among PM&E

alternatives or reduce uncertainty (see Sidebar 3.1). Particular challenges exist when trying to isolate causal roles for observed or predicted changes that may be simultaneously influenced by fishing, pollution, or climatic changes as well as by losses from entrainment and impingement. Here, too, no fixed rules apply. Rigorous and systematic confrontations between critical questions, data, and models frequently are not possible (Foster and Huber 1997; Hilborn and Mangel 1997; Suter 1993).

4. What data are/will be available to parameterize, calibrate, and validate different types of models? Here again, the scientist has to decide whether a possible increase in model complexity is consistent with the data available to guide that increase.

5. What resources (money, time, technical expertise, and software) are available? These resources bound the tradeoffs between model complexity and the effort to develop and apply a model. It may be more cost effective to make a decision with considerable uncertainty when the cost of implementing that decision compares favorably with that of reducing uncertainty by additional study (Clemen 1991). That is, it can be advantageous simply to act rather than to gather more information, even with considerable uncertainty about the consequences of the decision. Such may be the situation when a CWIS has no fish protection devices for impingement but the relative cost of determining the impact of impingement is high, and thus, the decision is made to install fish protection devices.

Fish population modeling does not involve especially difficult mathematics, and developing a model per se is not necessarily costly. However, substantial resources may be needed to estimate parameter values (and their variability), calibrate the model, perform sensitivity and uncertainty analyses, document the model [including quality assurance/quality control (QA/QC)], and interpret and present the model results in presentations, reports, and other publications (Ambrose et al. 1996). Hence, site-specific modeling as a response to the weakness of 316(b) regulatory language is balanced against a considerable commitment of resources for industries or agencies with little experience in assessing the impacts of entrainment and impingement. There is a natural desire, then, on the part of regulators to look for technological criteria, such as CWIS technologies [e.g., fine-mesh traveling screens, cylindrical-wedge wire screens, and Ristroph screens; see Taft (2000)] and operational performance standards (e.g., intake approach velocity no greater than 0.5 ft/sec) or other less complex and superficially less uncertain proxies, as a substitute in assisting decision making. This predicament is characteristic of many complex decisions, not just decisions in environmental policy or 316(b) (Payne et al. 1993).

The above questions reflect a top-down view of model selection. The modeling approach selected needs to reflect what is viewed as constructive by decision makers and stakeholders as well as by scientists. As a result, modeling is not an ancillary part of a decision process that "knows" which questions to ask, but is an activity that can guide and shape the decision-making process itself by bridging science and policy needs (Figure 3.2). The questions also are not answered all at once. Instead, answers evolve through the modeling and decision-making processes as more is learned about the water body, fish populations, and technology options.

The pattern that has emerged for selecting modeling approaches in 316(b) assessments is to start with a simple screening model and to increase in model complexity as the situation merits. This pattern makes good sense, knowing that a decision needs to be made in a short time frame and that perfect knowledge is neither required nor attainable in any case. This approach has meant, for example, starting with models of individual losses or fractional losses without including density dependence (EPRI 1999; EPRI in press). The next-more-complex approach has been age-based or stage-based matrix projection modeling, with or without density dependence. Even more complicated and realistic modeling approaches have emerged in highly contested cases where millions of dollars for retrofitting cooling towers are at stake. The increased complexity may involve the modification of existing code, new computer codes, and new modeling approaches (e.g., individual-based modeling). A similar tiered sequence of increasingly complex modeling approaches is typical in other fields (e.g., 1-D, 2-D, and 3-D hydrodynamic and water quality models).

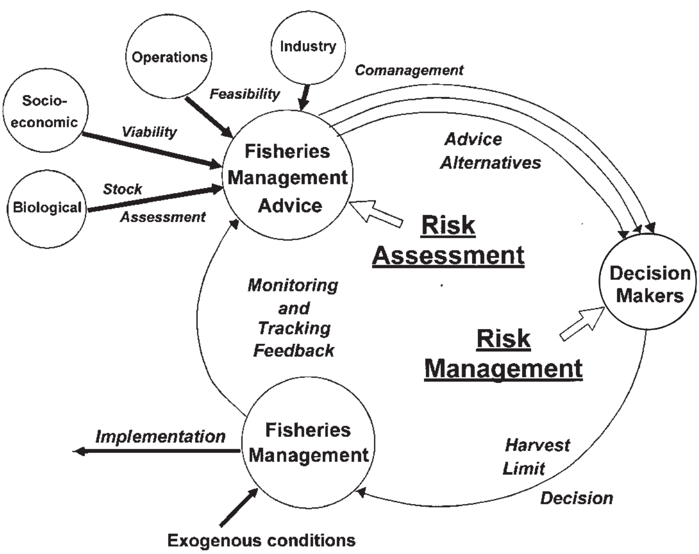

FIGURE 3.2. Conceptual view of a proposed decision analysis framework for fisheries management, including risk assessment and risk management components (Lane and Stephenson 1995, 1998).

However, more realistic and thus more complex models have not always proved as effective as simpler models in contributing to the decision-making process (see Sidebar 3.1). With the renewed interest in 316(b) decisions, modelers should carefully revisit the tradeoffs involved in increasing model complexity.

The "stopping-time" problem for scientists is to judge when stakeholders and decision makers can no longer benefit from additional data collection, analysis, or modeling. When to stop depends on the values at stake (e.g., the low cost of modifying existing traveling screens versus the high cost of switching from once-through cooling to closed-cycle cooling). Scientists, particularly those involved in modeling, must also be sensitive to recognizing when decision makers or stakeholders are effectively asking for unverifiable predictions as a means of imposing a needed policy judgment onto the science base. For assessments of entrainment and impingement, the challenge is evaluating an often modest increase in mortality against a background of high natural variability and other confounding factors. High natural variability frequently negates the value of scientific information in the decision-making process, such as occurred in attempts to attribute bird mortality to the *Exxon Valdez* oil spill (Wiens 1996).

As far as resolving the most contentious debates between the parties, scientists usually have no "silver bullet" to settle litigious disputes. The many reasonable options scientists can provide may just reinforce some stakeholders' wish (on all sides of fish protection disputes) to make 316(b) decisions through the courts. The only real solution for this dilemma is for stakeholders and regulators to develop an environment of trust in which models, endpoints, and associated measures and decision criteria can be proposed, criticized, and modified in the decision-making process. Indeed, this solution is what has happened with some site-specific 316(b) decision making [e.g., Barnthouse (1988)]. For almost three decades, no "official" 316(b) regulatory guidance has been provided, but regulators nonetheless have apparently often been able to make reasonable decisions.

3.4 Tree of Aquatic-Impact-Assessment Measures and Site Specificity

At the same time that scientists are interacting with decision makers and stakeholders, they are answerable to the scientific community for the choices made. Thus, some kind of schematic organization of modeling choices is required to indicate roughly where modeling complexity should start and end, given the decision-making context. Such an organization of modeling space is also a useful means for communicating among scientists, regulators, and stakeholders the menu of options and the advantages and disadvantages of those options.

For 316(b), a tree of aquatic-impact-assessment measures (and corresponding methods) is a useful way to visualize the variety of modeling approaches that has evolved over the past three decades to assess the impacts of entrainment and impingement at power generation facilities (Figure 3.3). The two primary branches of this tree are predictive methods and retrospective methods. Refinements to some of these methods continue to be made [e.g., Heppell et al. (2000)]. Thus, availability of assessment methods is not a limitation.

Predictive methods can be arrayed by level of biological organization (i.e., individual losses, fractional losses, population projections, and ecosystem/community) (see Figure 3.3). As one "climbs" in the tree of methods across levels of biological organization from left to right, the spatial and temporal scales of the assessment typically increase. Associated with this pattern is a shift from spreadsheet methods giving snapshots of individual or fractional losses to simulation models involving population projections many years into the future. Density dependence (or

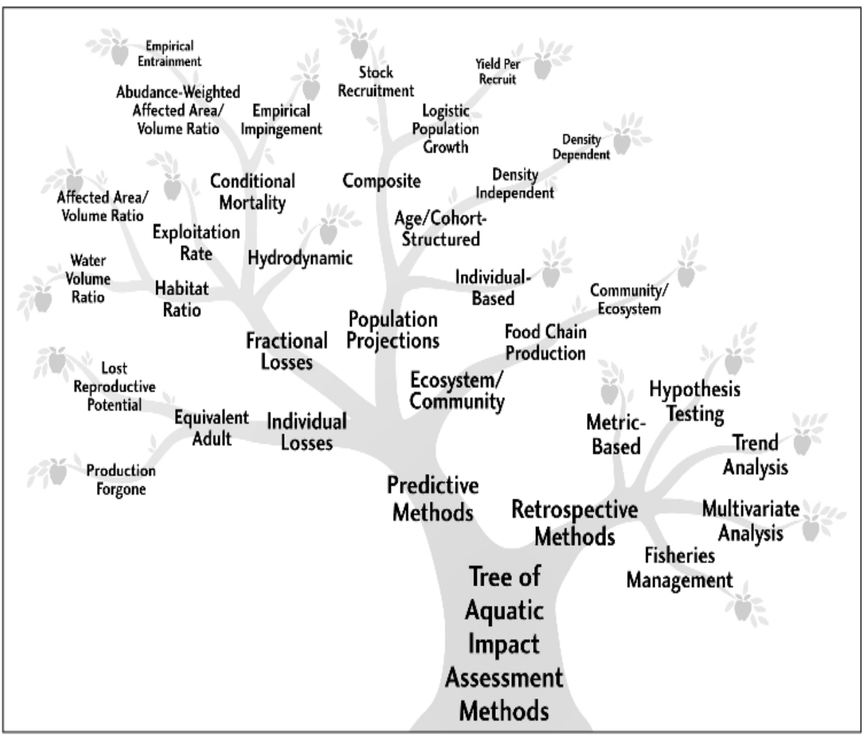

FIGURE 3.3. Tree of aquatic-impact-assessment measures (and corresponding methods) used in assessing the impacts of entrainment and impingement on fish [based on EPRI (1999)].

compensation) does not generally rear its challenging head until one is dealing with population projections (Van Winkle 2000). The "apples" on the ecosystem/community limb of the tree represent assessment methods that are "maturing" but that are generally viewed as not being sufficiently "ripe" at present to be useful for decision making. In this way, the tree also helps answer questions relating to complexity and realism versus usefulness.

Retrospective methods use data collected at a site to evaluate the character, function, quality, and/or integrity of the water body and/or to evaluate whether or not a change in a population/community/ecosystem has occurred that may be related to the operation of the power plant (EPRI 1999) (see Figure 3.3). These methods are best applied to assess changes as a result of power-plant operation at facilities that have been operating for several years. Thus, the methods are most applicable for existing facilities rather than for new facilities. However, monitoring and other studies at existing facilities during the past three decades have resulted in large databases that provide a perspective and valuable guidance for assessing the impacts of entrainment and impingement at new facilities (e.g., Mayhew et al. 2000).

Site specificity explains why so many modeling approaches have developed for the same, relatively uncomplicated, issue of mortality resulting from entrainment and impingement. Several factors contribute to this history of site-specific assessments and decision making. Each assessment of entrainment and impingement tends to involve unique features because each ecosystem is unique with respect to its fish species and hydraulic and water-quality characteristics. Technology choices also are site specific. For example, a Gunderboom cannot be used where there are strong currents or heavy natural-debris loads. In addition, the industry, decision makers, and stakeholders (and their social or institutional constraints) tend to be site specific and unique. A consequence from a regulatory perspective is that a simple model and approximate data may be adequate for one 316(b) assessment, while another superficially similar situation may require more-complex models and additional data. It is also counterproductive to make regulators and others force-fit their knowledge into a predefined mold to maintain the appearance of uniform and fair regulations.

If site specificity is as important as we believe, then industries, regulators, and stakeholders faced with overly rigid 316(b) rules may be forced to codify into approved formats their understanding of the factors influencing the impacts of entrainment and impingement at their unique site. Or, an overly conservative approach (e.g., making dry cooling towers the BTA) may also be a convenient way to evade assessing 316(b) impacts, including the negative impacts of efficiency penalties and increased use of fossil resources. Such "conservatism" may be just shifting concerns from the entrainment and impingement of fish to concerns about energy costs, increased use of fossil fuels, and environmental impacts of alternative energy technologies.

While the 316(b) language has been criticized for its lack of detail, the site-specific nature of many fish population impacts may imply that any comprehensive definitions of BTA and AEI will be equally generic. Hence for 316(b), the scientific problem of assessing the impacts on fish of entrainment and impingement may depend, in part, on local AEI definitions. The scientists involved in modeling, therefore, may be implicitly or explicitly tasked with both characterizing AEI and helping decide how best to assess it on a site-specific basis. A decision analysis approach in which values, endpoints, and associated measures and decision criteria are identified and developed on a site-specific basis may be preferable to approaches that assume no need for further learning (Gregory et al. 1993). Such an approach is also consistent with a broader perspective, that ecological decision making almost always depends on local biological context (National Research Council 1986). At the same time, industry proponents of a flexible, site-specific 316(b) approach (Utility Water Act Group 2000) have to recognize that a rule stating "take a local, risk-based approach" implies an open-ended process and has its own risks.

A final factor contributing to site-specific assessments of entrainment and impingement is that 316(b) determinations occur in a regulatory setting. In this setting, the rules of engagement are dictated by lawyers who are likely to respond differently than scientists to perceived advocacy opportunities. Given that retrofitted natural-draft cooling towers can cost more than $100 million, the economics of BTA causes the assessments to be contentious, litigated, and increasingly complex as cases remain unresolved for long periods of time. The cumulative effect of the above site-specific factors accounts for the surprising variety and uses of modeling approaches. We see this variety as a virtue, reflecting local decision-making practices. Such flexibility can be open to abuse, but the EPA's role also can be to monitor decision-making practices to ensure global fairness and integrity. Clearly, such a role is needed if detailed 316(b) regulations resist codification, as they have for decades.

3.5 Decision Making and EPA's Ecological-Risk-Assessment Process

To increase the effectiveness of science and modeling as part of the 316(b) decision-making process, it would be constructive if assessments adhered to an accepted overall risk assessment process. This recommendation means that an adequate process would be defined for posing appropriate scientific questions and for being able to adaptively learn from the answers. It does not mean that all data, modeling choices, and other steps in the process are determined in advance. The EPA ecological-risk-assessment process provides such a framework (Figure 3.4). Alternative approaches are used in other countries and by other organizations within the United States.

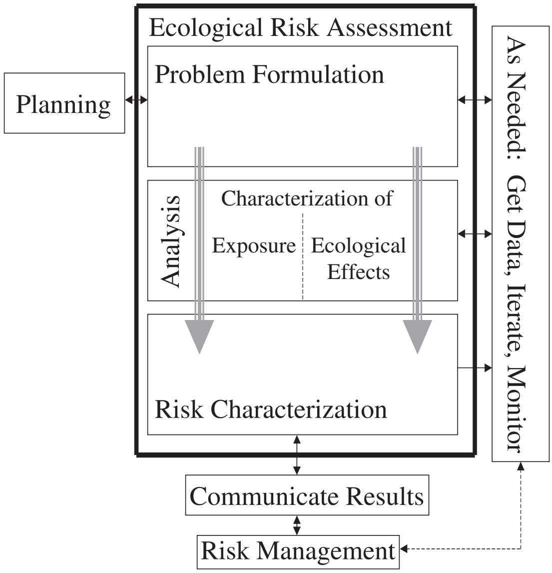

FIGURE 3.4. Flowchart illustrating EPA's process for ecological risk assessment, including the three major components of problem formulation, analysis, and risk characterization, leading to an integration of risk assessment and risk management (USEPA 1992, 1998).

McCarty and Power (2000) and Power and McCarty (1998) provide analyses of these alternatives. We have focused on the EPA's framework because the EPA has responsibility for 316(b).

Although some of the EPA terminology reflects the toxicity background from which the framework evolved, EPA's definitions of key terms readily generalize to other types of anthropogenic stress, such as the entrainment and impingement of fish (see Sidebar 3.2). This approach does not represent a static black-and-white road map. Rather, it is a representation of a dynamic scientific, social, and political process, a process involving individuals and organizations with different backgrounds, values, and objectives. Others have recently suggested using the EPA framework for ecological risk assessment (USEPA 1998) for 316(b) assessments and for environmental decision making in general (Dey et al. 2000; Gentile and Harwell 1998; Harwell and Gentile, Chapter 5, this volume).

As mentioned in the introduction of this chapter, the term AEI first appeared in Section 316(b) of the Federal Water Pollution Control Act of 1972. The term was not operationally defined and thus, not surprisingly, has since been defined in many different ways (Anderson and Gotting 2001; May and van Rossum 1995). The EPA still appears to be "risk adverse" to defining this term (EPA 2000). The term AEI is operationally defined, however, by the EPA ecological-risk-assessment process, which involves specifying endpoints and associated measures and decision criteria on a site-specific basis. Thus, a formal definition codifying AEI once and for all may not be needed or even constructive.

In concluding this section, we should recognize that the entire approach of site-specific, risk-based environmental assessments can be rejected. For example, the Riverkeeper position on 316(b) is that the Clean Water Act uses technological criteria, not environmental outcomes, to improve wastewater-effluent quality. Thus, such criteria should be used to regulate CWISs without exception (Riverkeeper et al. 2000). This rejection of a risk-based environmental perspective is a legitimate, if potentially costly, response to the predicament of balancing regulatory effort and environmental protection. The Riverkeeper approach explicitly notes the risk of an open-ended, site-specific process being co-opted by the regulated community (Riverkeeper et al. 2000). A credible approach to CWIS regulation, therefore, may depend on a compromise between regulatory uniformity and local flexibility that avoids such pitfalls.

3.6 Challenge of Agreeing on Management Objectives, Endpoints, and Associated Measures and Decision Criteria for 316(b) Assessments

Management goals have typically not been the focus of disagreement in 316(b) decision making (see Sidebar 3.2). For example, the goal of preserving aquatic organisms and the ecosystems they inhabit in waters used by CWISs is sufficiently broad and vague that all parties can safely agree with it. As a result, such a goal by itself is of limited value for decision making. Disagreement is common, however, when management objectives, endpoints, and associated measures and decision criteria are selected to make a management goal operational (see Sidebar 3.2).

For example, given a management objective that focuses on selected fish populations as the endpoint, should the measure for the preservation of these fish populations be in terms of the number of fish killed by entrainment and impingement or the population-level consequences of these losses (Anderson and Gotting 2001; May and van Rossum 1995; Utility Water Act Group 2000)? If the latter, what population-level measure should be used? As described previously, two possible, but quite different, measures that could be selected from the "tree" of possible measures are the number of equivalent adults lost and the population projections of the risk of population decline over the lifetime of the power plant (see Figure 3.3). The latter can be predicted only by using a stochastic simulation model involving projections far into the future and will appear by some parties to be too complicated and uncertain. However, other parties might reject substitution of an intermediate endpoint, such as equivalent adults lost, that does not reflect the potential dynamics of the population. All parties might agree to its use, however, if coupled with requirements for monitoring and reconsideration at each 5-year repermitting interval. Alternatively, the decision might be to make a more risk-adverse decision rather than waiting until more refined knowledge is available. That is the decision maker's prerogative. While the scientist then has little more to contribute, his or her prior input can critically influence this overall decision process.

Regardless of the measures selected, the next step of agreeing on decision criteria for these measures is even more controversial. For example, how many individual fish of a representative indicator species can be killed by entrainment and impingement before some modification of the CWIS is required? 1? 10^4? 10^9? Or what observed or predicted percentage reduction in year-class strength or in the adult population triggers the decision that some modification of the CWIS is required to reduce losses from entrainment and impingement? 1%? 10%? 20%?

Multiple answers to such questions are possible because they involve a balancing of science, societal values, and politics (Keeney 1992; Lackey 1994, 1998, 1999). Such balancing becomes increasingly site specific if the objectives of the stakeholders differ substantially. In addition, no single scientifically sound basis exists for specifying measures and associated risk criteria. The answer could depend on the water-body type (coastal, river, estuary, lake, or reservoir) and how that resource has been locally managed and valued. The same population impact on an already highly impacted waterway could be considered differently from that occurring on a productive, previously unimpacted estuary. Indeed, clarifications of where, and to what extent, such value judgments may matter should be a key policy task.

3.7 Recommendations for 316(b) Assessments

Recommendations for guiding 316(b) assessments are emerging, especially when the management objectives are focused on fish populations as the endpoint (see Sidebar 3.2). These recommendations help place in a useful perspective the role of modeling as part of any assessment of entrainment and impingement. They also reflect an attempt to balance what is scientifically sound and what experience indicates will be accepted in the sociopolitical and legal process of 316(b) decision making.

1. We recommend that the 316(b) analysis plan capitalize on the considerable body of knowledge that has accumulated during the past three decades from assessments of entrainment and impingement and from

monitoring. Experience has shown that potential impacts must be considered at different spatial and temporal scales and different levels of biological organization. Not all scales and levels need to be analyzed in detail, depending on the severity of estimated impacts. Results of analyses at each of these scales need to be considered in a weight-of-evidence approach.

2. We recommend that estimated values for any given measure include consideration of the normal variability in that measure (Ambrose et al. 1996; Coutant 2000). As in any risk assessment, scientific certitude is an illusion; thus, a precautionary approach is appropriate (Hilborn et al. 2001; Schnute and Richards 2001). This precautionary approach allows establishment of more conservative levels of acceptable loss when faced with higher uncertainty.

3. We recommend that 316(b) decisions require continued monitoring of selected measures with reassessments at each repermitting interval (Ambrose et al. 1996; Coutant 2000). This approach of adaptive resource management is particularly appropriate when uncertainty is high, fishery resources at risk are highly valued, and other negative or positive changes (e.g., water quality or regional temperature regime) are occurring in the system. The frequency of this monitoring and reassessment might be relaxed in the future if additional data continued to support the conclusions of the original scientific assessment of no AEI.

4. We recommend that analyses and model applications focus on relative risk (USEPA 1998) by comparing estimates of short-term impacts (e.g., 5 to 10 years, as opposed to 50 to 100 years) of alternative management actions and decisions and not on absolute or long-term impacts (Barnthouse et al. 1984; Van Winkle 2000). Emphasizing model predictions of risk of percent reduction or quasi-extinction over the lifetime of a power plant *alone* is not likely to be accepted. Nor are results of meta-analyses of time series of data on spawning stock and subsequent recruitment *alone* likely to be accepted (e.g., spawner-recruit curves and associated indices). Both scientists and nonscientists have valid reasons and past experience to be skeptical about such model predictions and analyses claiming to provide an adequate basis for making site-specific decisions concerning long-term, population consequences (Boreman 1997; Hilborn et al. 2001; Hutchings 2001; Rose 2000; Rose and Cowan 2000; Schnute and Richards 2001; Van Winkle 2000). Scientists need to be aware when regulators or stakeholders are expecting (or interpreting) more certain conclusions than science can provide.

5. We recommend that, if a population declines over a period of years during which losses from entrainment and impingement cannot be judged as trivial, the responsible scientific conclusion is that to some unknowable extent these losses may have contributed to the decline. Because of confounding changes in physical, biotic, and anthropogenic variables during the same period, it will never be possible to prove that losses from entrainment

and impingement caused the decline or that they had nothing at all to do with the decline.

3.8 Conclusions

We have presented our ideas on how the process of modeling the impacts of entrainment and impingement on fish populations can serve as a bridge between science and policy as part of a decision-making process involving industry, regulators, and stakeholders. Given the litigious nature of 316(b) determinations, however, this ideal may not be possible or may be only partially successful. We want to point out, however, that, within individual organizations involved in the decision-making process, initial agreement on how to answer the difficult questions that must be answered is rare. Consequently, even within individual organizations, modeling can effectively serve as a bridge between science and policy.

We have emphasized the importance of viewing the modeling process from a top-down, decisions-and-values approach and not just a bottom-up, find-the-best-model approach. We recommend viewing these two approaches as complementary, with neither approach dominating. A primary responsibility of regulators and resource managers is to make decisions, decisions concerning what to do (or not do), when, and how. Such decisions commonly benefit if approached within an analysis framework with explicit consideration of benefits, costs, and uncertainty of alternative decisions. The discipline of ecological risk assessment emphasizes the importance of defining endpoints and decision criteria. Definitions of endpoints and decision criteria, in turn, specify the objectives for modeling, what models are most appropriate, and how and when the modeling process and results might most effectively interact in the broader decision-making process.

We have summarized EPA's framework for ecological risk assessment and their definitions of key terms (see Sidebar 3.2) to highlight how such a systematic and rational framework can help put the 316(b) regulatory process on a constructive path. Science (including modeling) contributes primarily during the analysis component (see Figure 3.4). However, if that is the only place scientists contribute, their support of the decision-making process may be minimal. To be more effective, they also must be part of the problem formulation and risk characterization components (see Figures 3.2 and 3.4). For the reasons discussed above, this broader influence is essential for 316(b) and for other ecological management decisions as well.

Acknowledgments. This paper has benefitted from discussions with, and reviews by, numerous individuals, including D.E. Bailey, M.S. Bevelhimer, J. Chandler, C.C. Coutant, V.H. Dale, D. Dixon, and H.I. Jager, and an anonymous reviewer. Participation of W. Van Winkle in the Workshop on Effective Use of Ecological Modeling in Management, Oak Ridge, Tennessee, October 2000, was supported by Oak Ridge National Laboratory.

References

Ambrose, R., R. Schmitt, and C. Osenberg. 1996. Predicted and observed environmental impacts: Can we foretell ecological change? Pages 345–369 *in* R.J. Schmitt and C.W. Osenberg, editors. Detecting Ecological Impacts: Concepts and Applications in Coastal Habitats. Academic Press, New York, New York, USA.

Anderson, W. and E. Gotting. 2001. Taken in over intake structures? Section 316(b) of the Clean Water Act. Columbia Journal of Environmental Law **26**:1–79.

Barnthouse, L.W. 1992. The role of models in ecological risk assessment: A 1990's perspective. Environmental Toxicology and Chemistry **11**:1751–1760.

Barnthouse, L.W. 2000. Impacts of power-plant cooling systems on estuarine fish populations: The Hudson River after 25 years. Environmental Science & Policy **3**(Supplement 1):S341–S348.

Barnthouse, L.W., J. Boreman, S.W. Christensen, C.P. Goodyear, W. Van Winkle, and D.S. Vaughan. 1984. Population biology in the courtroom: the Hudson River controversy. BioScience **34**:14–19.

Barnthouse, L.W., J. Boreman, T.L. Englert, W.L. Kirk, and E.G. Horn. 1988. Hudson River settlement agreement: Technical rationale and cost considerations. Pages 267–273 *in* L.W. Barnthouse et al., editors. Science, Law, and Hudson River Power Plants: A Case Study in Environmental Impact Assessment. Monograph 4. American Fisheries Society, Bethesda, Maryland, USA.

Boreman, J. 2000. Surplus production, compensation, and impact assessments of power plants. Environmental Science & Policy **3**(Supplement 1):S445–S449.

Christensen, S.W. and T.L. Englert. 1988. Historical development of entrainment models for Hudson River striped bass. Pages 133–142 *in* L.W. Barnthouse et al., editors. Science, Law, and Hudson River Power Plants: A Case Study in Environmental Impact Assessment. Monograph 4. American Fisheries Society, Bethesda, Maryland, USA.

Clemen, R.T. 1991. Making Hard Decisions: An Introduction to Decision Analysis. PWS-Kent, Boston, Massachusetts, USA.

Coutant, C.C. 2000. What is "normative" at cooling water intakes? Defining normalcy before judging adverse. Environmental Science & Policy **3**(Supplement 1):S37–S42.

Dey, W.P., S.M. Jinks, and G.J. Lauer. 2000. The 316(b) assessment process: Evolution towards a risk-based approach. Environmental Science & Policy **3** (Supplement 1):S15–S24.

Electric Power Research Institute (EPRI). 1999. Catalog of Assessment Methods for Evaluating the Effects of Power Plant Operations on Aquatic Communities. TR-112013. Electric Power Research Institute, Palo Alto, California, USA.

Electric Power Research Institute (EPRI). 2002. Evaluating the Effects of Power Plant Operations on Aquatic Communities: Guidelines for Selection of Assessment Methods. Electric Power Research Institute, Palo Alto, California, USA. EPRI Report 1005176.

Foster, K. and P. Huber. 1997. Judging Science: Scientific Knowledge and the Federal Courts. MIT Press, Cambridge, Massachusetts, USA.

Gentile, J.H. and M.A. Harwell. 1998. The issue of significance in ecological risk assessments. Human and Ecological Risk Assessment **4**:815–828.

Gregory, R., S. Lichtenstein, and P. Slovic. 1993. Valuing environmental resources: A constructive approach. Journal of Risk and Uncertainty **7**:177–193.

Heppell, S., C. Pfister, and H. de Kroon. 2000. Elasticity analysis in population biology: Methods and applications. Ecology **81**:605–606.

Hilborn, R. and M. Mangel. 1997. The Ecological Detective. Princeton University Press, Princeton, New Jersey, USA.

Hilborn, R., J.J. Maguire, A.M. Parma, and A.A. Rosenberg. 2001. The precautionary approach and risk management: Can they increase the probability of successes in fishery management? Canadian Journal of Fisheries and Aquatic Science **58**:99–107.

Hutchings, J.A. 2001. Conservation biology of marine fishes: Perceptions and caveats regarding assignment of extinction risk. Canadian Journal of Fisheries and Aquatic Sciences **58**:108–121.

Keeney, R. 1992. Value-Focused Thinking: A Path to Creative Decisionmaking. Harvard University Press, Cambridge, Massachusetts, USA.

Lackey, R.T. 1994. Ecological risk assessment. Fisheries **19**:14–18.

Lackey, R.T. 1998. Fisheries management: Integrating societal preference, decision analysis, and ecological risk assessment. Environmental Science & Policy **1**: 329–335.

Lackey, R.T. 1999. Salmon policy: Science, society, restoration, and reality. Environmental Science & Policy **2**:369–379.

Lane, D.E. and R.L. Stephenson. 1995. Fisheries management science: The framework to link biological, economic, and social objectives in fisheries management. Aquatic Living Resources **8**:215–221.

Lane, D.E. and R.L. Stephenson. 1998. A framework for risk analysis in fisheries decision-making. ICES Journal of Marine Science **55**:1–13.

Lohner, T.W., G. Seegert, J. Vondruska, and E. Perry. 2000. Assessment of 316(b) impact on Ohio river fish populations. Environmental Science & Policy **3**(Supplement 1):S249–S259.

Lorda, E., D.J. Danila, and J.D. Miller. 2000. Application of a population dynamics model to the probabilistic assessment of cooling water intake effects of Millstone Nuclear Power Station (Waterford, CT) on a nearby winter flounder spawning stock. Environmental Science & Policy **3**(Supplement 1):S471–S482.

May, J.R. and M.K. van Rossum. 1995. The quick and the dead: Fish entrainment, entrapment, and the implementation and application of Section 316(b) of the Clean Water Act. Vermont Law Review **20**:375–493.

Mayhew, D.A., L.D. Jensen, D.F. Hanson, and P.H. Muessig. 2000. A comparative review of entrainment survival studies at power plants in estuarine environments. Environmental Science & Policy **3**(Supplement 1):S295–S302.

McCarty, L.S. and M. Power. 2000. Approaches to developing risk management objectives: An analysis of international strategies. Environmental Science & Policy **3**:311–319.

Nagle, D.G. and J.T. Morgan, Jr. 2000. Forward. A draft regulatory framework for analyzing potential adverse environmental impact from cooling water intake structures. Environmental Science & Policy **3**(Supplement 1):ix–xiv.

National Research Council. 1986. Ecological Knowledge and Environmental Problem-Solving: Concepts and Case Studies. National Academy Press, Washington, District of Columbia, USA.

Payne, J., J. Bettman, and E. Johnson. 1993. The Adaptive Decision Maker. Cambridge University Press, New York, New York, USA.

Power, M. and L.S. McCarty. 1998. A comparative analysis of environmental risk assessment management frameworks. Environmental Science & Technology **32**:224A–231A.

Riverkeeper, Inc., et al. 2000. Comments on EPA's Proposed Regulation for Cooling Water Intake Structures at New Facilities under Section 316(b) of the Clean Water Act. Natural Resources Defense Council, New York, New York, USA.

Rose, K.A. 2000. Why are quantitative relationships between environmental quality and fish populations so elusive? Ecological Applications **10**:367–385.

Rose, K.A. and J.H. Cowan, Jr. 2000. Predicting fish population dynamics: Compensation and the importance of site-specific considerations. Environmental Science & Policy **3**(Supplement 1):S433–S443.

Schnute, J.T. and L.J. Richards. 2001. Use and abuse of fishery models. Canadian Journal of Fisheries and Aquatic Science **58**:10–17.

Shrader-Frechette, K.S. and E. McCoy. 1993. Method in Ecology. Cambridge University Press, New York, New York, USA.

Suter, G.W. 1993. Ecological Risk Assessment. Lewis Publishers, Boca Raton, Florida, USA.

Swartzman, G., R. Deriso, and C. Cowan. 1977. Comparison of simulation models used in assessing the effects of power-plant-induced mortality on fish populations. Pages 333–361 *in* W. Van Winkle, editor. Assessing the Effects of Power-Plant-Induced Mortality on Fish Populations. Pergamon Press, New York, New York, USA.

Taft, E.P. 2000. Fish protection technologies: A status report. Environmental Science & Policy **3**(Supplement 1):S349–S360.

U.S. Environmental Protection Agency (USEPA). 1992. Framework for Ecological Risk Assessment. EPA/630/R-92/001. USEPA, Washington, District of Columbia, USA.

U.S. Environmental Protection Agency (USEPA). 1998. Guidelines for Ecological Risk Assessment. EPA/630/R-95/002F. USEPA, Washington, District of Columbia, USA.

U.S. Environmental Protection Agency (USEPA). 2000. National pollutant discharge elimination system. Regulations addressing cooling water intake structures for new facilities. www.epa.gov/owm/316b.htm and Federal Register **65**:49060, August 10, 2000, Section VII.F.

U.S. Environmental Protection Agency (USEPA). 2001. Planning for Ecological Risk Assessment: Developing Management Objectives. EPA/630/R-01/001A. Washington, District of Columbia, USA.

Utility Water Act Group. 2000. Comments of the utility water act group on EPA's proposed 316(b) rule for new facilities and ICR No. 1973.01, Federal Register **65**, August 10, 2000. Submitted November 9, 2000. Hunton & Williams, Richmond, Virginia, USA.

Van Winkle, W. 2000. A perspective on power generation impacts and compensation in fish populations. Environmental Science & Policy **3**(Supplement 1): S425–S431.

Van Winkle, W., K.A. Rose, and R.C. Chambers. 1993. Individual-based approach to fish population dynamics: An overview. Transactions of the American Fisheries Society **122**:397–403.

Veil, J.A. 2000. Potential impacts of 316(b) regulatory controls on economics, electricity reliability, and the environment. Environmental Science & Policy **3**(Supplement 1): S1–S6.

Wiens, J. 1996. Oil, seabirds, and science: the effects of the Exxon Valdez oil spill. BioScience **46**:587–597.

4
Large-Scale Regional Assessments: Lessons Learned from the Southern Appalachian Assessment

David N. Wear

4.1 Introduction

In the fall of 1994, the Southern Appalachian Assessment (SAA) was chartered to address a broad complement of issues regarding the uses and roles of public land and resources in the southern Appalachian Highlands. The overall objective of the assessment was to

> facilitate ecosystem management by providing comprehensive, interagency, ecological, social, and economic data as a foundation for natural resource management [Southern Appalachian Man and the Biosphere Cooperative (SAMAB) 1996*a*].

In pursuit of this objective, the SAA sought to compile a compendium of background information to define ecosystem conditions and to pursue ecosystem management on public lands. The SAA compiled information at the landscape scale, addressing all lands within the region. In many ways it plowed new ground in the conduct of regional interdisciplinary analysis and in the use of collaborative methods to address controversial resource management issues. This paper examines the processes and outcomes of the SAA, with an eye toward identifying lessons that can be transported to other public ecosystem management efforts.

The SAA can be viewed as a mechanism for applying scientific knowledge to the full complement of ecosystem management issues in a specific place. It therefore provides one model of organization in a broad spectrum of potential science–management collaborations. Topics addressed by the SAA were very wide in scope and were pursued in a descriptive fashion. The foci of the SAA were on compiling information to define the status of a regional-scale system and making information available for the subsequent analysis of specific management issues. It was not focused on solving specific management problems or supporting specific decisions. Rather, its intent was to frame the perspectives of resource stewards and to enhance the quality of information available to managers.

The SAA was not strictly a modeling exercise but was a mechanism for compiling information through databases, models, and individuals' expertise to create a broad knowledge base. Where appropriate, available models were applied to great advantage. In addition, the SAA influenced subsequent modeling in two ways. (1) It defined a set of critical issues that needed to be addressed with models. For example, following the assessment, national forest managers spent more effort analyzing forest-age structures in their planning analysis. (2) It also defined needs for new models and provided impetus for subsequent model development and analysis. One example is the development of landscape-level models for forecasting land development in the Southern Appalachians (Wear and Bolstad 1998).

The introduction to the SAA report describes the effort as something analogous to a medical checkup for an ecosystem. In many ways, this metaphor captures the spirit of an effort designed as an anticipatory rather than a problem-solving analysis. The outcomes of the assessment also need to be viewed in this light (i.e., as a means to shed light on current conditions, emerging trends, and potential emerging problems). Ultimately, the success of an effort like the SAA needs to be evaluated in terms of its contribution to improving the overall quality of natural resource decisions. This type of evaluation is difficult because many of the resource issues that public land managers address are extremely complex, dynamic, and perhaps intractable. The adaptive nature of ecosystem management suggests that the management approach as well as the resource questions will change over time. The SAA or any other effort of its kind is necessarily directed at a moving target.

4.2 Motivation for the Assessment

Southern Appalachia has a strong regional identity related both to its unique and diverse natural setting and its unique and, until relatively recently, somewhat isolated culture. It is essentially a rural place with 70% of the land area in forest cover and another 15% in agricultural uses (SAMAB 1996*d*). While public ownership is small compared to western parts of the United States, the 17% of the land that is in various federal and state ownerships defines one of the highest concentrations of public lands east of the Mississippi.

A convergence of changes and controversies had, by the early 1990s, defined the need for a broadly inclusive ecological/social assessment in the Southern Appalachians. Public land management, in general, and national forest management, in particular, were becoming increasingly contentious throughout the United States. During this period, management philosophies were shifting toward landscape-level ecosystem management, but specific ecosystem management strategies had yet to be defined. In addition, the integration of local economies and culture with the nation's economy and culture as a whole had led to an important set of social changes [e.g., changing employment patterns and perspectives on resource management (Dunlap 1991)]. These changes, coupled with an increasingly mobile population, resulted in population growth and demographic change, largely emanating from only a few areas in the region. The resulting and ongoing land-use changes, mainly low-density residential developments, had and still have the potential to reshape the unique environmental characteristics of the region (Turner et al. 1996).

Concomitant with shifts in population and land use have been important changes in local economies. The region's agricultural production has declined as transportation systems have effectively integrated Southern Appalachian agricultural markets with broader regional and national markets. The other two major land-based sectors, wood products and recreation and tourism, while still important parts of the local economy, have experienced important changes in their structures. For example, the region's wood product markets now simultaneously focus on very high-quality products (e.g., harvests of furniture-grade red oaks and other fine lumber) and on low-quality products [e.g., harvest of pulpwood for the production of both paper products and reconstituted structural materials (Haynes et al. 1995)]. The recreation and tourism sector has experienced an expansion in demand for activities as well as a broadening of the tourism trade with new foci on high-adventure and ecotourism trips. Timber harvesting and tourism are not often complementary activities, so expanding demands for both types of output have increased conflict between the two sectors of the local economy. This conflict is borne out in public-land-management debates.

Social changes and economic growth have also had important direct implications for the natural environment. Air pollution derived from other regions of the eastern United States (e.g., the Ohio Valley and Atlanta metropolitan area) has impacted visibility and damaged high-elevation ecosystems in the Appalachians (SAMAB 1996*c*). Additionally, forest insect and disease populations have greatly influenced the structure and function of forested ecosystems. The best-known historical episode is the chestnut blight (*Cryphonectria parasitica*), which eliminated the dominant canopy tree species and completely restructured the region's forests in the 1930s [e.g., Hepting (1974)]. Since then, exotic insects, such as the balsam woolly adelgid (*Adelges piceae*) and gypsy moth (*Lymantria dispar*), have emerged as important forest pests that continue to impact the region's forest cover [e.g., Liebhold et al. (1992)]. Emerging exotic diseases portend additional impacts. For example, the recent emergence of dogwood anthracnose (*Discula destructiva*) has raised concerns regarding the viability of a species that has direct tourist appeal as well as ecological significance (Daughtrey et al. 1996).

Water knits together the region's landscape and connects headwaters in the Southern Appalachians with many growing population centers, including Richmond, Atlanta, Knoxville, and Charlotte. In the headwaters, land use and resource management influence not only the quality but also the quantity of water delivered to these areas. As these southern metropolitan areas experience rapid population growth, water indeed may become the most valuable resource commodity produced by the Southern Appalachian region. Its in situ value is likewise high in terms of ecosystem function and recreation appeal, and certain headwater areas are especially vulnerable to damage from alterations, especially ongoing land-use changes (SAMAB 1996*b*).

These social and economic forces combine with a broad suite of biophysical interactions in forest ecosystems to define a varied and decidedly complex environment for public land management in the Southern Appalachians. While much research had investigated specific aspects of these complex systems, the SAA was the first attempt to bring together a system-level interdisciplinary assessment of all these issues.

Another important motivation for conducting an assessment was provided by changes in the form of the U.S. Department of Agriculture (USDA) Forest Service planning. In the Forest Service planning system, long-range plans require periodic updating, and the planning process is designed to trigger new analysis whenever new resource issues emerge. The constellation of issues described above, along with a fundamental shift in public-land-management philosophy had, in the years leading up to the assessment, indicated a need to revisit plans for all the national forests in the region. The need for a comprehensive regional evaluation of resource issues in support of national forest planning provided one of the most substantial motivations for conducting a regional assessment.

Shifts toward ecosystem management on the national forests also defined a fundamental need for information on forest systems at a regional level. Ecosystem management, an emerging and changing approach to resource management, demands a new and extended complement of knowledge (Gottfried et al. 1996). Defined as a hybrid of traditional resource management, conservation biology, and landscape ecology, ecosystem management requires a broader scientific foundation for management as well as information and knowledge compiled at broader scales (Christensen and Franklin 1997). For example, effective decisions on a national forest may depend on understanding the functional role of that national forest in its broader regional landscape (Swallow and Wear 1993). This approach also suggests a need to gauge disturbance regimes throughout ecosystems and, therefore, a need for understanding the social as well as the ecological context of natural resource decisions. Ecosystem management clearly expands the information needs of resource managers. Modeling has a strong role to play in integrating these multiple dynamics and playing out their cumulative effects on resource systems.

4.3 Organization of the Assessment

While the USDA Forest Service had the strongest and most direct need for knowledge to support science-based ecosystem management, other agencies had similar needs. Institutional barriers between federal agencies

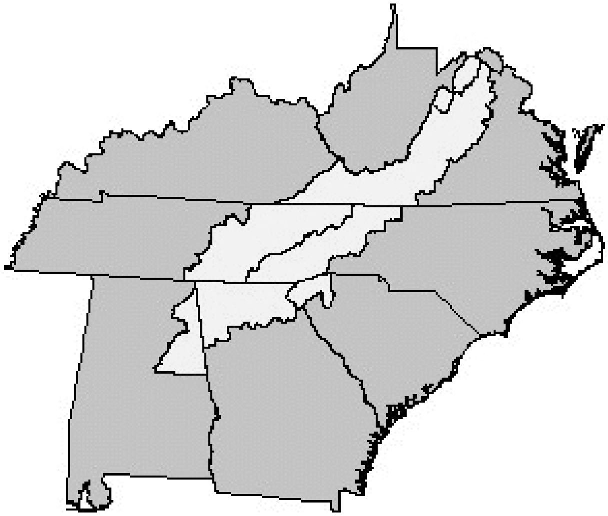

FIGURE 4.1. The Southern Appalachian Assessment area (light shading).

and between federal and state agencies are formidable and can provide a strong disincentive for cooperation, especially when natural resource agencies' budgets are in decline. Fortunately, a unique mechanism for coordinating the activities of agencies in matters regarding the Southern Appalachians already existed. Chartered in 1988, the Southern Appalachian Man and the Biosphere Cooperative was established to provide a mechanism for developing cooperative initiatives between public and non-governmental groups to address issues of regional interest (see SAMAB 2001). While the interagency agreement for SAMAB did not explicitly commit agencies to any kind of specific support, it provided the essential institutional framework for bringing together these multiple interests when appropriate, and perhaps more importantly, it documented a common interest in the Southern Appalachian region. This organization proved to be a critical foundation for forming and conducting the SAA.

Through SAMAB, an executive team was convened to define the process and to sort out logistical aspects of the assessment, including interagency coordination. The initial step was to clearly define the geographic and conceptual scope of the SAA. The conceptual scope of the assessment was developed through a series of public meetings. With a facilitated-workshop approach, these meetings solicited input on the resource issues that needed attention. These issues were then used to develop a set of specific questions regarding resources and their uses in the Southern Appalachians. Once the questions were defined, the executive committee, working through two assessment co-leaders from the USDA Forest Service, grouped issues into thematic areas and recruited assessment teams for each area. The four broad theme areas were: terrestrial, water, air, and social/cultural/economic. Researchers, managers, and analysts comprised the teams.

As shown in Figure 4.1, the geographic scope of the assessment was defined as a contiguous 37.4-million-acre area, primarily in the mountains but also in the interspersed ridge-and-valley areas stretching from northern Virginia to northeastern Alabama. Public ownership comprises about 17% of the land area in this region, with more than 90% of the public land managed as national forests (Figure 4.2). The assessment addressed issues at landscape and regional scales, necessarily evaluating both public and private lands in the region.

Figure 4.3 shows the configuration of the various assessment teams, the executive team, a public affairs team, and a writing/production team. The assessment involved the efforts of more than 100 participants, representing 10 federal and several state agencies as well as various universities in the region.

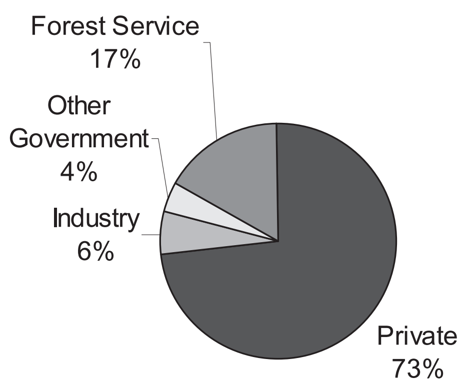

FIGURE 4.2. Ownership of timberland in the Southern Appalachian Assessment area. (Source: USDA Forest Service, Eastwide Database, Hansen et al. 1992.)

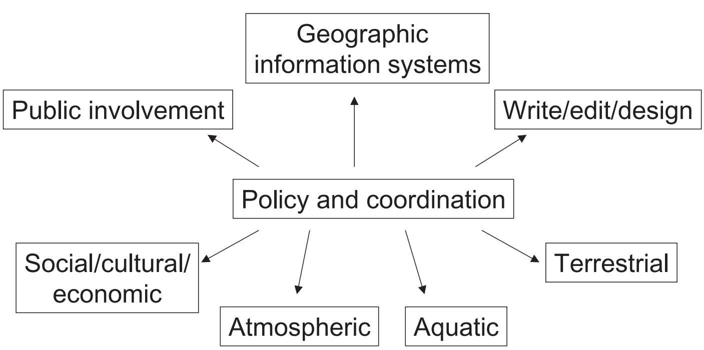

FIGURE 4.3. Interagency assessment teams used to conduct the Southern Appalachian Assessment.

4.4 Process

The SAA endeavored to bring together the best available knowledge to address the assessment's questions in a short time. From organization to publication, the assessment took only 2 years to complete. Organizers of the SAA took lessons from earlier regional assessments but had considerable latitude to design a process that matched the issues at hand. Four conceptual guidelines framed the resulting effort: (1) the assessment would compile information, but it would not prescribe action or lead directly to specific decisions, (2) the assessment teams would not conduct new original research or compile new data but would use the best available existing information, (3) efforts would be strictly limited to answering the specific questions of the assessment, and (4) the process would be accessible to the public.

The decision not to decide (i.e., designing the assessment as an information-gathering rather than as a decision-making process) had several important implications. Most significantly, it meant that an environmental impact statement and its attendant formal processes would not be required. This allowed the assessment's leaders to fit a process to the region's needs and allowed for considerable flexibility in designing that process, especially as it related to public involvement. Additionally, because there was no explicit resource management outcome involved, constituents could engage in the assessment's process without engaging in gamesmanship intended to influence the outcome of a decision.

The decision to use only available information and not to collect and analyze new data had two important implications. One was that the time frame of the assessment was compressed, thereby reducing the time commitment of scientists to the project. By limiting the time frame, the SAA was able to engage more scientists and perhaps scientists of higher caliber than would have otherwise been possible. Another important implication was that the costs of conducting the assessment were lower than would have been required had primary data gathering and analysis been pursued.

Assessment teams addressed only the set of specific questions developed through the public involvement process. Because the questions communicated the specific objectives of the assessment to the interested public and the participating agencies, they helped build trust between assessment organizers and the public. By treating these questions as a de facto contract (i.e., not engaging in unilateral change) the assessment organizers were able to define and control the limits of the scope of the SAA. Any change to a question required approval by the executive committee. Building trust was especially important in the Southern Appalachians, where 83% of the land being analyzed was in private ownership and concerns regarding government agencies analyzing data from private lands could have been substantial.

The SAA developed a process that was accessible to the public. All meetings of science teams and the executive team were managed as public meetings with advance notice and with mechanisms for discourse between the interested public and scientists and analysts conducting the assessment. This unprecedented approach to conducting the assessment's activities also served to build trust in the conduct of the assessment. Perhaps most importantly, it provided a platform for the discussion of complex resource issues among a broad complement of interest groups.

4.5 Assessment Results

A project can be evaluated in terms of its products (i.e., the reports and data sets) and its outcomes (i.e., perceptible changes in process, reductions in conflict, and new approaches to on-the-ground decision making). Products are tangible and readily measured, while outcomes may be much more difficult to pin down. In spite of being more difficult to measure, outcomes are more substantive consequences of an effort like the SAA. While government reports have a propensity to gather dust, changes in institutions and ways of doing business can have important and enduring effects on the condition of land and resources.

4.5.1 Products

The initial product of the SAA was a five-volume set of documents and several data sets addressing the specific questions in each of the four theme areas (Southern Appalachian Man and the Biosphere Cooperative 1996*a–e*). The reports summarized existing knowledge regarding ecological and social systems within the region, a synthesis of data, and a summary of key findings. Five thousand copies of the four technical reports and nine thousand copies of the summary report were produced and rapidly disseminated. The reports were also made available in a downloadable form on the World Wide Web. These products were subsequently used by both public resource managers and public interest groups to address forest-planning issues on the region's seven national forests.

It is implausible to provide a complete listing of the findings presented in the technical documents. Resource conditions and trends were documented, and several emerging issues and concerns were identified. As a sampling of these findings, consider that the SAA

1. Documented and quantified social demographic and attitude changes in the region (SAMAB 1996*d*, pp. 17–70)
2. Documented changes in the economic structure of the region (SAMAB 1996*d*, pp. 71–76)
3. Identified the structure of timber supplies and demands (SAMAB 1996*d*, pp. 89–116)

4. Examined the role of public lands in evolving timber markets (SAMAB 1996*d*, pp. 117–125)
5. Charted changing demands for recreation (SAMAB 1996*d*, pp. 169–173)
6. Defined changes in recreation opportunities resulting from congestion (SAMAB 1996*d*, pp. 159–162)
7. Charted changes in terrestrial habitats and the relative position of public lands in providing various types of habitat (SAMAB 1996*e*, pp. 21–38)
8. Documented recent and anticipated changes in early-successional habitats (SAMAB 1996*e*, pp. 26–28)
9. Identified rare plant communities and their distribution by forest ownership classes (SAMAB 1996*e*, pp. 11–25)
10. Charted the effects of various health factors on forest ecosystems, such as oak decline and gypsy moth (SAMAB 1996*e*, pp. 103–131)
11. Evaluated trends in forest vegetation caused by human and other influences (SAMAB 1996*e*, pp. 93–102)
12. Identified changes in atmospheric pollutants and their potential impacts on forest ecosystems (SAMAB 1996*c*, pp. 53–62)
13. Examined the potential contribution of prescribed burning to particulate levels (SAMAB 1996*c*, pp. 21–26)
14. Defined the current and potential future effects of human activities on the quality of water flowing from the Southern Appalachians (SAMAB 1996*b*, pp. 89–120)
15. Examined recent changes in the demand for water in the region (SAMAB 1996*b*, pp. 121–132)

In addition to the findings presented in technical reports, another tangible product of the assessment was a suite of data sets addressing ecological and social components of the region. These data sets were made available on compact disks and on the World Wide Web (http://samab.org/data/SAA_data.html). Planners as well as researchers made direct use of the data sets in subsequent analyses.

4.5.2 Outcomes

Outcomes are difficult to measure for a process like the SAA, where the objective was to improve the knowledge base for conducting ecosystem management. To ascertain the types of outcomes that accrued, I interviewed several forest planners and scientists in the region who were either or both (1) involved in the SAA and (2) engaged in the forest planning that was conducted following the assessment. This informal survey provided some insights into the various ways these groups perceived, used, and valued the assessment. However, it should not be viewed as a representative sample.

National forest planners in the Southern Appalachians drew directly from the assessment findings to conduct the initial stages of national forest planning. These stages, collectively termed "the analysis of the management situation," are designed to set the context of the planning exercise by placing each national forest in its physical, biological, and social settings and to define the broad issues to be addressed by each plan. For planning conducted prior to the SAA, each of the seven national forests within the region had completed independent "analyses of the management situation." The SAA provided the first coordinated ecosystem-level view of these national forests that was clearly linked to their impacts on ecosystems in the Southern Appalachians.

The results also provided a mechanism for coordinating subsequent phases of planning across the forests and represented a substantial broadening of scope in forest planning. By taking a regional and ecosystem approach, the assessment allowed managers to develop a perspective on the comparative advantage of the national forests for influencing both ecological and economic systems. For example, the assessment showed that private lands were generally providing adequate amounts of early-successional wildlife habitat, while a scarcity of late-successional habitat was evident (SAMAB 1996*e*, p. 27). A comparison of age-class distributions between ownerships indicated that national forests had a comparative advantage for producing the latter type of habitat. Likewise, analysis of timber markets indicated that national forests had a relatively minor role to play in total fiber production, but controlled a disproportionately large share of the inventory of the highest-quality timber (SAMAB 1996*d*, p 117). This observation suggested a strong position of national forests in an important segment of the local timber economy, and conversely it identified segments where national forests did not have a strong position.

This coordinated approach to analysis both avoided the costs of duplicate data and information gathering and improved the quality of data brought to bear on that planning. It therefore seems probable that the SAA provided a more cost-effective approach to this information gathering. More importantly, the SAA provided a means for considering national forests within the context of the entire ecosystems and social systems within which they reside, a critical first step in the design of effective ecosystem management strategies (Christensen and Franklin 1997). It also provided for the first time an integrated social/ecological knowledge base and database for use by forest managers and analysts.

Another important outcome of the SAA was that it established what Wondolleck and Yaffee (2000) have termed a "community of interest" focused on Southern Appalachian ecosystems. Prior to the SAA, scientists, planners, and the public at large had all addressed various, sometimes common, issues regarding the Southern Appalachians but in separate and generally nonintersecting spheres. The assessment, through its public involvement process, brought these groups together to form a new broad community of interest, thereby focusing the attention of all groups on a common set of resource questions. Perhaps more importantly, the assessment provided a structured platform for discourse among these varied groups.

A community of interest often is ephemeral, and this one could easily have dissipated at the conclusion of the assessment, but it has been maintained through two important mechanisms. One is an annual conference still held by SAMAB to address regional ecosystem issues from both research and management perspectives. The other is through the forest-planning process. The USDA Forest Service adopted and extended the SAA's public involvement process for conducting national forest planning in the region. In addition to using the same approach to public involvement, the Forest Service also chose to conduct a coordinated planning approach, in effect coordinating their ecosystem management plans at a regional scale. The Forest Service formally defined the role of the SAA in defining "an ecological approach to planning" in a notice filed in the *Federal Register* (1996). The relationships between public interest entities and public land managers established through the SAA have provided a durable and broad platform for discourse on ecosystem management issues within the region.

Another outcome of the SAA, and one that may have far-reaching effects, was the establishment of relationships between managers and researchers in the Southern Appalachians. There have been three consequences. One is ongoing consultations with researchers as planners encounter new problems on their respective forests. Another is a complement of management-relevant studies that have been established in the wake of the SAA. The SAMAB reports 19 research projects that specifically use data compiled through the SAA, and several other projects are also under way (SAMAB 1999). A third outcome was the establishment of the Southern Appalachians as a focal area for coordinated interdisciplinary research within the Southern Research Station of the USDA Forest Service (USDA Forest Service 1997).

According to conventional wisdom, imitation is the highest form of flattery. Two assessments, the Ozark-Ouachita Highlands Assessment (USDA Forest Service 1999) and the Southern Forest Resource Assessment, have been spawned in the southeastern United States since completion of the SAA. In both cases, multiple-agency approaches have been used, and assessment organizers have modeled their approaches on the SAA. For example, the structure of the public involvement processes and science–management collaborations developed by the SAA have been adopted in very similar form in both efforts.

4.6 Lessons

Several lessons can be taken from the efforts of the SAA. How well they transfer to other efforts may be variable, but all should provide useful insights into how to frame questions as well as how to approach science–

management collaboration when addressing complex ecosystem management issues.

Lesson 1. Effective ecosystem management on public lands requires meaningful collaboration among managers/planners, scientists, and the interested public. Ecosystem management can be viewed as a science-based approach to managing natural resources, thereby requiring interaction between scientists and managers. However, ecosystem management is also a process that requires making difficult decisions (i.e., making tradeoffs) involving substantial public assets and should therefore involve the full suite of interested and affected parties. To leave out the public interest suggests (falsely) that mangers can isolate "scientifically correct" management solutions to these complex problems. It is important to remember that knowledge can illuminate the potential consequences of alternative actions, but only rarely does it lead to an unambiguous conclusion regarding the correct decision (Cortner et al. 1999).

The SAA developed an effective approach to the three-way exchange of information. Important elements included (1) developing early public ownership in the process through an initial public scoping of issues, (2) settling on a fixed set of questions to guide the assessment as it addressed issues (this defined a tacit contract with the interested public and was a foundation upon which additional trust could be built), and (3) providing complete access to assessment deliberations through the use of a structured public meeting format, again promoting trust in the process.

This lesson has implications for modeling efforts that are targeted toward resource management. For the modeling results to be accepted, stakeholders need to be involved enough to build ownership of the process. The modeling process should be designed to address a specific set of questions. The model should be available, and its documentation should be clear, so that the stakeholders accept the modeling process. Access to modeling decisions (e.g., defining inputs and forecast assumptions) seems necessary to build trust.

Lesson 2. Where jurisdictions overlap, meaningful coordination of different government agencies can enhance, indeed may be requisite for, the development of effective ecosystem management strategies. Because ecosystem management addresses the structure and function of very large, complex systems, it clearly defines a situation where considerable returns might accrue to collaboration. Clearly, coordination of actions across multiple landowners and other institutional entities can enhance the quality of resource management and the quality of ecosystems. However, federal and state agencies often can only address portions of these systems in pursuit of their different missions. The SAA formed an effective multiagency collaboration that was facilitated by a unique cooperative arrangement. SAMAB links nine federal agencies in an institutional framework that provides a mechanism whereby efforts within the Southern Appalachians can be linked to or filtered by other relevant agencies but does not bind members to specific levels or forms of support. This type of organization allows for a place-based approach to agency activities that can greatly complement mandate-based activities through coordination.

Modelers should bear in mind that agencies at different levels of government may have responsibility for managing different components of ecosystems. For example, national forests manage for wildlife habitat needs, but state game agencies have responsibility for managing wildlife populations. For models to effectively inform management, the various parties who "own" components of the problem need to participate as partners in informing the development and application of relevant model components. Without this type of cooperation, decisions based on the model may not have standing among the affected parties.

Lesson 3. Applying existing data, models, and knowledge to problems can enhance and improve resource management efforts. Another way of stating this lesson is that innovative management solutions do not necessarily require innovative or new science. Creative application of knowledge to these complex problems can be very productive. Given the adoption of technology and findings from the SAA in forest planning that followed, it can be argued that existing knowledge regarding ecosystems had not been fully applied in these management and planning spheres. Researchers, acting through assessments, can serve a very important purpose by translating and delivering information from science and by delivering the knowledge in a form that can be consumed by planners and mangers.

An important aspect of this lesson is that the most effective application of science to ecosystem management may not come through the standard pursuit of science. Rather than specify and challenge hypotheses through new investigations, scientists may provide the greatest service through the review, synthesis, and distillation of existing knowledge. These types of effort may not hold currency within the scientific community and, therefore, may discourage scientists from participating in ecosystem assessments. This problem poses a critical challenge for both research and land management organizations.

This lesson implies that models that apply existing knowledge to current problems may yield considerable benefit. A corollary to the lesson is that modelers should avoid the common trap of solving the scientist's problem instead of the manager's problem. Modeling efforts that link relevant knowledge from different disciplines (e.g., economics and ecology) may be especially beneficial to managers.

Lesson 4. The greatest return from assessment activities may be in derivative activities that follow the assessment activity proper. An integrated management–science assessment or problem-solving effort can provide a useful connection among scientists, resource planners, and managers. In the SAA, these results took two forms. One was the establishment of relationships between individuals. Planners working within the region developed several contacts with scientists working in the region. Additional derivative effects took the form of research projects developed either to address questions raised by the assessment or facilitated by data sets compiled through the assessment. Accordingly, there could be substantial returns to installing a process for promoting and extending these types of relationships. In the wake of SAA, SAMAB has continued to play an important role in enabling dialogue within the broad community of interest that emerged from the assessment (e.g., through its annual conference on Southern Appalachian issues).

From the modeler's perspective, an assessment activity offers an opportunity to thoroughly define a set of questions immediately relevant to managers. The assessment proper calls for a short-run analysis that takes advantage of existing knowledge. The follow-up to an assessment may be a long-run effort to align research efforts with management needs.

4.7 Discussion

Bioregional assessments, as a relatively new genus of scientific inquiry, provide a distinct and important set of challenges for the development and application of models. Clearly, they address multiple problems in complex systems where models could provide useful insights. By virtue of their connections to public interests and management challenges, bioregional assessments have the potential to define the most important questions that need to be addressed (i.e., they can focus the attention of scientists on the questions that *need* to be addressed rather than on the questions that *can* be addressed). They also serve to define the critical linkages between important causes and effects and between models of various disciplines. Assessments such as the SAA can be viewed as meta-models. That is, they take vast quantities of inputs from interested publics and a variety of data sources, process this input through computer models and the organic computers of scientists and resource analysts, and yield a set of outputs in the form of both quantitative and qualitative findings. However, these meta-models are far removed from the mechanistic and internally consistent integrated ecosystem modeling frameworks that have been anticipated for some time (Holling 1978). Instead, the assumptions, scales, and relative certainties of the various components can differ widely within assessments, and the lack of interdisciplinary integration may identify one of their greatest weaknesses (Johnson et al. 1999). Indeed, assessments may provide their greatest service in pointing out the ultimate limits of current understanding, modeling, and approaches to ecosystem and social analysis for addressing broad-scale and complex ecosystem management issues.

Perhaps it is best to view broad assessments as a necessary initial step in defining the scope and structure of an integrated modeling framework that could provide a comprehensive analysis of policy and management-relevant questions at appropriate scales. Assessments may indeed be needed to both define the critical questions and identify the links between modeling components before such modeling could proceed. Scientists involved in these efforts are likely to find many of their models incapable of producing information at scales that match the questions at hand. Accordingly, broad assessments could and should encourage scientists to question and redirect the focus of the questions they pursue in their studies and the design of their models.

References

Christensen, N.L. and J.F. Franklin. 1997. Ecosystem function and ecosystem management. Pages 1–23 *in* R.D. Simpson and N.L. Christensen, editors. Ecosystem Function and Human Activities: Reconciling Economics and Ecology. Chapman and Hall, New York, New York, USA.

Courtner, H.J., M.G. Wallace, and M.A. Moote. 1999. A political context model for bioregional assessments. Pages 71–82 *in* K.N. Johnson, F. Swanson, M. Herring, and S. Greene, editors. Bioregional Assessments: Science at the Crossroads of Management and Policy. Island Press, Washington, District of Columbia, USA.

Daughtrey, M.L., C.R. Hibben, K.O. Britton, M.T. Windham, and S.C. Redlin. 1996. Dogwood Anthracnose: Understanding a disease new to North America. Plant Disease **80**:349–358.

Dunlap, R.E. 1991. Trends in public opinion toward environmental issues: 1965–1990. Society and Natural Resources **4**:285–312.

Federal Register. 1996. Revised land and resource management plans for the national forests in Alabama, Chattahoochee/Oconee National Forests, Cherokee National Forest, Jefferson National Forest, and the Sumter National Forest. Federal Register **61**:40183–40191, August 1, 1996.

Gottfried, R.R., D.N. Wear, and R.G. Lee. 1996. Institutional solutions to market failure on the landscape scale. Ecological Economics **18**:133–140.

Hansen, M.H., F. Thomas, and J.F. Glover. 1992. The Eastwide Forest Inventory Database Users Manual. General Technical Report NC-151. North Central Forest Experiment Station, U.S. Department of Agriculture Forest Service, St. Paul, Minnesota, USA.

Haynes, R.W., D.M. Adams, and J.R. Mills. 1995. The 1993 RPA Timber Assessment Update. USDA Forest Service General Technical Report RM-GTR-259. Fort Collins, Colorado, USA.

Hepting, G.H. 1974. Death of the American chestnut. Journal of Forest History **18**: 60–67.

Holling, C.S. 1978. Adaptive environmental assessment and management. John Wiley & Sons, New York, New York, USA.

Johnson, K.N., F. Swanson, M. Herring, and S. Greene. 1999. Bioregional Assessments: Science at the Crossroads of Management and Policy. Island Press, Washington, District of Columbia, USA.

Liebhold, A.M., J.A. Halverson, and G.E. Elmes. 1992. Gypsy moth invasion in North America: A quantitative analysis. Journal of Biogeography **19**:513–520.

Southern Appalachian Man and the Biosphere Cooperative (SAMAB). 1996*a*. The Southern Appalachian Assessment: Summary Report. Report 1 of 5. U.S. Department of Agriculture Forest Service, Southern Region, Atlanta, Georgia, USA.

Southern Appalachian Man and the Biosphere Cooperative (SAMAB). 1996*b*. The Southern Appalachian Assessment: Aquatic Technical Report. Report 2 of 5. U.S. Department of Agriculture Forest Service, Southern Region, Atlanta, Georgia, USA.

Southern Appalachian Man and the Biosphere Cooperative (SAMAB). 1996*c*. The Southern Appalachian Assessment: Atmospheric Technical Report. Report 3 of 5. U.S. Department of Agriculture Forest Service, Southern Region, Atlanta, Georgia, USA.

Southern Appalachian Man and the Biosphere Cooperative (SAMAB). 1996*d*. The Southern Appalachian Assessment: Social/Cultural Economic Technical Report. Report 4 of 5. U.S. Department of Agriculture Forest Service, Southern Region, Atlanta, Georgia, USA.

Southern Appalachian Man and the Biosphere Cooperative (SAMAB). 1996*e*. The Southern Appalachian Assessment: Terrestrial Technical Report. Report 5 of 5. U.S. Department of Agriculture Forest Service, Southern Region, Atlanta, Georgia, USA.

Southern Appalachian Man and the Biosphere Cooperative (SAMAB). 1999. Use of the Southern Appalachian Assessment and Database. URL: http://samab.org/saa/usesaa.html.

Southern Appalachian Man and the Biosphere Cooperative (SAMAB). 2001. The Southern Appalachian Man and the Biosphere web site. URL: http://samab.org/About/about.html.

Swallow, S.K. and D.N. Wear. 1993. Spatial interactions in multiple-use forestry and substitution and wealth effects for the single stand. Journal of Environmental Economics and Management **25**:103–120.

Turner, M.G., D.N. Wear, and R.O. Flamm. 1996. Land ownership and land cover dynamics in the Southern Appalachian highlands and Olympic Peninsula. Ecological Applications **6**:1150–1172.

U.S. Department of Agriculture (USDA), Forest Service. 1997. Strategic Framework for the Southern Research Station. USDA Forest Service Miscellaneous Publication, Asheville, North Carolina, USA.

U.S. Department of Agriculture (USDA), Forest Service. 1999. Ozark-Ouachita Highlands Assessment: Summary Report. USDA Forest Service Miscellaneous Publication, Asheville, North Carolina, USA.

Wear, D.N. and P. Bolstad. 1998. Land-use changes in Southern Appalachian landscapes: Spatial analysis and forecast evaluation. Ecosystems **1**:575–594.

Wondolleck, J.M. and S.L. Yaffee. 2000. Making Collaboration Work: Lessons from Innovation in Natural Resource Management. Island Press, Washington, District of Columbia, USA.

Part 3

Key Issues

Section I: Barriers

5
Overcoming Barriers to the Use of Models in Environmental Decision Making

Mark A. Harwell and John H. Gentile

5.1 Introduction and Organizing Frameworks

The issue of addressing barriers to the use of models in environmental decision making can best be considered in the context of (1) the organizing framework developed by the U.S. Environmental Protection Agency (USEPA 1992) for conducting ecological risk assessments; (2) the associated process for developing policy-relevant conceptual models of ecological systems and their responses to stressors (Gentile et al. 2001); and (3) the emerging analytical/deliberative process to engage scientists, decision makers, stakeholders, and the public in bringing science to bear on environmental decision making developed by a panel of the National Research Council (NRC 1996). This chapter briefly discusses these frameworks and considers several issues that need to be addressed to enhance the utility of ecological models.

5.1.1 Framework for Ecological Risk Assessments

Ecological risk assessment is a relatively new field derived from evaluating risks to human health from toxic chemicals (NRC 1983). The technique combines the quantifiable terms of hazard (the inherent ability to cause harm) and exposure (the quantity experienced by humans) into a probabilistic assessment of health risk.

Recognizing that the human-health-based risk assessment framework of the NRC "red book" was inadequate to address the wealth and complexity of ecological risk issues, the USEPA developed an ecological risk assessment paradigm (Harwell and Gentile 1992; USEPA 1992, 1996, 1998; Fava et al. 1992; Gentile et al. 1993; van Winkle and Kadvang, Chapter 3, this volume) that has subsequently been widely used in environmental assessments. Ecological risk assessment is the process of evaluating the likelihood that adverse ecological effects occur as a result of exposure to one or more stressors. The ecological risk assessment framework provides a systematic method for identifying, organizing, and analyzing diverse environmental information to produce a qualitative or quantitative statement that assesses the magnitude and probability of adverse effects. The risk assessment process can also be used less rigorously to provide a basis for developing a relative ranking of potential risks. Relative risk assessments can reduce the dimensionality of the problem, provide the basis to prioritize research activities and allocate resources, and assign relative risks among options [see Harwell and Kelly (1987); Harwell et al. (1992); USEPA SAB (1990*a*,*b*)].

The framework for ecological risk assessments (Figure 5.1) has at its core the elements of *stress regime (exposure) characterization* and *ecological effects characterization*. The purpose of this paradigm is to provide a systematic framework for identifying and quantifying the causal pathways linking anthropogenic or natural processes, their resulting environmental stressors, and ecological effects. The stress regime characterizes exposure to one or more stressors, including the temporal/spatial patterns and variability of multiple natural and anthropogenic stressors (Harwell and Gentile 2000). Ecological effects characterization must address the inherent diversity of ecosystems and the extreme range of scales (in time and space) that simultaneously operate in ecosystems. These two elements of ecological risk assessments are analyzed through a three-step process: problem

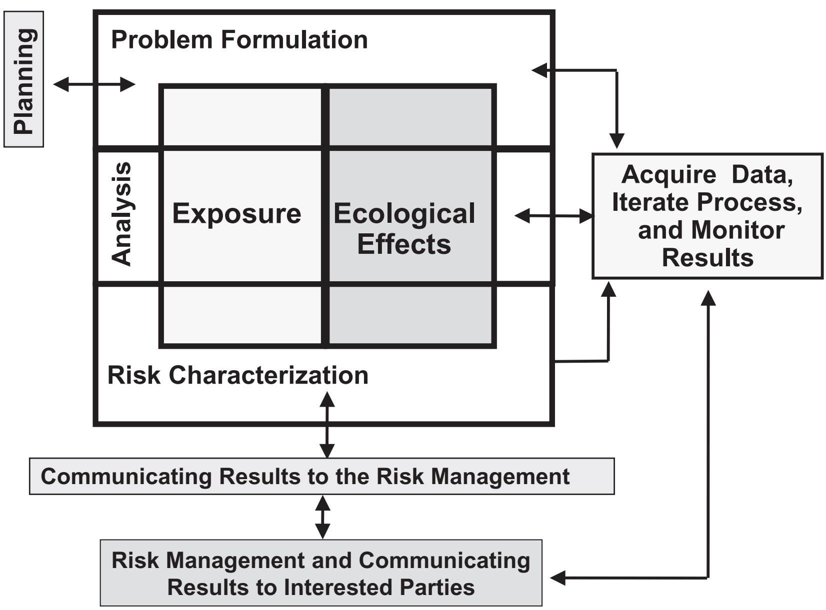

FIGURE 5.1. The USEPA ecological risk assessment framework [From USEPA (1992) (please note that this figure is a variation of Figure 4 in Chapter 3 by van Winkle & Kadvang, this volume)].

formulation, analysis, and risk characterization. These steps can be viewed as an iterative, highly interactive modeling process that evolves to address the unique types of questions in each phase.

The purpose of the problem formulation stage (Figure 5.2) is to define the spatial, temporal, and biological scope of the risk assessment. Problem formulation involves an initial planning step that integrates scientific, management, stakeholder, and public preferences into a clear statement of goals and objectives for the study. The problem formulation stage is centered on (1) identifying the at-risk components of the ecosystems and the environmental stressors that may affect those components; (2) characterizing stress–response relationships, including the spatial extent of the co-occurrence of the stressors and at-risk components; (3) selecting ecological endpoints for assessing environmental condition that capture the health of the system in a socially relevant context; and (4) developing conceptual models that describe, qualitatively or quantitatively, the potential causal relationships among human activities, societal drivers, environmental stressors, and co-occurring ecological systems.

What separates the ecological risk paradigm from other (e.g., human health) risk paradigms is the challenge of defining the appropriate endpoints that reflect the intersection of scientific and social values. Evaluating ecological health requires a suite of ecological endpoints spanning organizational scales (population, community, ecosystem, and landscape; Harwell et al. 1990; Kelly and Harwell 1990; Harwell and Gentile 1992). Ecological endpoints are ecosystem-specific and are selected to separate all

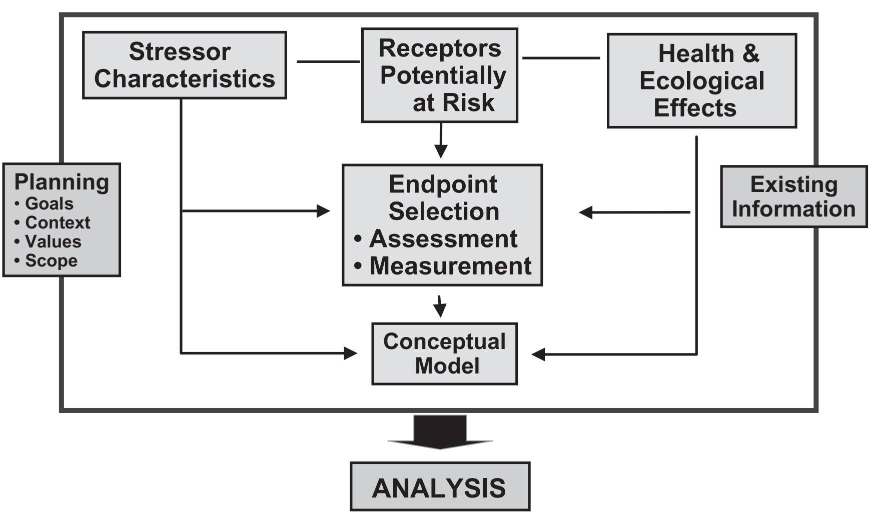

FIGURE 5.2. The problem formulation phase of the ecological risk assessment framework [Source: USEPA (1996)].

possible ecological effects from those effects that are significant to the ecosystem and/or to society (Harwell and Long 1992; USEPA 1992, 1998; Gentile and Harwell 1998). Criteria for selecting endpoints include (1) identification of their ecological importance (e.g., important structures and processes) or societal importance (e.g., economic or aesthetic species, water supply, and flood protection); (2) consideration of organizational hierarchy, including species, ecosystem, and landscape scales; (3) susceptibility to the stressors of concern; (4) identification of critical structural and functional attributes that can be used to characterize the state (health) or change of health of the regional environment; and (5) signal-to-noise ratio (that is, the ability to discriminate changes in endpoints from natural variability) (Kelly and Harwell 1990). Selection of ecological endpoints is critical for our purposes here, because each and every selected endpoint should be addressed in an ecological risk assessment. Consequently, the most effective and, therefore, most used, models will be those that incorporate and provide output specific to the selected ecological endpoints.

Problem formulation addresses the critical issue of *reference or benchmark conditions* (Figure 5.3). Benchmarks are essential if scientists, decision makers, stakeholders, and the public are to understand the

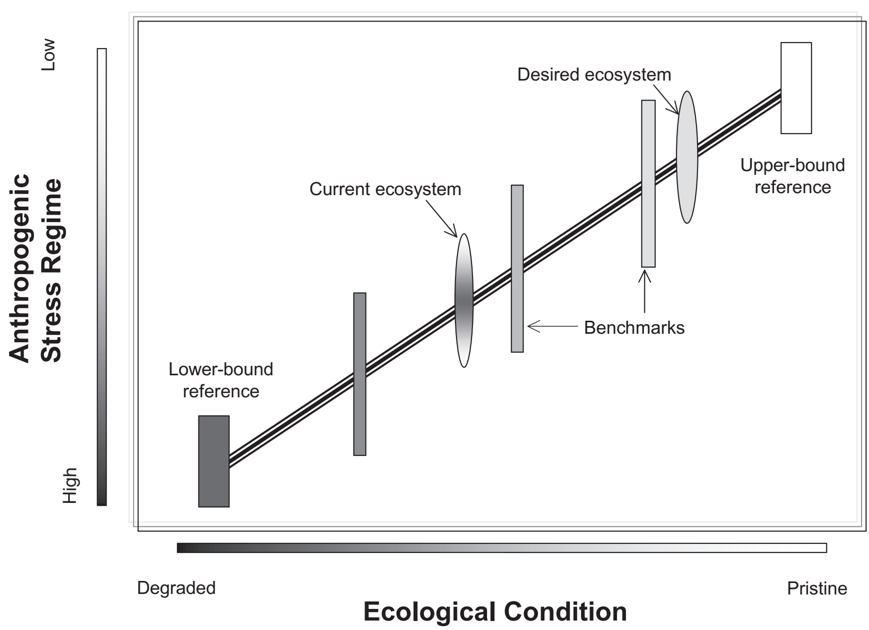

FIGURE 5.3. Benchmark, reference, and desired ecological conditions [From Harwell et al. (1999*b*)].

relationships among historical, present, and potential future environmental conditions. That is, the reference conditions provide the context for evaluating environmental goals and the success or failure of management to achieve those goals or desired ecological conditions (Harwell et al. 1999*b*). Again, a central objective for using models for ecological assessments would be to project the state of the ecological systems vis-à-vis those reference, benchmark, and desired conditions. For example, the reference conditions (Figure 5.3, rectangles) refer to both upper (minimal perturbation) and lower (maximum perturbation) bounding conditions for the essential ecosystem characteristics of concern for the assessment. For many situations, the upper boundary may be unattainable (e.g., restoring the Everglades to 1800 predevelopment conditions). The lower boundary could represent the elimination of the habitat completely. The desired conditions (Figure 5.3, ellipses) are meant to represent the ultimate desired goal to be achieved (the target state of the system at the completion of restoration). In many cases, the extant ecological condition is far removed from the desired condition, and progress towards restoration would be indicated more clearly if a set of intermediate conditions were established as benchmarks or milestones for managers and scientists to assess the efficacy of their actions and progress towards the goals. Note that benchmarks are needed on both sides of the current condition to determine the direction of response.

In addition, all states (reference, desired, current, and benchmark) have both an ecological component and a stressor component. It is important to note that nothing in this framework is meant to signify static conditions. Rather, each benchmark or reference condition and the characterization of the actual ecosystem explicitly incorporate natural variability as well as processes like succession or other directional changes over time and space.

The analysis phase of the ecological risk assessment focuses on developing and testing methods and models, conducting experiments, and analyzing data to characterize stress regimes and to establish stress–response models. The ecological stress–response relationships are essential to predicting ecological consequences from resulting changes in the stress regime, which provides the risk manager and decision maker the ability to evaluate, a priori, alternative management or remedial options.

Finally, risk characterization integrates stress and effects into a predictive and probabilistic statement of the risks and uncertainties that is to be used along with societal and economic factors by the decision maker. As such, the risk characterization phase of the risk assessment, like problem formulation, is a critical point of intersection among the risk assessor, decision makers, and the public (NRC 1996).

Thus, when viewed from the ecological risk assessment perspective, modeling needs in support of decision making differ for the different phases of the assessment process (problem formulation, analysis, and integration). The focus of problem formulation is on the development of appropriate conceptual models (discussed below) that clearly describe the potential causal linkages between the ecosystems and ecological attributes at risk, the stressors potentially affecting these ecosystems and attributes, the scientific bases for analyses, and the particular management issues being addressed. Quite different model needs exist for the analysis and characterization phases. For the analysis and risk characterization phases, model needs focus on the development, availability, and application of quantitative models that address the selected ecological endpoints and can assess the condition of those endpoints in the context of reference, benchmark, and desired ecological conditions. For these more quantitative and predictive models that are useful for the analysis and integration phases of the ecological risk framework, the central issue is the degree of confidence scientists, stakeholders, and decision makers have in the model results.

5.1.2 Utility of Conceptual Models

The term *conceptual model* can be viewed as qualitative or descriptive statements or hypotheses concerning the nature of causal relationships among human activities, the resulting anthropogenic stressors, and their impacts on human and ecological systems (USEPA 1992, 1998; Barnthouse and Brown 1994; C. Harwell et al. 1999*a*; Suter 1999*a*,*b*; Foran and Ferenc 1999; Harwell and Gentile 2000; Gentile et al. 2001). Conceptual models are an especially important initial step in the analysis of multiple stressors and of the cumulative ecological effects as well as in understanding the ecological consequences of management alternatives at regional scales. For site-specific environmental assessments, conceptual models should be developed as a tool for describing the causal relationship between human activities, environmental stressors, at-risk valued ecological resources, and their associated ecological endpoints and measures. This tool can then be used for a variety of management and communication purposes. A properly developed conceptual model effectively captures the scientific understanding of an ecosystem and its response to natural and anthropogenic stressors. The process of constructing a conceptual model can engage the scientific community in an important dialogue to articulate more clearly the individual perspectives of scientists regarding how an ecosystem functions and responds to stress. Assumptions and proposed relationships must be made explicit and defended, and in the process, a consensus of the scientific community may emerge. The conceptual model can do much more, however. It can be an extremely effective tool for communicating to nonscientists or to scientists who have not previously focused on the environmental problem at hand. The communication function is very important for this class of complex problems for the very reason that they are complex, and a well-presented graphical representation of the conceptual model can make clear and transparent to all what is meant by particular terms or categories, what linkages are considered relevant, etc. If the conceptual model development process continues through a relative ranking exercise, then the graphic can readily show what linkages, inputs, system components, etc. are most important and which are relatively minor. Further, if done properly, the conceptual model development process can identify the most important uncertainties about the ecosystem. Finally, the conceptual model can be an extremely useful management tool for thinking though the potential efficacy of management options.

Our experience is that the success or failure of science in support of environmental decision making, including models as one set of assessment tools, fundamentally relates to the explicit definition of the ecological goals, ecological endpoints, and reference ecological conditions for the specific problem at hand. Conceptual models are very important tools in this process, serving to facilitate the synthesis of existing scientific understanding and, along with the active participation by decision makers and stakeholders, to define the assessment questions and ecological goals. Two brief examples will serve to illustrate these points. In the Everglades restoration, a process of stakeholder involvement, directed at the Governor's level, was instituted to define spatially explicit goals for the assessment. This process, in concert with scientific workgroups, translated those goals into specific hydrologic, water quality, and ecological endpoints and performance criteria that will be used to guide the restoration. Without a general consensus on these points, the process would have stalled or been mired in litigation. A second example involves a large superfund site where stakeholder participation was minimal. In this situation, scientists took the lead in developing a detailed set of temporal and spatial goals for both source remediation and ecological recovery that provided the benchmarks for judging the efficacy of the assessment. The following is a list of specific issues relating to this level of confidence in the decision context.

5.2 Issues Related to Confidence in Ecological Models for Use in Decision Making

Here we will discuss criteria that, if satisfied, will reduce the uncertainty and increase confidence when using conceptual and quantitative predictive models. In so doing, we address one of the major barriers to the acceptance of models in ecological risk assessments. The specific points are not necessarily listed in any order of importance, but inadequate attention to one or more points will increase uncertainty and thus create barriers to using models. Conversely, addressing these points is one mechanism by which uncertainty can be reduced and the barriers can be overcome.

5.2.1 Generic Issue

How well does the conceptual model capture the understanding of the ecological system and its stressors, both natural and anthropogenic? We, as cognitive beings, are constantly creating a variety of mental conceptualizations (models, if you will) of our daily activities. We use these to represent relationships among a variety of variables. The conceptual models used in ecological assessments, like all models, are merely representations of reality as we perceive it. As such, they are neither right nor wrong but a continuum of representations of reality with varying degrees of uncertainty. The more information and understanding we have, the better our "model" will capture the essential features of our perceived reality. The purpose of the conceptual model is to capture, in general terms, our understanding of the complexity of critical ecological systems and the potential causal relationships of ecological responses to environmental stressors. This approach is nothing new; in fact, we intuitively develop conceptual models prior to constructing analytical or numerical models. What is unique is that, in this process, the conceptual model is explicit and developed from a consensus of scientists and nonscientists and, thus, is totally transparent. If done well, scientists and nonscientists alike will have increased confidence that the essential elements and relationships of the ecosystem are captured in the conceptual model, and that model will address successfully the goals of the environmental problem at hand. It is at this early stage of the assessment process that one begins to identify the important sources of uncertainty. If the conceptualization is not performed adequately, then there is a high probability that the assessment will address the wrong questions and the results will be unreliable at best and irrelevant at worst.

5.2.2 Aggregation

Is the model developed at the appropriate level of aggregation or disaggregation? Again, because of the complexity of ecosystems, any model, be it conceptual or predictive, must reduce the dimensionality of the problem to a manageable level, thereby aggregating details into more synthetic state variables or processes. However, too much aggregation can lead to loss of critical information about stress–effect relationships, or may lose the ability to address key ecological endpoints of concern. Conversely, too much disaggregation can lead to overwhelming information, unachievable data needs, or losing the important results in a maze of details. Any of these cases can lead to dismissal of a conceptual or simulation model as unrealistic.

5.2.3 Extrapolation

To what degree can the model be extrapolated? If a model was developed for one system or one set of stressors, can it be used for another set of circumstances? In dealing with this issue, it is helpful to separate the actual extrapolation from the predictive outputs of the model. For example, some hydrodynamic models can be transferred and used in different locations. However, the predictive utility will be a function of the site-specific data collected to set boundary conditions and to parameterize the model. Similarly, for conceptual models, the structure and processes, both physical and ecological, may be generalized, but ultimately the utility will be a function of how well site-specific parameters are represented, particularly the exposure pathway and process components. For example, an ecological effects submodel dealing with nutrient effects on seagrasses may be highly generalizeable and applicable to several sites where seagrasses exist. Thus, the successful extrapolation of quantitative models relates to the ability of the model adequately to represent the problem setting and the steps used in model calibration and validation to the specific issue at hand. In addition, extrapolation may be dependent on how successful the model has been when used in other cases. If the model has been widely used for a class of problems (e.g., hydrodynamics), confidence is enhanced that the extrapolation issues have been addressed. If the model has not used for the types of problems of concern, then an increased burden is placed on demonstrating the applicability of the model.

5.2.4 Accuracy and Precision

How well does the model meet the decision-making needs with respect to accuracy and precision? Different decisions demand differing degrees of accuracy and precision. For example, selecting among different management options may simply involve ranking the risks of one option over another, and that relative assessment is sufficient without a high level of precision. In other cases, a comparison among options may require quantitative assessments with high precision and accuracy. For example, a water quality model used to predict the discharge concentrations of toxic pollutants to comply with water quality criteria requires a high degree of accuracy and precision. The issue is (1) to determine, a priori, the required level of accuracy and precision for the particular decisions to be made and (2) to assure that the models selected will meet the criteria. The key here is that each decision has its own needs relative to model accuracy and precision and models must be tailored to meet those goals and needs.

5.2.5 Goals, Endpoints, and Benchmarks

How well do conceptual and simulation models relate to the specific ecological goals, associated ecological endpoints, and target benchmarks? As discussed above, the identification of ecological goals is necessary if appropriate decision making is to result. That is, ecological goals are the articulation of societal interests in the environment, and ecological endpoints are those decision-making attributes of the ecosystem that relate to the goals. Thus, for a model to be used successfully, it must relate to the environmental goals and address one or more specific endpoints; otherwise, the model is simply irrelevant to the decision-making process, a situation that occurs all too frequently. Similarly, the models must be able to relate the results to the reference and benchmark conditions (see Figure 5.3); otherwise, there is no way to evaluate the consequences or significance of the results. Issues involved here include having a database that covers the baseline ecological conditions (e.g., historical, reference, and pristine conditions), a model construct that captures phase shifts in system states under certain stress regimes, or models that can distinguish among alternate benchmark conditions. If the model cannot reflect these characteristics, then there is a significant likelihood that the model results will be misleading. For example, if a model of an estuarine community does not include the discontinuous shift from one dominant benthic habitat to another (e.g., seagrass to hard bottom) associated with an environmental gradient, such as sediment depth, then the model cannot reliably to assess impacts to that ecosystem from a stressor that affects that gradient.

5.2.6 Model Complexity, Communication to Different Audiences, and Terminology

How well do the models communicate complexity in understandable terms to different audiences? Communication can be an important barrier to the acceptance of models. There are two facets to the communication issue: appropriately targeting the discussion to the audience and adequately communicating the complexity of the model basis and outputs. Audiences for models may include scientists who are knowledgeable in modeling, scientists and other stakeholders who are not familiar with models, and decision makers. Similarly, models span a continuum of complexities from those that are so complex that the details can only be understood by other modelers, to those that are more accessible and understandable to decision makers, to those designed to be policy friendly. The policy-friendly models often have such user-friendly characteristics as (1) ease of changing inputs to reflect different management options or scenarios and (2) outputs that are visual and synthetic.

A critical facet of communicating models is to explain adequately the basis or overall construct of the model and its component elements. In addition, one needs to explain the sources of data, their limitations, the range of applicability, the important relationships built into the model, etc. The results or outputs of the models should be transparent. One technique is to use visualization tools to make output relationships clear. In general, the more attention placed on these communication issues, the more the model will be used, and the more confidence will be generated in its results.

Finally, terminology can be an important barrier to model communication. It is important that the terminology associated with the model is described in sufficient detail so that the user understands what is being said. A generic problem is that modeling terminology (and, for that matter, risk assessment terminology) includes many terms that have specific meaning in their respective contexts but that are also used by others to mean different or less explicit things. Unless these terms are made very clear, miscommunications and misunderstandings will inevitably ensue, clearly creating another barrier to the effective use of the models.

5.2.7 Uncertainty

What are the uncertainties, and how are they characterized and communicated to nonscientists? Scientists and especially modelers are used to dealing with uncertainties, but managers and the public are not. Uncertainties can arise from a host of sources, including inadequate understanding of the specific system or stress–response relationship, inadequate databases to parameterize the model, important relationships that are not included in the model or have lost their reliability through over aggregation, and natural variability in physical environmental conditions. Some uncertainties can be addressed through improved data collection or improved model development; other uncertainties cannot be reduced, such as variability in weather events. In any case, the modeler must characterize uncertainties in terms that are understandable to the various audiences and must provide an evaluation of the significance of the uncertainties to the decision to be made. For the ideal case, there may be many sources of uncertainty, but the model outputs are so rigorous that the uncertainties would not alter the conclusions. In other cases, the uncertainties are very significant and may result in an incorrect decision; this result is common and is a risk all decision makers face. Finally, how uncertainty is handled within the model is an issue. For example, will the model use a Bayesian statistical approach, use Monte Carlo simulations, or bound the range of potential parameter values? This topic is much-debated and one that deserves equal attention to how we explain the uncertainties. Therefore, the uncertainty in risk assessments needs to be made explicit to the decision maker, and models must have a truth-in-packaging aspect, in terms of both the uncertainties and the analytical approaches used to quantify them. If both of these elements are made explicit, then the decision makers can have far greater confidence in the results.

5.2.8 Data and Extrapolation

What are the sources, reliability, density over time and space, and applicability to the specific problem at hand of the data used in the model? A universal issue is the question of the appropriateness of the data used to develop, parameterize, calibrate, and validate the model. Models are simplifications based on sets of information, some of which are specific to the ecosystem, ecological component, or stressor at hand. Some data are derived from information on other systems, at other locations, or affected by other stressors. Thus, there is a continual issue of how appropriate the information used to develop the model is and how well it reflects the actual response characteristics of the ecosystem and stressor of concern. If the data sources and applicability are clear, documented, and relevant, then model confidence is greatly enhanced. Data are often not site-specific to the ecosystem or species of concern. For example, toxicological data on dose responses often are based on one or two species of fish that can be tested in the laboratory as a surrogate for toxicity to a fish species of concern in the ecosystem but that cannot be tested experimentally. In that situation, a case needs to be made on how well the tests can be expected to fit the species of concern, based on, for example, physiological, taxonomic, or ecological similarities. Likewise, data may be derived from another ecosystem, such as taken at one lake but applied to another lake. Moreover, many times data relate to one stressor, but another is being assessed, or there are multiple stressors involved. Again, the case has to be examined as to how reliably the extrapolation can be made (in the context of resulting uncertainties and the significance of those uncertainties). Confidence in results is built when the case can be made that the important relationships are broadly based to cover the specific assessment, such as through reliance on first principles or through demonstration in other similar cases where the information has been appropriate. A significant model barrier that continues to require considerable attention, but is beyond the scope of this paper, is that of cumulative effects from multiple stressors [see Gentile and Harwell (2001)].

5.2.9 Model Development

What are the model development costs in money and time; how long will model development take; when will a reliable model be sufficiently ready for decision support; and what is the value added by having the model? Even when it is clear that a model would be useful for a decision-making process, the question arises of costs and time delays in producing the model and, thus, the decision. Some decisions cannot be delayed until adequate model development occurs; in that case, other than relying on another already developed model, there is little to be done for the initial decision (although the case might be made to proceed with model development anyway in order to have the tool available for future decisions or to refine the initial decision.) In other cases, the utility of the model may be very high, in which case the decision maker has to weigh the pros and cons of delaying a decision. The value-added assessment basically relates to the judgment that the model will substantively increase the likelihood of making a better or more-defensible or lower-risk decision. In other words, the availability of the model, and any costs associated with delaying decisions, need to be weighed just as uncertainties are weighed.

5.2.10 Scenarios and Sensitivity Analyses

Do the models have the ability to assess the efficacy of specific management options? An important use of models is to assess the implications of alternate management options or other changes in the system of concern. Properly developed models can provide tremendous insights by being scenario friendly (i.e., able to be used in a straightforward manner to test different input or parameter conditions). For example, a model being used to assess the potential consequences of global change on a wetland ecosystem would be much more useful (and therefore more used) if it is easy to change the specific weather drivers such as inter- and intra-annual variability in precipitation, combinations of elevated temperatures and altered humidity, or potential evapotranspiration. Allowing pairwise comparison of model outputs of selected endpoints with scenarios that are identical except for one specific factor is a powerful tool for assessing alternatives and for assessing the importance of one variable over another. Sensitivity analyses, which examine the relative change in selected output(s) with change in one or more variables, can be enormously helpful in identifying important uncertainties or major research needs. Conversely, they can also be important for identifying those aspects that do not greatly influence the outcome. The more a model can be used for scenario and sensitivity analyses and the more that visualization techniques are incorporated into the model to illustrate the message of these analyses, the more useful the model will be in terms directly relevant to the decision process.

5.2.11 Absolute versus Relative Results

Can the questions being asked of the model be put into a comparative risk context? Generally it is much easier to be accurate in predicting a relative result than an absolute one. That is, many times a model is more reliable in comparing the relative risks between two options than it is in predicting the absolute outcome for either option. Thus, the demand placed on a model in a comparative risk assessment may be less, effectively reducing the importance of uncertainties in the model results. Another way to look at a comparative ecological risk assessment is as a special case of scenario analyses, except that each major option may itself be examined in the context of a suite of scenarios. For example, if two alternate fuels were being considered for a power plant on a bay and the ecological risks being assessed are associated with spills of the fuels in transportation to the power plant, then the risks of each fuel type can be assessed with a suite of scenarios of the specific conditions of the fuel spills (e.g., different weather or tide conditions). The comparative ecological risk assessment in this case may require quantitative predictions for each scenario, but with all other aspects being the same, the fuels can be directly compared, and management decisions can be informed about their comparative risks.

5.2.12 Competing Models

If more than one model is available, how can differences be resolved? It is difficult enough to build confidence in one model, but the presence of a second or third model can either increase or diminish the confidence levels. If models are independent but give similar results, confidence may be enhanced. But if the model results are diametrically opposed, then the burden becomes one of showing which (if either) model is reliable for the question at hand. For very complex situations, such as climate change or projected hurricane tracks simulated by general circulation or regional climate models, even the public has become used to differing results from the differing models. Sometimes it is clear which advice to follow, and other times it is not so clear at all (except after the hurricane hits). Such matters tend to be resolved through experience, determining under what conditions one model or the other is more reliable. But for something like global change, waiting to see how things actually occur can be costly. Then, the causes of model differences become very important, and research must be done to resolve those differences.

5.2.13 Model Errors and Incorrect Decisions

What happens when a model gives what later is found to be incorrect results and a incorrect decision is made? A serious concern for model usage by decision makers is when some model, maybe not even the one to be used for the present assessment, is found to have been poorly conceived and parameterized and incorrect decisions were made, resulting in adverse consequences. This situation diminishes confidence in all models. It is an inevitable consequence of living with decision making in the presence of uncertainty that decision makers have to accept the risk of being incorrect, and the model gets the blame. When scientists and decision makers use models to give answers even when insufficient information and understanding exist, as often they must, an incorrect decision will sometimes happen. The issue of transparency is very important here and can be handled in a couple of ways. The first is to show explicitly how the other model is constructed conceptually and then to clearly demonstrate the assumptions and limitations of the model, including the major sources of uncertainty. The second and more useful approach is to recognize that a range of potential outcomes is possible and to provide an estimate of their likelihoods as well as an estimate of what is the most probable outcome. It is also important to remind decision makers that models are simply a construct of reality and, as such, are not absolute; thus, presenting a range of plausible outcomes is not only desirable but justified. Nevertheless, there is a greater burden on the scientist to build a better model, to increase confidence in the model, and to communicate the applicability and limitations of the model in a more transparent manner.

5.2.14 Decision Context

What to do when being sued? The discussions of uncertainty, use of scenario and sensitivity analyses, extrapolation, and other issues discussed above are all affected by the nature of the decision process. One obvious case is where the model is to be used to produce predictions for an adversarial or litigation process as opposed to being used by a decision maker to choose among alternative options. Sometimes, the confidence burden is much higher because an adversary can attempt to challenge the veracity of the model. And models are ripe for attack by the very nature of the uncertainties, extrapolation issues, complexity, and use for predicting results outside the range of the experimental evidence. For example, it would be easy to argue that data based on one species may be wrong when applied to another, even taxonomically similar, species for the simple reason that cases can be found where that extrapolation gives wrong results. On the other hand, in many cases, a particular model is widely used in litigation, even when it can be demonstrated to be misleading or inappropriate, because of the precedent of using that model.

5.2.15 Library of Case Studies

How to build on other experiences? One important mechanism to counteract some of the issues related to extrapolation, model inconsistencies, or living with uncertainties is the development of a library, or at least a bookshelf, that documents the use of complex models in complex environmental decision-making situations. Ideally, when a sufficient number of such case examples are documented, a decision maker will have clear guidance on the issue at hand and on the utility of models to address that issue. For example, a wide range of models and their results (e.g., hydrodynamic, stream flow, soil erosion, ecotoxicology, and ecosystem) have been incorporated into regulatory policy during the past three decades. The library should include not just these successes but also failures, where wrong decisions were made or where models were found to be incorrect in their predictions. Modelers tend not to publish failures, and, for that matter, decision makers do not often publicize mistakes. Yet these outcomes are often opportunities to reexamine critically the model construct and assumptions, resulting in a much improvement. The ultimate confidence in models used in the decision processes will ensue when there is a sufficient record of successes and clear guidance on what not to do.

5.3 Summary

Several key criteria can be proposed for successfully using models in environmental decision making (Figure 5.4). We have found that the development of a comprehensive ecological conceptual model in the problem formulation stage of the risk assessment process is essential, especially for complex environmental problems, such as

- Assessing how to remediate extensive contamination and ecotoxicity of heavy metals in the Coeur d'Alene watershed resulting from more than a century of silver mining operations (CH2M Hill and URS Corp. 2001)
- Evaluating the risks of alternate management options for the Fire Island barrier-beach ecosystem (U.S. Army ERDC and HGA 2000)
- Assessing the implications of the South Florida ecosystem restoration on a broad diversity of ecosystem types (Harwell et al. 1996, 1999*c*; Harwell and Gentile 2000)
- Exploring the security implications of environmental problems in the Caribbean (Stark et al. 1999).

In each of these case studies, the criteria illustrated in Figure 5.4 were applied successfully.

For predictive or more-quantitative models, particularly those applicable for the risk analysis and risk characterization/integration stages, the first

Ecological Conceptual Models — How well do they
- Capture the scientific understanding?
- Identify the ecological systems and attributes at risk?
- Define the ecologically and societally relevant endpoints?
- Illustrate important stress-effect pathways?
- Capture the complexity of the problem with an appropriate degree of aggregation and disaggregation?
- Communicate to the three audiences and achieve buy-in?

Doing the conceptual model correctly is a key issue with respect to barriers to use in decision making.

Ecological Analytical/Simulation Models — How well do they
- Provide confidence in results?

FIGURE 5.4. Success criteria for conceptual and predictive models.

barrier to using models relates to relevancy issues, which are resolved when the conceptual models are adequately developed. The second barrier to model usage is confidence that the model will provide reliable results that are sufficient for decision making; this criterion relates to a host of specific details in model development, validation, and application. Each of these details has to be addressed satisfactorily in order to overcome those barriers. But that in itself is inadequate, because experiences by decision makers, nonmodelers, and stakeholders involving the use of other models for other environmental assessments or resource management decisions may greatly influence and bias their perspective of the barriers for the assessment at hand. Barriers are diminished the more that models are successfully used and are perceived as having significantly improved the decision-making process by making more correct, timely, cost-effective, or defensible decisions. Conversely, the more models are used unsuccessfully, or at least perceived as so used, the more barriers are raised for future model use. For example, models that lead to the wrong decision, to a decision that does not hold up to adversarial scrutiny, to a decision that is too costly, or to a decision that addresses the wrong problem decrease confidence in the use of models in general. This vulnerability is not limited to models; the same result occurs for other technological or scientific bases for uncertain or bad decisions, ranging from decisions about the swine flu to decisions about having pure oxygen atmospheres for Apollo capsules. But models are especially at risk. By definition, they are approximations of reality and, therefore, have inherent uncertainty, which in some circumstances can be substantial. Also, models are often presented as magical tools yet are too obscure for the decision maker to understand, thus requiring almost blind faith in their usage.

We are at a critical juncture in the use of models to solve environmental problems. Unlike the historic regulatory issues of the 1970s and 1980s that focused on local scales and point-source controls, environmental managers and decision makers must be prepared to make decisions at the watershed and regional scales and for periods that encompass multigenerational time scales. The economic and societal consequences of decisions at these scales are tremendous. To address this emerging class of environmental problems effectively, scientists and decision makers must now begin to rely on not a single model but a suite of models (e.g., climate, hydrologic, hydrodynamic, ecotoxicological, population, community, and ecosystem) to provide the necessary complexity to evaluate management options at these scales. By directing careful attention to the issues discussed above, especially the issues relating to confidence-building and to the communication of models, and taking particular care to select the most appropriate and defensible models in the first place, modelers and scientists can make great strides in overcoming the barriers to understanding and using models in environmental decision making.

References

Barnthouse, L.W. and J. Brown. 1994. Conceptual model development. Chapter 3 *in* Ecological Risk Assessment Issue Papers. EPA/630/R-94/009. U.S. Environmental Protection Agency Risk Assessment Forum, Washington, District of Columbia, USA.

CH2M Hill and URS Corp. 2001. Final Ecological Risk Assessment, Coeur d'Alene Basin Remedial Investigation/Feasibility Study. U.S. Environmental Protection Agency, Seattle, Washington, USA.

Fava, J., L. Barnthouse, J. Falco, M. Harwell, and K. Reckhow. 1992. Peer Review Workshop Report on a Framework for Ecological Risk Assessment. U.S. Environmental Protection Agency Risk Assessment Forum, Washington, District of Columbia, USA.

Foran, J.A. and S.A. Ferenc. 1999. Multiple Stressors in Ecological Risk and Impact Assessment. Special Publication Series. Society of Environmental Toxicology and Chemistry, Pensacola, Florida, USA.

Gentile, J.H. and M.A. Harwell. 1998. The issue of significance in ecological risk assessments. Human and Ecological Risk Assessment **4**:815–828.

Gentile, J.H. and M.A. Harwell. 2001. Strategies for assessing cumulative ecological risks. Human and Ecological Risk Assessment **7**:239–246.

Gentile, J.H., M.A. Harwell, W. van der Schalie, S. Norton, and D. Rodier. 1993. Ecological risk assessment: A scientific perspective. Journal of Hazardous Materials **35**:241–253.

Gentile, J.H., M.A. Harwell, W.P. Cropper, Jr., C.C. Harwell, D. DeAngelis, S. Davis, J.C. Ogden, and D. Lirman. 2001. Ecological conceptual models: A framework and case study on ecosystem management for South Florida. Journal of Science and the Total Environment **274**:231–253.

Harwell, C.C., C.W. Deren, G.H. Snyder, W.D. Solecki, J. Wilson, and M.A. Harwell. 1999*a*. Use of a conceptual model of societal drivers of ecological change in South Florida: Implications of an ecosystem management scenario. Urban Ecosystems **3**:345–368.

Harwell, M.A. and J.R. Kelly. 1987. Page 127 *in* Unfinished Business: A Comparative Assessment of Environmental Problems. Appendix III. Ecological risk work group. EPA Office of Policy, Planning, and Evaluation. U.S. Environmental Protection Agency, Washington, District of Columbia, USA.

Harwell, M.A., C.C. Harwell, D.A. Weinstein, and J.R. Kelly. 1990. Characterizing ecosystem responses to stress. Pages 91–115 *in* W. Grodzinski, E.B. Cowling, A.I. Breymeyer, A.S. Phillips, S.I. Auerbach, A.M. Bartuska, and M.A. Harwell, editors. 1990. Ecological Risks: Perspectives from Poland and the United States. National Academy Press, Washington, District of Columbia, USA.

Harwell, M.A., W. Cooper, and R. Flaak. 1992. Prioritizing ecological and human welfare risks from environmental stresses. Environmental Management **16**:451–464.

Harwell, M.A. and J. Gentile. 1992. Report of the EPA ecological risk assessment guidelines strategic planning workshop (Miami, Florida, May 1991). U.S. Environmental Protection Agency Risk Assessment Forum, Washington, District of Columbia, USA.

Harwell, M.A. and J.F. Long. 1992. US MAB Human-Dominated Systems Directorate Workshop on Ecological Endpoints and Sustainability Goals. University of Miami, Center for Marine and Environmental Analyses, Miami, Florida, USA.

Harwell, M.A., J.F. Long, A.M. Bartuska, J.H. Gentile, C.C. Harwell, V. Myers, and J.C. Ogden. 1996. Ecosystem management to achieve ecological sustainability: The case of South Florida. Environmental Management **20**:497–521.

Harwell, M.A., V. Myers, T. Young, A. Bartuska, N. Gassman, J.H. Gentile, C.C. Harwell, S. Appelbaum, J. Barko, B. Causey, C. Johnson, A. McLean, R. Smola, P. Templet, and S. Tosini 1999*b*. A framework for an ecosystem integrity report card. BioScience **49**:543–556.

Harwell, M.A., J.H. Gentile, A. Bartuska, C.C. Harwell, V. Myers, J. Obeysekera, J. Ogden, and S. Tosini. 1999*c*. A science-based strategy for ecological restoration in South Florida. Urban Ecosystems **3**:201–222.

Harwell, M.A. and J.H. Gentile. 2000. Environmental decision-making for multiple stressors: Framework, tools, case studies, and prospects. Pages 169–235 *in* S.A. Ferenc and J.A. Foran, editors. Multiple Stressors in Ecological Risk and Impact Assessment: Approaches to Risk Estimation. Society of Environmental Toxicology and Chemistry, Pensacola, Florida. USA.

Kelly, J.R. and M.A. Harwell. 1990. Indicators of ecosystem recovery. Environmental Management **15**:527–545.

National Research Council (NRC). 1983. Risk Assessment in the Federal Government. National Academy Press, Washington, District of Columbia, USA.

National Research Council (NRC). 1996. Paul Stern and Harvey Feinberg, editors. Understanding Risk: Informing Decisions in a Democratic Society. National Academy of Sciences panel on risk characterization. National Academy Press, Washington, District of Columbia, USA.

Stark, J., F. McNeil, A.T. Bryan, M.A. Harwell, J.H. Gentile, W.P. Cropper, Jr., D. Lirman, and J.S. Ault. 1999. Environmental Stresses and Regional Security in Latin America and the Caribbean: The Cases of the Upper Paraguay River/Pantanal and the Wider Caribbean. A report by the Dante B. Fascell North-South Center and the Center for Marine and Environmental Analyses, University of Miami, Florida, USA.

Suter, G.W. 1999*a*. Developing conceptual models for complex ecological risk assessments. Human and Ecological Risk Assessment **5**:375–396.

Suter, G.W. 1999*b*. A framework for the assessment of ecological risks from multiple activities. Human and Ecological Risk Assessment **5**:397–414.

U.S. Army Engineer Research and Development Center and Harwell Gentile & Associates, LC (U.S. Army ERDC and HGA). 2000. Conceptual Models for Coastal Long Island Ecosystems: Fire Island to Montauk Point Reformulation Study. Draft Report ERDC/EL SR. U.S. Army Engineer Research and Development Center, Vicksburg, Mississippi, USA.

U.S. Environmental Protection Agency (USEPA). 1992. Framework for Ecological Risk Assessment. EPA/630/R-92/001. USEPA, Washington, District of Columbia, USA.

U.S. Environmental Protection Agency (USEPA). 1996. Watershed Risk Assessments: Ecological Risk Assessment Planning and Problem Formulation. EPA 630/R-96/004. Risk Assessment Forum. USEPA, Washington, District of Columbia, USA.

U.S. Environmental Protection Agency (USEPA). 1998. Guidelines for Ecological Risk Assessment. EPA/630/R-95/002F. USEPA, Washington, District of Columbia, USA.

U.S. Environmental Protection Agency Science Advisory Board (USEPA SAB). 1990*a*. Reducing Risk: Setting Priorities and Strategies for Environmental Protection. SAB-EC-90-021. USEPA SAB, Washington, District of Columbia, USA.

U.S. Environmental Protection Agency Science Advisory Board (USEPA SAB). 1990*b*. The Report of the Ecology and Welfare Subcommittee, Relative Risk Reduction Project. Reducing Risk, Appendix A. SAB-EC-90-021A. USEPA SAB, Washington, District of Columbia, USA.

6
Barriers to the Use of Ecological Models in Decision Making

Virginia H. Dale, Chris Rewerts, Webb Van Winkle,
Mark A. Harwell, Mike Vasievich, and Steve Hodapp

6.1 Introduction

Situations where the use of ecological models would be appropriate include the implementation of regulations and plans, formation of regulatory policies and laws, resource management planning, purchase of land and other private investment decisions, trade policy, environmental security issues, the NEPA (National Environmental Protection Act) process, litigation, land-use planning, education, and research. In any circumstance where the issues are complex, influences and flows are unclear, feedbacks occur, or outcomes are determined by multiple factors, models can be used to provide clarity and help to discern the role of potential influences.

Although ecological models might be used in many situations to facilitate decisions being made about resource use, often models are not used or are used ineffectively. Several barriers exist to the successful adoption and deployment of ecological models for decision making. These obstacles can be organized into five generalized categories: communication, organizational issues, risk aversion, logistical concerns, and the capability of models themselves. This chapter discusses these types of barriers and presents conditions under which they might be expected to operate. Primary questions to resolve in considering impediments to implementation of ecological models are, "Who are the participants?" and "What are the circumstances in which models are used?" That is, who are the model developers, who applies the model, and who are the decision makers? What are the attributes of the problems? At what stages will the model be used? Who will interpret the model results? Only by knowing the participants in the model formulation and in the decision-making process and the dimensions of the problems can one determine the extent to which the concerns addressed below are actual barriers to the use of models. Therefore, the roles of the players in the decision-making process as promoters or impediments to the use of models is discussed. Several solutions to the obstacles are presented in the following chapters that deal with the following concerns:

- Evolving approaches and technologies that will enhance the role of ecological modeling in decision making
- Data issues
- The toolkit concept
- Science and management investments needed to enhance the use of ecological modeling and decision making

Together, these chapters present the current status of the use of ecological models for resource management and suggest ways to enhance their roles.

6.2 Types of Barriers

6.2.1 Communication Barriers

The first and probably most discussed hindrance to the use of models in environmental decision making is that of communication (Figure 6.1). Unquestionably, language barriers exist, because the terms that modelers use are not all common to everyday language and sometimes are even used in very different ways than lay language. For example, ecologists consider *disturbance* to be part of the natural order of an ecological system; whereas

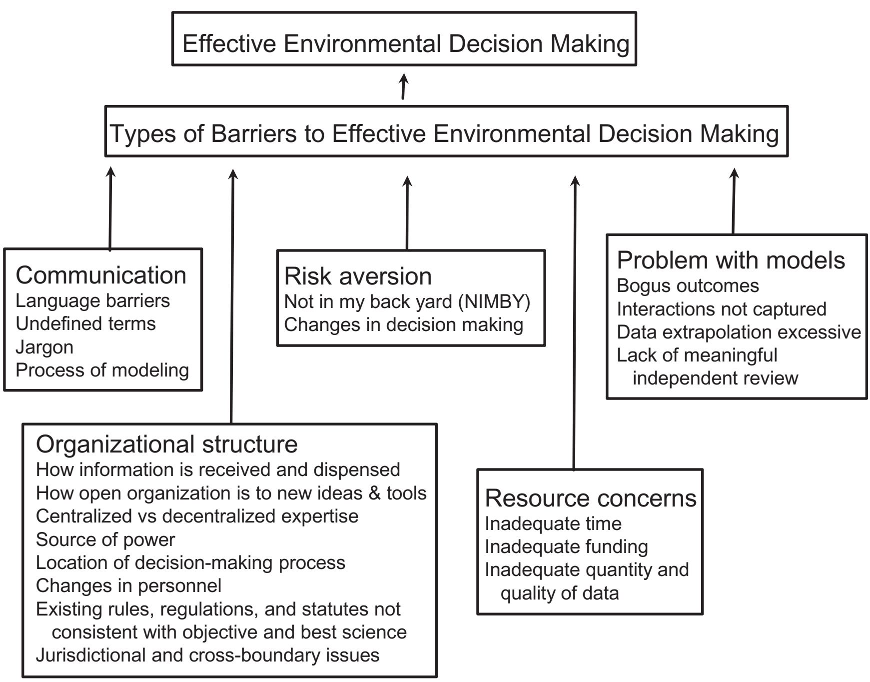

FIGURE 6.1. Types of barriers to effective environmental decision making.

in general terminology, a *disturbance* is an unnatural and disruptive event. Similarly, modelers use *uncertainty analysis* to determine the influence on model output of a parameter, given the actual variation it represents, but the lay definition for *uncertainty* is merely the unknowns. Some terms, such as *validation* and *verification*, have become so confused in the modeling literature that there are calls to abandon them altogether (Mitro 2001). Other terms have unique meanings depending on the application (e.g., to a mathematician a *vector* is a quantity specified by its magnitude and direction; to a disease specialist it is a transport agent). Furthermore, the general public sometimes adopts scientific terms but may use them inappropriately.

The call for improved communication skills among biologists (Cannon et al. 1996) should be particularly heeded by mathematical ecologists and others who bridge between models and decision making. Attending to the need to define terms and avoid jargon is part of the communication process, and educating others about the process of modeling is also important. The specialized words used by modelers not only add to confusion in communication, but they can also make it seem as if modelers form an exclusive clique. The specificity of language used by scientists contributes to the belief that models constitute a special way of communicating and thus provide value in their own right.

6.2.2 Institutional Barriers

How an institution is organized (or is perceived to be organized) influences how information is received and dispensed and how open the organization is to the use of new ideas or tools, such as models. For instance, in-house expertise may be considered more valuable than out-of-house expertise for a particular company, agency, or group. Such groups are not amenable to the adoption of models that were developed elsewhere. The validity of the high regard for in-house expertise is not always strong (or even tested), but the outcome is that the best expertise may not be used or collaborative enterprises are not pursued. This loss of opportunity is a barrier to the implementation of particular perspectives and tools, including models. Communication barriers largely involve language, but also depend on organizational structure.

The tension between centralized and decentralized expertise can also become an obstacle in the implementation of models. For instance, some Latin American countries have a strongly centralized government, but decisions about resource use are often made in a decentralized manner. The monetary and political resources lie with the centralized government, but tools, such as modeling, are not always deployed in such a way as to recognize the role of local decisions. Thus, the source of power and also the location of the decision-making process should both be a part of model design (especially inputs and outputs). Similarly, as alternative methods for urban stormwater management are proposed in Germany (Mehler and

Ostrowski 1999) and elsewhere, it is clear that economically and ecologically sound combinations of central and decentral measures will be a part of future designs. Yet, present approaches, other than traditional combined sewer systems, are limited because of use of existing planning tools, technologies, and stormwater-balance and pollution-load models.

Finally, changes in personnel are quite frustrating to the implementation of models in a decision-making process. Often, it seems that just as one supervisor, sponsor, or client becomes knowledgeable about a modeling process and is comfortable with adapting it to particular issues, a new person or organizational structure is put in place, and the learning process must begin all over again or, even worse, is curtailed together. For example, in the 1980s the U.S. Environmental Protection Agency (USEPA) stopped work on modeling of integrated assessment as part of the investigation into acidic deposition because a change in leadership caused the elimination of several programs, including the one that supported this type of modeling. But retrospective analysis of the National Acidic Precipitation Analysis Program (NAPAP) targeted the lack of integrated assessment as one of its key flaws (Russell 1992). The ongoing need to reiterate the value of models is necessary within an organization, especially when changes in personnel or structure occur.

Existing rules, regulations, and statutes of institutions often focus environmental decision making on concerns that may differ from the ones a model would examine. The concept that a model provides clarity in addressing ecological issues may be contrary to the philosophy that existing rules, regulations, and statutes provide the best means for an institution to deal with its resource management concerns. Thus, current procedures are sometimes a barrier to the use of models in brainstorming. Finally, there are often jurisdictional and cross-boundary issues that impede the use of models. For example, a model developed by one agency may not be adopted by another agency, not because it is a poor or inappropriate model, but just because it was not homegrown. Such jurisdictional boundaries often mean that the best modeling tools are not widely adopted.

6.2.3 Risk Aversion

Whether an institution or individuals who are leaders in the institution are likely to use models partially depends on how adverse they are to risk. The natural aversion of humans to risk is a barrier to the use of models in decision making. This avoidance is particularly strong when the risk seems to be near at hand in space or time. The not in my back yard (NIMBY) attitude is so pervasive that it is now part of the lingo of siting of waste (Rabe 1994). It is a part of human nature that people want to reduce or avoid risky situations. On the surface, the use of models seems to imply taking a risk for those who are unfamiliar with the tools. However, just the opposite is typically the case. Models allow explicit quantification of risks and require that the relationships between component parts be set forth. Making clear such values and relations means that the ramifications of decisions are more fully specified. Thus, risks are reduced.

Any part of the decision-making process that may be changed also causes a series of risks. Modelers themselves are uncomfortable with errors inherent in their inputs and outputs and spend much effort checking the data that is part of the model or validating the model (e.g., by backcasting to see if historical events can be modeled and investigating any discrepancies). Another concern is that managers typically do not want to be in situations where their power or influence can be undermined by a change in understanding. The use of models allows risks to be quantified and represented in spatial and temporal dimensions that are meaningful to individuals. Often, models allow the playing out of various alternatives, including those that prove undesirable. For instance, one may project the use of resources 20 years into the future, even if an organization may not wish to go through the steps of implementing how current policy would play out to that 20-year vision. Models allow simulated resource use and management to occur according to scenarios that might not be acceptable to management or public concerns.

6.2.4 Resource Concerns

Resource concerns constitute a fourth generalized barrier to the use of ecological models and can often be traced to inadequate time and funding. Both risk issues and resource hindrances in the use of ecological models in decision making often arise from within institutions. Organizations may not have the appropriate resources, in terms of people, facilities, or structures that support the use of ecological models. For instance, qualified personnel who understand the use of models, are familiar with the language of models, or are able to envision the applicability of modeling results are frequently lacking. Not everyone may have access to a computer or other equipment required to run a model. They may not have been trained in the software being used, or the user interface may be inadequate or downright user surly. The time required for model development is often on the scale of years and may be out of sync with the interval for which the tool is needed to make decisions. Thus, sometimes models are used only if they can be adopted from other situations (and therefore may not be appropriate for the given application).

More often, a model is not used because of time constraints. A way around this barrier is greater forethought by those who fund the development of models for environmental decision making so that the suite of models appropriate for the majority of decisions would be developed beforehand and made available to both the scientific and the decision-maker audience when they need it. The funding required for model development is often a barrier because the need for data accumulation, conceptualization, and development of a model is often not given enough value.

One metric of the low value given to conceptual models is how rarely conceptual models by themselves are published in the scientific literature. Typically, it is the *application* of conceptual models that is published. But in actuality, the development of the conceptual model is often the more useful task, and the applicability of the conceptual model to a variety of situations needs to be further explored. Data availability can also be a logistical barrier to the use of models for resource management. Without the requisite baseline data at the appropriate temporal and spatial scales, it is not useful to develop or use a model.

6.2.5 Problems with Models

The last generalized barrier is the capability of the models themselves. Often, the data are not available or are insufficient, the key processes are not well understood, or the tools needed to develop a model quickly and apply it to the situation are lacking so that the model is not developed and/or adopted to the particular situation at hand. There is great hope, however, that with expanding capabilities in technology, in the Internet, and in databases and tools for model development this barrier will be overcome quickly. Models may not be available that address the primary concerns of resource managers. However, as more managers get involved in partnerships with those who develop models, pertinent questions are more often considered, and models are specialized to address specific needs.

Another type of barrier to models is the potential for the abuse of models, thus making it harder for legitimate models to be accepted. One possible abuse of models is that they can show outcomes with convincing realism (aka glitz) but can be totally bogus. An additional potential abuse is concern about interactions that are not captured by a model. The holistic perspective of many models provides opportunities for the arguments about factors not included in the analysis to spin off into infinite hyperbole. For example, insights gleaned from models of global environmental values could easily be sidetracked by discussions about concerns in the inadequacy of such models (Costanza et al. 1997). A third type of model abuse occurs when data are extrapolated beyond the range of reasonable use. Data are often so sparse that relationships are not plausible or knowable. Such extrapolation mistakes can be accidental or on purpose. The effect on the model projection is the same. This potential barrier to the use of models can best be reduced if the assumptions and sources of information for a model are clearly specified.

The lack of independent review of models also constrains their effective use. However, applying the peer review process to models is typically not possible because the reviewer does not have access to the model. Instead, running models in a common environment may be the most effective way to elucidate their behavior (e.g., Dale and Swartzman 1984; Rose et al. 1991). Of course, obtaining such a serious and credible review can be quite time consuming and expensive. A related issue is the absence of any formalized way to peer review models and of standardized ways to report models, how they were built, the assumptions made, etc. (Aber 1997). Finally, the awe with which some model results are accepted is inappropriate. All models should be carefully evaluated and their assumptions, uncertainties, and sensitivities fully explained in the context of the application.

6.3 Barriers to Specific Players in the Decision-Making Process

There are barriers to the use of ecological models that are specific to the players that are a part of decision making. As mentioned earlier, one of the key questions involved in developing a model is deciding who the participants are. In many situations, the key participants are modelers who typically have a science background; managers who have a science, engineering, or a policy background; and stakeholders who have a diversity of backgrounds but who almost always have a passion for the situation (Figure 6.2). The experience of modelers has two implications. First, the science culture exerts great pressure to publish new findings. This expectation may produce a desire to develop a new model or to use a model in a new way so that the results are worthy of publication. However, often it is the adoption of an existing model with or without minor modifications that is most useful for the situation. Second, science often focuses within a discipline rather than being cross-disciplinary. This narrow focus becomes an issue in developing models for managing environmental resources because, often, much can be learned from crossing disciplines. For example, McMahon et al. (2001) report on developments in network analysis that have built upon interdisciplinary approaches. They find that social network analysis is similar to the analysis of trophic structure in ecological communities and of energy flow and nutrient transfer because both deal with the problem of how to conceptualize and test interactions within complex systems. Also, it may be that the ecological applications can benefit from the social-network-analysis applications.

The barriers for managers largely relate to the background of that particular manager and the fact that decisions need to be made in a timely manner. Managers typically are not familiar with the terminology and approach adopted by modelers. This lack of background applies to the particular situation as well as to modeling language, such as uncertainty, validation, scenario analysis, etc. Most models do not produce a single answer, yet this is exactly what the resource manager is seeking. Thus,

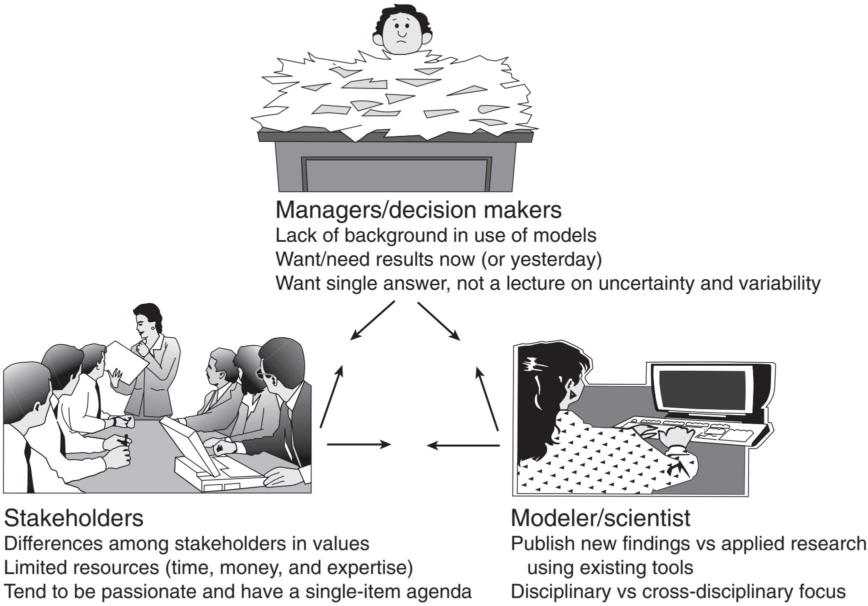

FIGURE 6.2. The key participants in environmental decision making and their experience relative to the use of models.

having modelers explain the value of depicting a range of variation around mean tendencies is important to the broad adoption of models.

The barriers attributed to stakeholders largely come from this group being so diverse. Conflicts in values and differences in background and understanding often occur within this group. Furthermore, the group typically has extremely limited resources of time and expertise, restricting its ability to spend the time necessary to learn about model application and versatility. But sometimes stakeholder groups include experts who have the knowledge and background to make a contribution to the use of models and decision making. Other times, models are developed that facilitate stakeholder interactions. For example, stakeholder opinions are an explicit part of a cropping model for a Tasmanian agricultural catchment (Walker et al. 2001). A model has even been used to demonstrate how stakeholder contributions can be effectively integrated into the decision-making process by building upon the capacity of grassroots conservation organizations, such as local wildlife clubs in Kenya (McDuff 2001). Software is beginning to be developed that provides stakeholders ways to use resources on the World Wide Web for multicriteria analysis and decision making, critical examination of the underlying assumptions, and thus incorporating qualitative and subjective considerations into quantitative factors for decision making [e.g., Zhu and Dale (2001)].

6.4 Solutions

Various solutions exist to overcome the barriers presented above. The first is collaborative decision making, which is an iterative process that involves all the participants in a decision. Wondolleck and Yaffee (2000) discuss the barriers to the effective collaborative processes, several of which are similar to the obstacles to effective use of models for resource management. Successful engagement by stakeholders must involve the capability, trust, collaborative relationships, understanding, joint fact finding, dealing with conflict, will, and a learning organization (Wondolleck and Yaffee 2000). The use of models in such collaborative decision-making processes typically enhances the brainstorming ability of the interaction (e.g., Karacapilidis and Papadias 2001). Furthermore, web-based models and toolkits [discussed by Bartell (Chapter 11, this volume) and Holland et al. (Chapter 12, this volume)] should allow users to retrieve data stored in remote databases to further document their arguments and to stimulate exploration for which decisions best reflect their interests and intentions. Models permit various scenarios to be examined and role playing, which allows alleviation of potential problems in conflicting goals among the group. However, since some groups may have incentives not to reach closure, they may be adverse to the acceptance of model results, which can lead to a hesitancy to use models at all.

A second major solution to these barriers is improved technology transfer and greater communication. As the use of computers spreads, more people become familiar with the language involved in model development and use and with the conceptual background of models. Also, there is greater familiarity with the techniques of model development and the data available for models. It will be interesting to see if the next generation that has grown up with the use of computer games will be more accepting of a gaming approach to scenario exploration and simulation, which is basically a model. The types of developments discussed in this volume (e.g., toolkits of models) should enhance the use of models in resource management.

Interestingly, the wide adoption by the general public of weather-model projections, which are a part of every weather report heard on radio or television, was based upon initial efforts by small groups and individuals to commercialize the use of weather models. The development and use of weather models went hand-in-hand with the acquisition of data for those models. The mission of the National Weather Service is the same as it was when first established under the U.S. Army in 1870: "to provide for taking meteorological observations . . . and for giving notice . . . of the approach and force of storms." But its mission has been made much easier by the advent of forecasting models, satellite data on clouds, and radar data on precipitation. In early years, the meteorological reports were taken by observer-sergeants at 24 stations and transmitted by telegraph to the central office. Flags were used to display the forecast. In 1948, the first primitive computer numerical forecasts were made on the Electronic Numerical Integrator and Computer (ENIAC). In 1955 the Weather Bureau began development of the Barotropic model, which became the first operational, numerical, weather prediction tool. All weather forecasts begin with observations of weather conditions all over the world, and these observations are now entered into supercomputers that use mathematical models of the atmosphere to make predictions. Today the pollen count, air quality, ultraviolet index, and water temperature are often a part of the weather report. Thus, weather projections are based on a complex set of environmental measures of the atmosphere, oceans, and land.

The weather-model example shows that it is useful to have research focused on case studies of environmental decision making showing both success stories and failures of how a given problem was addressed and resolved. Such case studies show the delineation of issues of the scientists, stakeholders, and decision makers and how models can be used.

A set of particular techniques can help deal with the barriers associated with risk:

- Present variable results in an understandable manner.
- Design the model or tools in terms of the management decisions and concerns. That is, characterize the risk in terms that can be applied to the particular decision.
- Deal directly with risk. Although aversion to risk and decision making in a risky environment are barriers that need to be surmounted, there are often external forces that compel managers to act and thus address risks. Thus, the USEPA has adopted a risk-based approach to environmental problems that requires placing issues within a risk framework (USEPA 1992). [This approach is discussed by Van Winkle and Kadvany (Chapter 3, this volume) and Harwell and Gentile (Chapter 5, this volume).]

The consensus-building approach of designing a way to deal with resource management problems shares the risk between potential adversaries. This consensus-building process is quite fragile yet doable as is illustrated by the long-term interactions of the Applegate Partnership in the Pacific Northwest. That community-based group is made up of representatives from industry, conservation groups, governmental agencies, research scientists, and residents who cooperate to protect and restore the health of the 500,000-acre Oregon watershed and to provide economic and community health (Shipley 1995). The Partnership strives to provide leadership in facilitating the use of natural resource principles that promote ecosystem health and natural diversity; to work with public land managers, private landowners, and community members to promote projects that demonstrate ecologically sound management practices; and to seek support for these projects through community involvement within the watershed. The Applegate Partnership successfully moved people from a point of gridlock to a common vision (Shipley 1995). Models are tools designed to increase the speed and clarity of such interactions.

6.5 Remaining Concerns

The above discussion raises several concerns. One is the value of modeling to decision making. Modeling and decision making are not parallel parts of resource management. Rather, modeling is a tool that can be used in various stages of management that informs a decision (Figure 6.3). Science is a part of the process when scientific information is used, patterns of unknowns are hypothesized, or the scientific method is adopted.

A second concern is the role of modeling at different stages of decision making. The type of models adopted varies for different stages, and the lessons that can be learned from such models are also different. In Figure 6.3, the ovals indicate where actions are required by the decision maker,

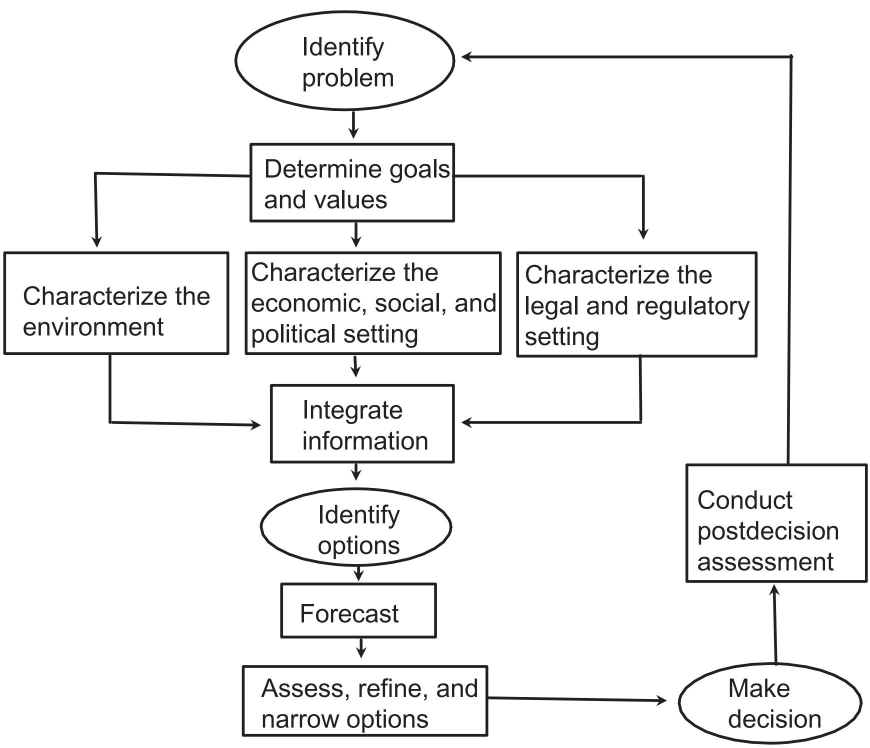

Figure 6.3. The environmental-decision-making process [from English et al. (1999)]. The ovals indicate where actions are required by the decision maker, and the rectangles suggest where models can be used.

and the rectangles suggest where models can be used. Thus, models can contribute to determining goals and values, characterizing conditions, integrating information, forecasting, assessing and narrowing options, and conducting postdecision analysis.

Another concern is who should be doing the modeling. Should only the modelers be using them, or should the modeler's goal be technical transfer of the model to the decision makers and their staff? This conundrum can be broken down along a continuum of scenarios:

- Modeling should be done entirely by the modelers.
- Modeling should be done by technical staff if the model is properly set up, the staff has been trained, and there is a clear understanding of how to use it and for what purpose (including presenting and interpreting results).
- The model should be made a part of the decision maker's routine operation.

There are situations for which each scenario applies. The ideal use of the model should be that which is most effective for the management issue and the state of the knowledge.

The final question is, How to establish a climate so that models are more frequently and effectively used? One answer to this question is to establish modeling capabilities and infrastructure within resource management organizations so that, when the need for models arises, people are ready to accept and implement the modeling approach. This infrastructure involves hardware and software that provide the capability to resource managers and even to stakeholders to run the models in the same way that the developers of these tools are able to do. It also involves education about the technology and language so that resource managers can read and understand the analysis. Often, modeling assistance comes from outside groups. A perspective open to the modeling process and results means that model projections are more likely to be accepted.

6.6 Conclusions

In this chapter, the discussion focused on situations in which models can, should, or have been used as well as on how models helped or could have helped the decisions. Our perspective is that models and sound science should be used because they can improve the decision process or the likelihood of making the best decision with the available data and the understanding of the processes involved. Such an adoption of models will cost more, take more time, and be potentially more complex, but it will improve the management of natural resources and will save money and other resources in the long term.

Acknowledgments. Reviews of an earlier draft of the paper by Robert Holst were quite helpful. Development of the chapter was funded by contracts to Oak Ridge National Laboratory (ORNL) from the Strategic Environmental Research and Development Program (SERDP), Army Research Office, and Engineering Research and Development Center of the Corps of Engineers as well as by the USDA Forest Service. Oak Ridge National Laboratory is managed by UT-Battelle, LLC. for the U.S. Department of Energy under contract DE-AC05-00OR22725.

References

Aber, J.D. 1997. Why don't we believe the models? Bulletin of the Ecological Society of America **78**:232–233.

Cannon, J.R., J.M. Dietz, and L.A. Dietz. 1996. Training conservation biologists in human interaction skills. Conservation Biology **10**:1277–1282.

Costanza, R., R. d'Arge, R. de Groot, S. Farber, M. Grasso, B. Hannon, K. Limburg, S. Naeem, R.V. O'Neill, J. Paruelo, R.G. Raskin, P. Sutton, and M. van den Belt. 1997. The value of the world's ecosystem services and natural capital. Nature **387**:253–260.

Dale, V.H. and G.L. Swartzman. 1984. Simulating the effects of increased temperature in a plankton ecosystem: A case study. Pages 395–428 *in* E. Shubert, editor. Algae as Ecological Indicators. Academic Press, London, UK.

English, M.R., V.H. Dale, C. Van Riper-Geibig, and W.H. Ramsey. 1999. Overview. Pages 1–31 *in* V.H. Dale and M.R. English, editors. Tools to Aid Environmental Decision Making. New York, Springer-Verlag.

Karacapilidis, N. and D. Papadias. 2001. Computer supported argumentation and collaborative decision making: the HERMES system. Information Systems **26**: 259–277.

McDuff, M.D. 2001. Building the capacity of grassroots conservation organizations to conduct participatory evaluation. Environmental Management **27**:715–727.

McMahon, S.M., K.H. Miller, and J. Drake. 2001. Social science and ecology—Networking tips for social scientists and ecologists. Science **293**:1604–1605.

Mehler, R. and M.W. Ostrowski. 1999. Comparison of the efficiency of best stormwater management practices in urban drainage systems. Water Science and Technology **39**:269–276.

Mitro, M.G. 2001. Ecological model testing: verification, validation, or neither? Bulletin of the Ecological Society of America **82**:235–237.

Rabe, B.G. 1994. Beyond NIMBY: Hazardous Waste Siting in Canada and the United States. The Brookings Institute, Washington, District of Columbia, USA.

Rose, K.A., R.B. Cook, A.L. Brenkert, R.H. Gardner, and J.P. Hettelingh. 1991. Systematic comparison of ILWAS, MAGIC, and ETD watershed acidification models: 1. Mapping among models inputs and deterministic results. Water Resources Research **27**:2577–2589.

Russell, M. 1992. Lessons from NAPAP. Ecological Applications **2**:107–110.

Shipley, J. 1995. The Applegate partnership. Watershed Management Council Newsletter **6**(3).

United States Environmental Protection Agency (USEPA). 1992. Framework for Ecological Risk Assessment. EPA/630/R-92/001. USEPA, Washington, District of Columbia, USA.

Walker, R., W. Landis, and P. Brown. 2001. Developing a regional ecological risk assessment: A case study of a Tasmanian agricultural catchment. Journal of Human and Ecological Risk Assessment **7**:417–439.

Wondolleck, J.A. and S.L. Yaffee. 2000. Making Collaboration Work: Lessons from Innovation in Natural Resource Management. Island Press, Washington, District of Columbia, USA.

Zhu, X. and A.P. Dale. 2001. JavaAHP: A web-based decision analysis tool for natural resource and environmental management. Environmental Modelling and Software **16**:251–262.

Part 3

Key Issues

Section II: Evolving Approaches

7
Network Theory: An Evolving Approach to Landscape Conservation

Timothy H. Keitt

7.1 Introduction

Habitat loss and fragmentation are ongoing and significant problems throughout the globe (Turner 1996; Riitters et al. 2000). Future biodiversity scenarios highlight the importance of habitat conversion to human land uses as the leading driver of biodiversity loss worldwide (Sala et al. 2000). Particularly disturbing is the habitat loss occurring within protected areas (Liu et al. 2001). Unchecked, current rates of habitat loss may have profound implications for future biodiversity (Pimm et al. 1996).

Given the magnitude of the problem, a case-by-case viability approach to conservation may be impractical. Even conceptually straightforward goals, such as the estimation of a species' extinction risk within a fixed period of time, are, in practice, exceedingly difficult to accomplish without large amounts of accurately measured field data (Dennis et al. 1991; Fieberg and Ellner 2000; Coulson et al. 2001). Confidence intervals on extinction risks estimated via population viability analyses (PVAs) are typically so large as to render the estimated value meaningless (Ludwig 1998). Brook et al. (2000) examined the output of a number of different PVAs and concluded that these models do provide precise predictions of extinction risk. However, their conclusions are unwarranted because their results demonstrate that PVA models are on average unbiased, but not necessarily precise for any one species. According to the analysis of Brook et al., individual PVAs are, in fact, likely to be imprecise for the single species targeted by the PVA (Ellner et al. 2002).

The viability approach is further limited by the difficulty of obtaining sufficient high-quality data across a large number of species. Scarce funding for conservation may be better spent mediating direct causes of habitat loss than attempting to elucidate subtleties of population demography across many species. As a result of these problems, a broader-scale approach, targeted at entire landscapes, may be necessary to maintain significant biodiversity in the future.

Approaches to landscape conservation have generally focused on either community representation or habitat occupancy. Representation approaches use computerized optimization techniques to select a subset of available habitats that maximize the number of species whose distributions fall within the reserve network [see Cabeza and Moilanen (2001) and references therein]. Additional criteria, such as the total cost of land acquisition, may be included in the optimization (Ando et al. 1998). Habitat occupancy approaches attempt to select a set of habitat reserves that will maximize habitat occupancy and hence minimize extinction risk. Occupancy approaches typically focus on the maintenance of habitat connectivity to preserve potential recolonization routes after local population extinctions.

Landscape conservation issues illustrate the need for new approaches to deal with the complexity of resource management issues. Network theory is a developing technique that uses recent advances in computer technologies. The discussion in this chapter of an applied problem that uses network theory thus serves as an introduction to the evolving modeling approaches for resource management.

In the remainder of this chapter, I discuss effects of habitat fragmentation on metapopulation survival and illustrate the importance of habitat connectivity using a simple metapopulation model. I then develop a mathematical framework for studying dispersal networks in a landscape and apply this framework to Mexican spotted owl (*Strix occidentalis lucidia*) habitat in the southwestern United States.

7.2 Habitat Connectivity and Occupancy in a Simple Metapopulation Model

The degree to which habitat may be interconnected via dispersal among populations is a key determinant of species survival in fragmented landscapes. Therefore, understanding how connectivity changes as habitat is lost is important to conservation-planning efforts. As habitats are lost from landscapes, typically one observes that the remaining habitats become increasingly isolated, a process referred to as fragmentation. From percolation theory (Stauffer and Aharony 1985), we know that habitat connectivity in randomly fragmented habitats exhibits abrupt nonlinear changes when the amount of habitat lost reaches a critical value (Gardner et al. 1987). The situation is illustrated in the left-hand column of Figure 7.1. If our goal is to walk from one side of the grid of habitat patches to the other by crossing from one white (habitat) cell to another vertically or horizontally to one of the four nearest neighbor cells, then theory tells us that the probability of doing so becomes vanishingly small when the amount of habitat lost is about 60%. Thus, for species that exhibit metapopulation

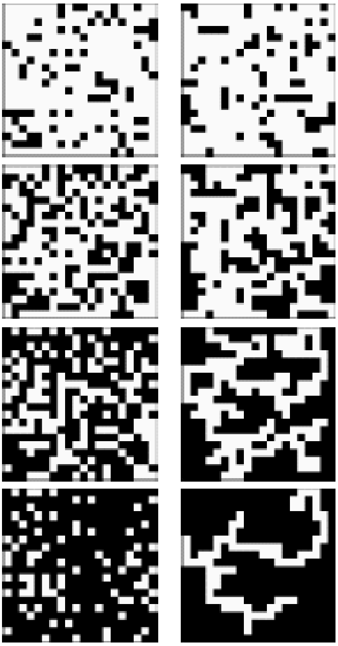

FIGURE 7.1. Random and nonrandom patterns of habitat loss. The left side shows random habitat loss. The right side shows habitat removed randomly, but with the requirement that the remaining patches (white) form a single, connected habitat cluster (spanning tree).

dynamics (Hanski 1999), the amount of habitat with viable populations can decrease dramatically at this critical threshold in landscape connectivity, possibly resulting in biodiversity collapse (see Figure 7.2).

Critical transitions in landscape connectivity have played an important role in the conceptual development of landscape ecology. However, for a number of reasons, the existing theory is quite limited in its application to real landscapes. First, real landscapes do not fragment randomly. Rather, forest fragmentation occurs in specific places, generally because these locations contain commercially valuable tree species, are highly suitable for agriculture, or are near existing settlements. The effect of nonrandom fragmentation of habitats on population persistence can be dramatic. For example, if we alter the fragmentation scenario so that all remaining habitat patches form a continuously connected habitat, the threshold effect is eliminated (right-hand column of Figure 7.1). Simulated metapopulation dynamics in these connected (spanning-tree) landscapes show a significantly reduced impact of habitat loss (Figure 7.2). Thus, it is essential that different patterns of habitat loss be understood before the theory can be applied.

Another limitation with traditional percolation theory is that it applies to regular grids or lattice structures and not to actual landscapes. Nevertheless, Keitt et al. (1997) showed how the basic concepts of percolation theory could be adapted to the analysis of real habitat distributions. They

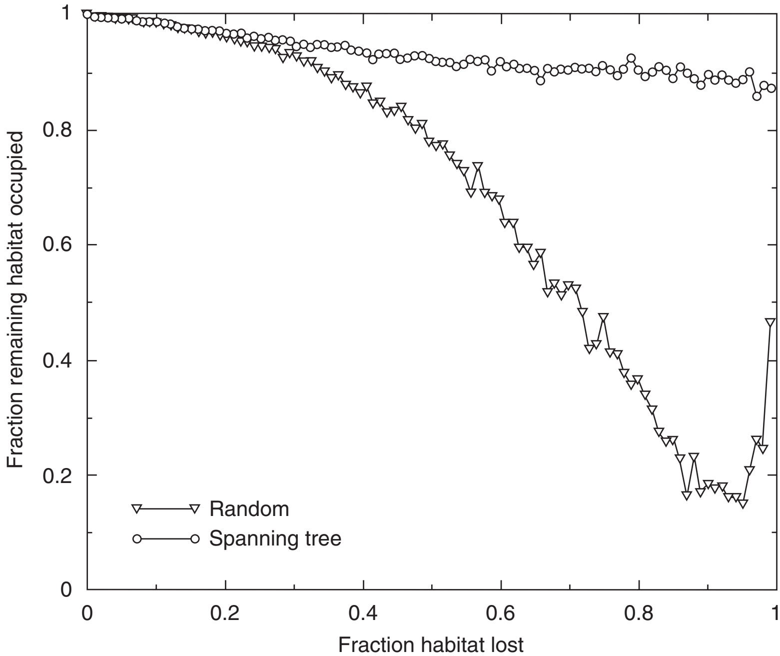

FIGURE 7.2. Simulated habitat occupancy with random and nonrandom habitat destruction. Random and spanning-tree results correspond to the artificial landscapes shown in Figure 7.1. Results are for a stochastic cellular automata with a constant probability of extinction in each grid cell. Colonization probability was one-fourth the number of occupied cells in a four-cell neighborhood. Dynamics alternated between colonization and extinction, and populations were surveyed after extinction. Low values of habitat occupancy indicate extreme vulnerability and impending extinction.

introduced a graph-theoretic model for landscape connectivity, where connections between patches are determined by interpatch distances rather than by adjacency on a lattice. They showed that critical transitions in connectivity occur not only for habitat loss but also as organisms' dispersal ability is decreased. In their study of Mexican spotted owls, they showed that critical dispersal distances for maintaining immigration into habitat patches were approximately 45 km in the southwestern United States. Dispersal distances shorter than 45 km resulted in isolated populations. They also demonstrated how these distances could be converted into parameter estimates for a probabilistic dispersal function. An advantage of their approach was that it allowed not only quantitative measures of connectivity in real landscapes but also sensitivity analysis to determine which patches were critical to the maintenance of immigration and gene flow in fragmented landscapes.

7.3 Landscape Networks

Percolation theory combined with graph models is a powerful step forward for landscape ecology. However, these models do not, as of yet, directly represent or reflect rates of dispersal among patches. An extension of these models is to include rates of movement among patches in the landscape. I call these landscape network models. A landscape network is a mathematical description of the functional relationships between landscape components, be they habitat patches, river segments, an agricultural mosaic, or any other subdivision of a landscape that can be defined. The focus of a landscape network model is flow of energy, materials, and information from one component to another. Typically these "components" will be discrete habitat patches, and we are interested in the flux of individuals moving between different patches. We could subdivide the landscape into a continuum of points or perhaps into different habitat categories rather than patches. For example, we might be interested in modeling the movement of amphibians between aquatic and terrestrial habitat types. Here, however, I focus on spatial landscape networks with discrete habitat patches.

To begin with, imagine a scenario in which a landscape is subdivided into a set of subregions. These subregions could be arbitrarily defined "cells" in a grid or could be defined to map onto existing habitat patches. Let us constrain this subdivision so that every point in the landscape falls within one and only one subdivision. A typical scenario is an archipelago of forest fragments embedded in a cleared, nonforest matrix. If we are interested in modeling the movement of a given species in relation to these habitat fragments, then the quantity of interest is the number of individuals that move between any given pair of fragments over some period of time, say a single generation. To do this, we need to label all the fragments. Let s_0 represent the nonforest matrix and $s_1, s_2, s_3, \ldots, s_N$ represent the N forest fragments. Given that dispersal among patches may be rare, it is appropriate to model these events as a stochastic process. In the simplest model, we need to know three things: (1) the probability of dispersing a distance x, (2) the probability that in leaving patch i we end up in patch j, and (3) the probability that we were in patch i to begin with. Dispersal data for many organisms [e.g., Kot et al. (1996)] indicate the probability of dispersing a given distance is often best fit by a function that decays as a power law in the tails. However, other functions may be appropriate, depending on the dispersal mode and life history of the organism modeled. If we assume that the organism disperses in a random direction and travels distance x, then the probability of moving from patch i to patch j, given that one starts in patch i, is

$$p(j \mid i) = p(m)\int_0^{\infty} p(x)p(x, j \mid i)dx$$

where $p(x,j|i)$ is the probability that an individual leaving from a point chosen in patch i lands on a point in patch j after traveling a distance x and $p(m)$ is the probability that migration occurs at all. To get from the conditional probability $p(j|i)$ to the probability of a transition from i to j, we must estimate the probability that the individual started in patch i. Then, $p(i,j) = \mathrm{p}(i)\mathrm{p}(j|i)$, where $p(i)$ is the probability the individual was found in patch i.

The matrix of probabilities **A** with elements $\mathrm{a}_{ij} = p(i,j)$ defines a landscape network. The network can be thought of as a graph (Harary 1969; Urban and Keitt 2001) in which each patch is a graph "node" and connections between patches are represented as graph "edges." We can assign distances to these edges, either as true distances between patches or as a "functional distance" related to transition probabilities between patches. A convenient measure of the functional distance is $\mathrm{d}_{ij} = 1/\underline{a}_{ij}$ (i.e., the mean time between immigration from i to j).

Estimation of p_{ij} can be accomplished in a number of ways. The dispersal function $p(x)$ and the migration probability p_m can be estimated by tracking animal movements (telemetry) or by mark-recapture methods. Once $p(x)$ is estimated, the patch transition probabilities $p(i,j)$ can then be estimated on the basis of a habitat map that provides the estimates of $p(x,j|i)$. For more complex dispersal behavior, migration rates can be estimated directly through simulation modeling of the migration process. The important point is that landscape network models directly incorporate actual patterns of habitat fragmentation into the model structure, as opposed to approaches that assume space is uniform [Hanski and Simberloff (1997) refer to these as "spatially realistic models"]. Thus, landscape network analysis is a powerful tool for analyzing real landscapes and can be used as a basis for building more complex population viability models.

As specified, the landscape network connected every patch to every other patch, albeit sometimes with very low probability. The dense network of connections makes graphical interpretation of the network difficult. A feature that is much simpler to analyze is the spanning tree of a network. A "tree" is simply a graph with no loops, and a spanning tree is a tree that contains all nodes (patches) in the network. In particular, the minimum-length spanning tree (MST) is an interesting feature of the network because it identifies the "backbone" or connected core of the landscape. The minimum spanning tree is the spanning tree that has the shortest total length; that is, it minimizes

$$\sum d_{ij} \forall ij \in \mathrm{MST}$$

Because the d_{ij} are defined in terms of immigration flux, the MST on the landscape network identifies the core habitat supporting a metapopulation.

7.4 A Case Study

An example system particularly suited to landscape graphs is the spatial population structure of the Mexican spotted owl. The Mexican subspecies of the spotted owl is distributed from Utah and Colorado south to central Mexico (USDI 1995). In 1993, the subspecies was listed as threatened under the Endangered Species Act. A graph-theoretic approach was used previously to characterize owl habitat connectivity across four southwestern states (Utah, Colorado, New Mexico, and Arizona) as part of a federally mandated conservation plan (Keitt et al. 1995, 1997). The habitat distribution for Mexican spotted owls is highly fragmented in the Southwest because suitable foraging and nesting sites are largely determined by topographic relief. Because of the arid climate and orographic effects, much Mexican spotted owl habitat is divided into "sky islands" surrounded by grasslands and desert. Juvenile spotted owls are known to disperse considerable distances in search of vacant nesting territories. Thus it is highly likely that dispersal success plays an important role in the genetic, demographic, and metapopulation structure of the Mexican spotted owl. Because dispersal success depends principally on the time and energy spent searching for suitable sites, the connectivity of suitable habitat patches is a prime concern when making habitat conservation decisions.

Figure 7.3 shows a map of potential spotted owl habitat in the Southwest overlayed by the minimum spanning tree of the landscape network. The forest map was derived from Advanced Very High Resolution Radiometer (AVHRR) satellite imagery (Evans et al. 1993; Evans and Zhu 1993). I used mark-recapture data from juvenile owls (USDI 1995) to parameterize the network. The minimum spanning tree highlights several types of patches. Large "core" patches have many connections (high "degree" in graph-theory parlance). These patches are almost certainly critical to survival of the metapopulation. "Bridge" patches have few connections but appear deep in the tree and sit between larger core patches. By "deep," I mean the minimum number of connections that must be crossed to reach a "leaf" of the tree. Leaf patches occur at the ends of tree branches and have only a single connection (degree = 1). Depth in the tree is a good proxy for patch importance. A simple, iterative algorithm for ranking the patches is to repeatedly remove the lowest quality (or smallest) leaf patch from the tree until there is only a single patch. Patches are ranked in order as they are removed. These rankings correspond well to rankings produced by patch deletion combined with sensitivity measures. Model results (Urban and

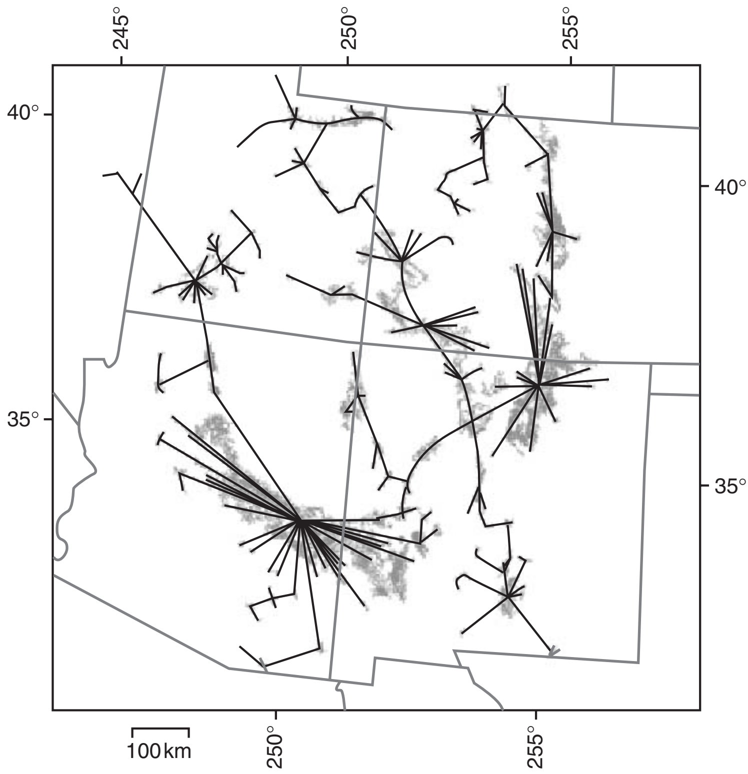

FIGURE 7.3. Minimum spanning tree overlayed on southwestern forest mosaic. Patches are regions with stands of ponderosa pine and other conifers and correspond to potential spotted owl habitat.

Keitt 2001) indicate that removing patches in this manner is nearly optimal for the maintainence of metapopulations.

7.5 Discussion

Even though natural systems are complicated and difficult to predict, there are a few lessons we can derive from the current theory. First, connectivity of landscapes can strongly influence their capacity to support a metapopulation (see also Hanski and Ovaskainen 2000). Thus, tools to analyze connectivity patterns in landscapes are essential to effective management and planning for metapopulation conservation. Landscape network theory, as presented here, is one such tool. By protecting both core and stepping-stone patches in a fragmented landscape, we can greatly increase the likelihood that a species will persist. However, analysis of landscape connectivity is but one small part of an integrated conservation management process. Often, the most difficult challenges involve formation of a consensus about the true nature of the problem and the identification of data, protocols, and analytical tools to be used as a basis for decision making. Fortunately, there have been significant advances in decision-support tools and natural-resource-modeling techniques (see Gustafson et al., Chapter 8, this volume). Formal system modeling languages are now available that allow both detailed specification as well as compact communication of the logical structure of models used in decision support. Coupled with advanced modeling techniques, these tools can provide substantial improvements in our ability to manage complex ecological systems.

References

Ando, A., J. Camm, S. Polasky, and A. Solow. 1998. Species distributions, land values, and efficient conservation. Science **279**:2126–2128.

Brook, B.W., J.J. O'Grady, A.P. Chapman, M.A. Burgman, H. Resit Akçakaya, and R. Frankham. 2000. Prediction accuracy of population viability analysis in conservation biology. Nature **404**:385–387.

Cabeza, M. and A. Moilanen. 2001. Design of reserve networks and the persistence of biodiversity. Trends in Ecology and Evolution **16**:242–248.

Coulson, T., G.M. Mace, E. Hudson, and H. Possingham. 2001. The use and abuse of population viability analysis. Trends in Ecology and Evolution **16**:219–221.

Dennis, B., P.L. Munholland, and J.M. Scott. 1991. Estimation of growth and extinction parameters for endangered species. Ecological Monographs **64**:205–224.

Ellner, S.P., J. Fieberg, D. Ludwig, and C. Wilcox. 2002. Precision of population viability analysis. Conservation Biology. **14**:258–261.

Evans, D.L. and Z. Zhu. 1993. AVHRR for forest mapping: national applications and global implications. Pages 76–79 *in* A. Lewis, editor. Looking to the Future with an Eye on the Past. Proceedings of the 1993 ACSM/ASPRS convention. American Society of Photogrammetry and Remote Sensing, Bethesda, Maryland, USA.

Evans, D.L., Z. Zhu, and K. Winterberger. 1993. Mapping forest distributions with AVHRR data. World Resource Review **5**:66–71.

Fieberg, J. and S.P. Ellner. 2000. When is it meaningful to estimate an extinction probability? Ecology **81**:2040–2047.

Gardner, R.H., B.T. Milne, R.V. O'Neill, and M.G. Turner. 1987. Neutral models for the analysis of broad-scale landscape patterns. Landscape Ecology **1**:19–28.

Hanksi, I. 1999. Metapopulation Ecology. Oxford University Press, Oxford, UK.

Hanski, I. and O. Ovaskainen. 2000. The metapopulation capacity of a fragmented landscape. Nature **404**:755–758.

Hanski, I. and D. Simberloff. 1997. The metapopulation approach, its history, conceptual domain and application to conservation. Pages 5–26 *in* I. Hanski and M.E. Gilpin, editors. Metapopulation Biology: Ecology, Genetics, and Evolution. Academic Press, San Diego, California, USA.

Harary, F. 1969. Graph Theory. Addison-Wesley, Reading, Massachusetts, USA.

Keitt, T.H., A. Franklin, and D.L. Urban. 1995. Landscape analysis and metapopulation structure. Chapter 3 *in* Recovery Plan for the Mexican Spotted Owl. Volume II: Technical and supporting information. U.S. Department of the

Interior, Fish and Wildlife Service, Southwestern Region, Albuquerque, New Mexico, USA.

Keitt, T.H., D.L. Urban, and B.T. Milne. 1997. Detecting critical scales in fragmented landscapes. Conservation Ecology **1**:4. URL: http://www.consecol.org/vol1/iss1/art4.

Kot, M., M.A. Lewis, and P. van den Driessche. 1996. Dispersal data and the spread of invading organisms. Ecology **77**:2027–2042.

Liu, J., M. Linderman, Z. Quyang, L. An, J. Yang, and H. Zhang. 2001. Ecological degradation in protected areas: The case of Wolong Nature Reserve for giant pandas. Science **292**:98–101.

Ludwig, D. 1998. Is it meaningful to estimate a probability of extinction? Ecology **80**:298–310.

Pimm, S.L., G.J. Russell, J.L. Gittleman, and T.M. Brooks. 1996. The future of biodiversity. Science **269**:347–350.

Riitters, K., J. Wickham, R. O'Neill, B. Jones, and E. Smith. 2000. Global-scale patterns of forest fragmentation. Conservation Ecology **4**:3. URL: http://www.consecol.org/vol4/iss2/art3

Sala, O.E., F.S. Chapin, J.J. Armesto, E. Berlow, J. Bloomfield, R. Dirzo, E. Huber-Sanwald, L.F. Huenneke, R.B. Jackson, A. Kinzig, R. Leemans, D.M. Lodge, H.A. Mooney, M. Oesterheld, N.L. Poff, M.T. Sykes, B.H. Walker, M. Walker, D.H. Wall. 2000. Biodiversity—global biodiversity scenarios for the year 2100. Science **287**:1770–1774.

Stauffer, D., and A. Aharony. 1985. Introduction to Percolation Theory. Taylor & Francis, London, UK.

Turner, I.M. 1996. Species loss in fragments of tropical forest: A review of the evidence. Journal of Applied Ecology **33**:200–209.

U.S. Department of the Interior (USDI), Fish and Wildlife Service. 1995. Recovery Plan for the Mexican Spotted Owl. Volume I. USDI, Albuquerque, New Mexico, USA.

Urban, D.L. and T.H. Keitt. 2001. Landscape connectivity: A graph-theoretic perspective. Ecology **82**:1205–1218.

8 Evolving Approaches and Technologies to Enhance the Role of Ecological Modeling in Decision Making

Eric Gustafson, John Nestler, Louis Gross,
Keith M. Reynolds, Daniel Yaussy, Thomas P. Maxwell, and
Virginia H. Dale

8.1 Introduction

Understanding the effects of management activities is difficult for natural resource managers and decision makers because ecological systems are highly complex and their behavior is difficult to predict. Furthermore, the empirical studies necessary to illuminate all management questions quickly become logistically complicated and cost prohibitive. Ecological models provide a means to formalize our conceptual understanding of how an ecological system works and allow us to check this understanding by testing model predictions. Validated models can then be used to make predictions about the effects of proposed management activities, giving decision makers useful information that would not be available from empirical data.

In this chapter, we discuss evolving modeling approaches and technologies for ecological modeling and application to decision making. We begin by discussing model conceptualization and design and showing how new approaches to model structuring might enhance problem formulation in decision making. We then discuss issues surrounding the construction and implementation of ecological models after the conceptual development has been completed and present evolving approaches that address these issues. Finally, we discuss technologies for communicating the structure of and output from models to improve their relevance and usefulness to decision makers and the stakeholders in the managed system.

8.2 Model Conceptualization and Design

Perhaps the biggest problems facing decision makers are (1) forging a consensus about what the true problems are and (2) agreeing on the data, protocols and analytical tools that will be used to produce the information on which to base decisions. All parties must understand the structure and limitations of a proposed model because models with the appearance of a “black box” will create suspicion and reduce cooperation. Modelers must clearly communicate to nonmodelers the structure and relationships within the model, and provide a method by which participants can suggest improvements to model design.

8.2.1 Approaches and Technologies

8.2.1.1 Logic-Based Model Specifications

Since the 1960s, ecological modeling has emphasized simulation of process. Early implementations were procedural and based on flow charts. Later implementations, trying to better cope with ecological complexity, have tended toward object-oriented models based on the universal modeling language (UML) (Boggs and Boggs 1999) or similar semantic models for object-oriented analysis and design. In either case, these implementations are fundamentally process oriented. However, ecosystem evaluation based on knowledge-based systems theory and logical abstraction shows promise for improving the tractability of ecosystem evaluation (Reynolds et al. 2000). Logic-based networks, flowcharts, and UML are all semantic models (Booch 1994), but logic-based networks are distinct from conceptual models by having a formal grammar and syntax. Two examples of logic-based approaches are fuzzy network models and Bayesian belief networks.

8.2.1.1.1 Fuzzy Network Models

Fuzzy logic networks are a powerful form of knowledge representation, ideally suited to the abstract problems posed by ecosystem evaluation. Similar in concept to a metadatabase, a knowledge base is a formal specification for interpreting information (Walters and Nielsen 1988). NetWeaver is such a knowledge base, having a formal grammar and syntax that makes the knowledge base an executable specification (Reynolds 1999). A NetWeaver knowledge base graphically represents the ecosystem state as linked networks of propositions. Two key properties of a NetWeaver proposition are its measure of truth (i.e., the degree of support for the proposition) and its logical specification, which is graphically constructed from operators (fuzzy, Boolean, and arithmetic), data, and other propositions. The implementation of fuzzy math in NetWeaver facilitates compact and efficient representation of large, abstract problems. For example, a prototype knowledge base evaluates forest ecosystem sustainability as prescribed by the Montreal Process (Reynolds 2001). Also, fuzzy math provides a set-theoretic implementation of uncertainty (see Section 8.4.1.3) as an alternative to the more familiar notion based on probability theory (Zadeh and Kacprzyk 1992).

Fuzzy network models (FNMs) for ecosystem evaluation are not a substitute for statistical and process models. Rather, FNMs are most valuable when used as logic frameworks for integrating the outputs from other models. Consider a hypothetical ecosystem evaluation in which 100 statistical models were developed and applied to various dimensions of the analysis and another 20 simulations of other system components were run. A logic framework for integrating all these results might be useful. Because FNMs are formal specifications for interpreting information, they are cognitive maps of the problem specification (Stillings et al. 1987). They help identify questions to be answered, the relevant intermediate states and processes, the information required, and how the results are related to each other. It is important to note that these logic networks are not just specifications, but are themselves models that can be fed data and produce interpretable output. Furthermore, in systems like NetWeaver, the specification provides an intuitive, graphical explanation for the derivation of results so the model is not a black box.

8.2.1.1.2 Bayesian Belief Networks

Another class of semantic models are Bayesian belief networks (BBNs) (Ellison 1996). Bayesian belief networks are based on probability theory, whereas FNMs are based on set theory. The practical implication of this difference is that BBNs are best suited to applications where the problem is relatively narrow and well defined and most conditional probabilities are known, while FNMs are best suited to applications where the problem is broad and abstract and a significant proportion of the conditional probabilities are unknown.

8.2.1.2 Data Visualization

Visualization of the relationships and interactions among variables can aid model formulation and design. When the relationships among variables are clearly understood, model design and behavior will be enhanced, and more realistic estimations and predictions will result. Most current statistical packages contain sophisticated graphics packages to allow two-dimensional (2-D) projection of a three-dimensional (3-D) data space. True 3-D viewing is possible with specialized projection systems and eyewear (polarized lenses, alternating liquid-crystal-display lenses, or virtual reality goggles). It is possible to visualize the interactions of five variables in a 3-D representation with length, width, height, color, and animation. For example, consider a representation of tree growth across a region with latitude being length, longitude being width, average monthly temperature being height, monthly growth rate being color, and time lapse as the animation. A good source for information on this topic is the Digital Visualization Analysis Laboratory of NASA (http://dval-www.larc.nasa.gov).

8.2.2 Translating a Conceptual Model into a Logic-Based Specification

To translate a conceptual model provided by a domain expert (or set of experts) into a logic-based network model, we begin with a simple conceptual model, such as that described by Bormann et al. (1994) for evaluating the sustainability of forest ecosystems (see Figure 8.1). The key concept of this model is that sustainable forest ecosystems can occur within the overlap between what is biophysically feasible and what is socially acceptable.

The model of Bormann et al. (1994) is easily translated into a logical representation (Figure 8.2), where each oval represents a logic network that evaluates a proposition. The ultimate proposition of interest concerns forest ecosystem sustainability, and this proposition depends on two premises: that social values are satisfied and that it is biophysically feasible to maintain the ecosystem in a specified condition. Each premise of forest ecosystem sustainability is abstract, but can be further elaborated by using the concepts discussed by Davis et al. (2001). For example, the proposition concerning the feasibility of biophysical condition depends on premises about maintaining suitable forest structure, composition, and ecosystem processes. If this model specification was implemented in NetWeaver, which is based on fuzzy math, the specification for biophysical feasibility could

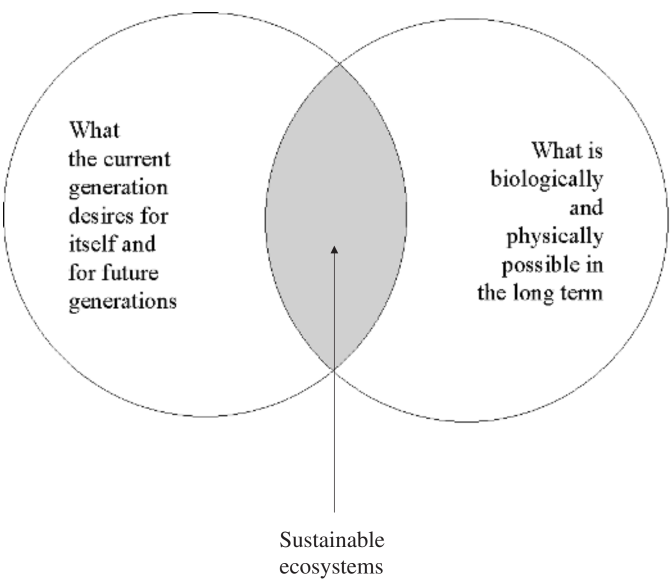

FIGURE 8.1. Conceptual model of forest ecosystem sustainability [adapted from Bormann et al. (1994)].

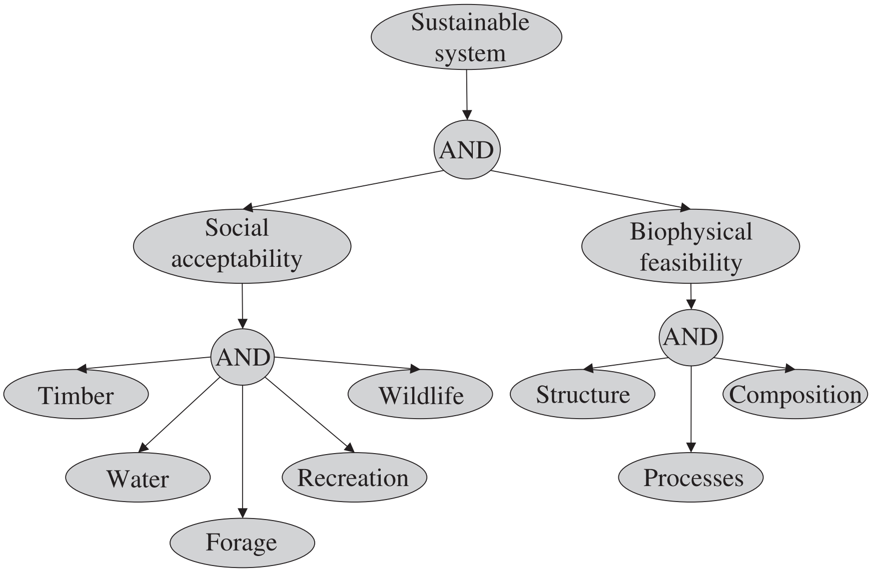

FIGURE 8.2. A logic-based representation of the conceptual model for forest ecosystem sustainability [From Fig. 1 in Bormann et al. (1994)] extended with concepts presented by Davis et al. (2001).

be stated as "the assertion of biophysical feasibility is true to the degree that structure, composition, and processes of the ecosystem are in a suitable condition."

The premises providing support for or against biophysical feasibility and social acceptability are still relatively abstract, but, in general, propositions become progressively more specific and concrete as the logic specification is extended to progressively deeper levels (see Figure 8.2). Continued development of the logic structure by the extension of each logic pathway would quickly produce propositions that could be evaluated by comparison to data.

Both the conceptual model (see Figure 8.1) and its translation into a logic-based representation (see Figure 8.2) are useful forms of model visualization. The logic-based form is particularly intriguing because it seamlessly integrates symbolic and spatial reasoning (Stillings et al. 1987). Indeed, when a logic network and its logical antecedents are viewed as propositions and premises, respectively, knowledge-base architectures produced by systems like NetWeaver provide an intuitive visual representation of a formal logical discourse (Halpern 1989). With respect to decision making, the logic model provides an intuitive and unambiguous specification of what is of concern, how elements are logically interdependent, what data are required to evaluate the concern, and, perhaps most importantly, how information is to be interpreted to arrive at a conclusion.

8.3 Model Implementation

Simulation modeling has traditionally been conducted in the realm of high-level procedural computer programming, creating programs that can be difficult to use and that produce complex output. Long time intervals between the design of a model and its implementation tend to decrease its relevance and utility. Furthermore, the nature of the code produced tends to make linking models problematic and prone to error. Emerging approaches are beginning to overcome limitations in designing, coding, and linking computer models, allowing more flexible implementation of models to answer specific questions posed by decision makers.

8.3.1 Approaches and Technologies

8.3.1.1 Markov Models

Markov models represent one widely used approach that underlies many ecological models. The main advantage (and also the main limitation) of a Markov model is revealed in the definition of the Markov property: given the present, the future is independent of the past. In such a model, no information other than the present state is required to predict the future. Markov models are therefore specified by some initial probability distribution of states, and a description of the probability of transition from any particular state to some other state at some future time. These transitions are specified by a transition matrix (for discrete-time models) or a transition probability-density function (for continuous-state models) of the probabilities of transition from one state to any other state in one time period.

Because Markov models ignore past history, they are relatively easy to construct from observations of a system. The major limitation is that, in many cases, history does matter, and projecting the future based solely on the current state may be quite inaccurate. For example, if a population is far from demographic equilibrium, then age structure significantly affects overall population growth rates. The effect of the "baby-boom" generation (the generation born between 1946 and 1960) on future demographics in the United States is a good example. Of course, one can extend the state space of the model by including a sequence of past states within the current state to make the Markov assumption more appropriate. However, this greatly increases the dimensionality of the problem and reduces the advantage of the Markov approach.

8.3.1.2 Agent-Based Models

Agent-based models are another class of models related to the Markov framework. Agent-based approaches simulate the autonomous behavior of agents (individuals) by constructing rules governing the physiology and behavior of those individuals. As the agents act according to the rules (moving, feeding, mating, avoiding predators, respiring, etc.), they interact with their surroundings and with other agents. Such models allow study of the relationship between individual actions and complex ecological systems (DeAngelis and Gross 1992). The models can be linked to geographic information systems (GIS) and to models simulating other species. There are few limits to the sophistication of these models. The state of individuals may include location, sex, size, social status, and fat content, and the behavioral rules may be related to environmental factors (e.g., temperature, water, nutrient availability, and habitat condition), other agents, physiological stress, environmental cues, or random actions. Model behavior can often be compared directly with empirical observations.

As an example, an individual-based, landscape-scale model was constructed to simulate the interaction of dispersing American martens with the spatial variability of energy (i.e., acquisition of prey) and mortality risk (by predation) associated with different habitat types (Gardner and Gustafson in press). Movement decision rules vary with the physiological state of the individual, such that martens tend to select habitats that minimize predation risk, except when energy reserves are low, in which case they select habitats that provide increased energy intake. Marten movements are simulated on heterogeneous, grid-cell landscapes, and the movement paths, percentage of dispersing martens killed or starved, and proportion of martens successfully dispersing to a new home range are measured. The agent-based approach is well suited to modeling the dispersal process because it formalizes the behavior of an individual and allows the study of how that behavior interacts with the landscape structure produced by management, disturbance, and development.

8.3.1.3 New Approaches for Dealing with Scale

A number of studies in theoretical ecology point to the importance of scale in ecological modeling (Kolasa 1989; Rahel 1990; Levin 1992; Holling 1992). Levin (1992) argues that "the problem of pattern and scale is the central problem in ecology." Kolasa (1989), Rahel (1990), and Holling (1992) acknowledge that spatial scale and temporal scale are paramount to understanding community dynamics.

Two scale considerations constrain realistic ecosystem simulation. First, ecological systems are comprised of processes that occur across a wide range of spatial and temporal scales. At one extreme lie small-scale, short-time-period processes, such as the collision of molecules. At the other extreme lie large-scale processes, such as global population dynamics (and associated movement patterns), that may span thousands of kilometers in space and decades in time. Studying one extreme or the other cannot provide a comprehensive view of ecological systems. Second, ecological systems have emergent properties that can only be described across multiple hierarchical levels (O'Neill et al. 1989). Hybrid modeling frameworks have been developed to explicitly resolve mismatches of scale.

8.3.1.3.1 Coupled Eulerian–Lagrangian Hybrid Models

Ecological-simulation approaches can be broadly separated into those using an Eulerian-reference framework and those using a Lagrangian-reference framework. In an Eulerian-reference framework, a modeler discretizes space into cells and then transports and conserves mass, momentum, and energy through a grid of cells (see Figure 8.3A). The subset of ecological processes best simulated using an Eulerian framework occur over small spatial scales and short time steps relative to both the spatial scale of discretization and the time step used to model transfers across cell boundaries. In aquatic systems, such processes can be averaged within cells and dispersed among cells with a relatively small accumulation of errors. For example, the accuracy with which a chemical transformation can be simulated is not substantially affected by changes in cell size as long as the cell size is large relative to the spatial scale of the process (see Figure 8.3A). This assumption appears to hold true for the simulation of chemical transformations, microbial degradation, algal photosynthesis, and other biogeochemical processes that occur over relatively small spatial and temporal scales.

In a Lagrangian-reference framework, the modeler disaggregates reality into smaller control volumes or particles (for brevity, we refer to both as particles) and tracks the changes in the particles through space and time

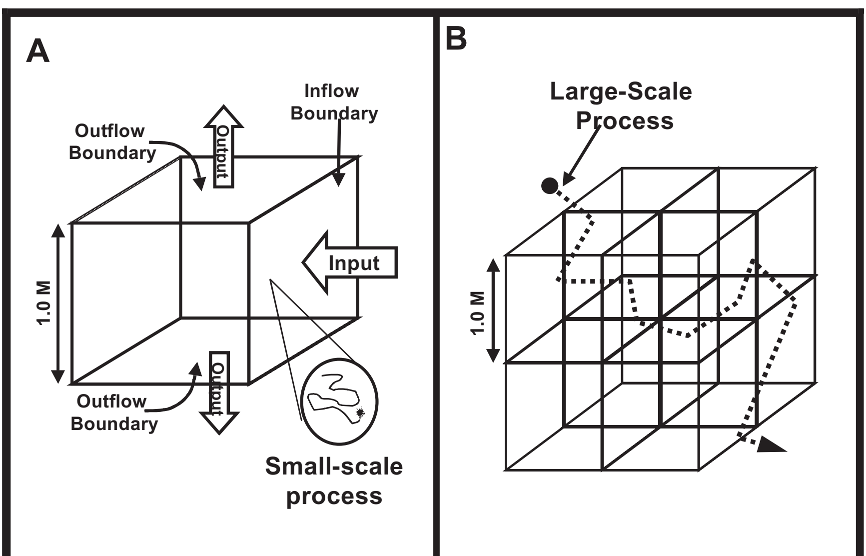

FIGURE 8.3. Comparison of Eulerian (A) and Lagrangian (B) reference frameworks. The grid in (B) is for scaling purposes only and does not represent part of the Lagrangian framework.

(see Figure 8.3B). The Lagrangian framework is required for the subset of ecosystem-level processes that violate Eulerian assumptions because (1) the scale of movement of the simulated process is great relative to that used in the Eulerian representation of the system or (2) movement dynamics associated with the contrasting process are sufficiently complex that they cannot be averaged into an Eulerian framework without propagating substantial error. For example, the effects of a highly mobile and abundant fish species on chemical transformations in a lake cannot be averaged in an Eulerian framework because fish schooling behavior and complex swim-path selection prevent biomass from being accurately distributed into cells at time steps. At the scale of discretization ($1\,m^3$) used in this example, fish may cross multiple cells in a single time step, or most of the fish may concentrate in a very small part of the physical domain represented by the model grid. The scale of fish movement exceeds the scales of advection and dispersion used to describe fluid motion and chemical transformations. This example requires use of the Lagrangian framework (see Figure 8.3B) because fish-movement capabilities are large relative to the scale of discretization. The agent-based models discussed in the previous section also use the Lagrangian frame of reference.

These two modeling frameworks have been combined into a single, unified framework termed the Coupled Eulerian–Lagrangian Hybrid (CEL Hybrid) Ecological Modeling System. The couple, a generic linking program built on particle-tracking concepts, is the unique information transformation/translation module of CEL Hybrid models that allows the analysis to switch between the two reference frameworks without information loss. Particle-tracking algorithms emulate the path made by a neutrally buoyant particle passively transported through a physical domain represented as a 3-D grid. They interpolate discontinuous information represented in an Eulerian grid to intermediate points of interest to generate a nearly continuous Lagrangian pathway (Martin and McCutcheon 1999). Particle-tracking logic enables the modeler to use the strength of a Lagrangian framework to maintain the integrity of individuals as they move through simulated space, while concurrently using the power of the Eulerian framework to simulate the physicochemical environment and other characteristics of the system over time and space. For example, Goodwin et al. (2001) describe how fish-movement rules based on particle-tracking logic can be programmed into a water-quality model, and Nestler et al. (2002) describe the accuracy of calibration of such an approach.

Closer examination of the Goodwin et al. (2001) model illustrates how dynamically coupled Eulerian-based and Lagrangian-based models can overcome scale discrepancies (Figure 8.4). They used a specialized coupling program, the Numerical Fish Surrogate (NFS) to simulate the sensory inputs and emergent behavior (Warburton 1997) of adult blueback herring (*Alosa aestivalis*), a cool-water fish species common in inland and coastal environments. This species moves extensively within a hydrosystem and

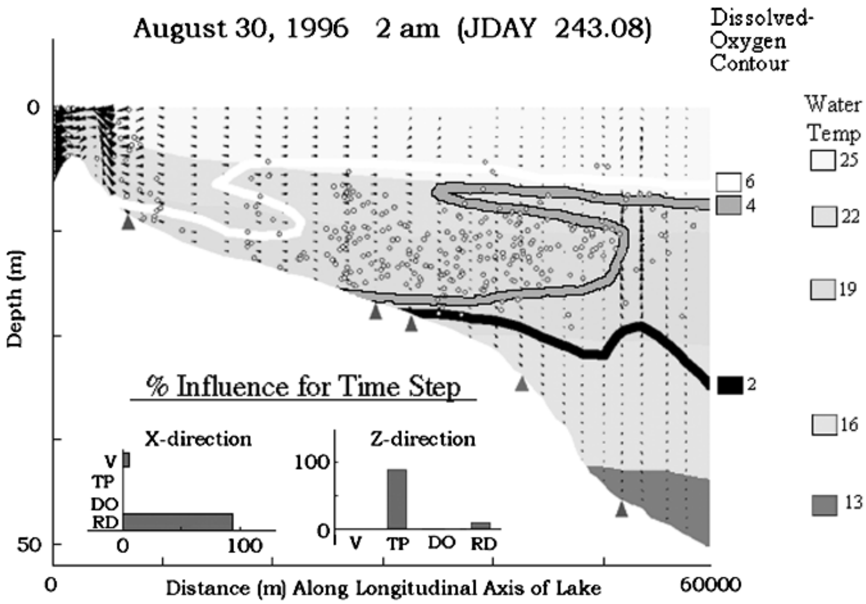

FIGURE 8.4. Visualization of output from coupled models. Open circles represent virtual fish; shaded fills represent water temperature (°C); contour lines represent selected dissolved-oxygen concentrations [mg/L (ppm)]; arrows represent velocity vectors; bar charts indicate instantaneous fish responses to various environmental factors for each movement direction. V = water velocity, TP = temperature, DO = dissolved oxygen, and RD = random number.

uses different habitats for spawning, rearing, feeding, and refuge, and no single model type is presently adequate to simulate its movement behavior. The Eulerian module is a 2-D (laterally averaged) water-quality model that is used to describe hydraulic and water-quality time histories in a grid framework. The Lagrangian module is a fish-movement model that emulates swim-path-selection behavior by the blueback herring in continuous space. The NFS is the coupling module that interpolates and translates information between the Eulerian and Lagrangian modules so that the strengths of each modeling reference framework can be effectively employed. Coupled models offer the potential to increase the accuracy of model predictions because an optimum reference framework can be used for different sets of environmental variables. For the example in Figure 8.4, the fit between modeled predictions and field data, summarized to the nearest meter vertically, was $R^2 = 0.93$. The best fit longitudinally, summarized to the nearest 5-km-long segment, was $R^2 = 0.67$.

8.3.1.3.2 Fractal Approaches

Other new approaches for dealing with scale exist. Nestler and Sutton (2000) employed a type of fractal geometry tool, the angle measurement technique, to describe changes at multiple scales in a regulated river to illustrate a multiscale analysis. They quantified how the distribution of energy at multiple scales in a river cross-section was changed by impoundment. The unregulated river channel possessed an evenly graded distribution of subchannels, each characterized by relatively low energy. Some years after regulation, the river had gradually changed into a high-energy main channel flanked by small-scale subchannels. This multiscale change in channel-bed form could not have been described with more conventional single-scale approaches.

There are substantial advantages to multiscale analysis. First, it is a more accurate representation of reality, so that the causes of and solutions to environmental degradation can be more accurately determined. Second, because scale is incorporated as a metric, different-sized organisms (responding to features at different scales) can be evaluated in a single analysis. By performing a spatial analysis as a first step, an investigator can optimally size sampling or simulation to reflect the dominant scales within a river system rather than impose an arbitrarily selected scale of analysis.

8.3.1.4 Declarative Modules

A well-recognized method for reducing conceptual and programming complexity involves structuring a model as a set of distinct modules with well-defined interfaces. Modular design facilitates collaborative model construction, allowing teams of specialists to work independently on different modules. Modules can be archived in distributed libraries and serve as a set of templates to speed future development.

The most common approach to model integration, which involves linking procedural models through the use of distributed object formalisms, is greatly limited by the fact that the various submodels are, by their nature, overspecified as modules. That is, in the process of implementing a submodel in a procedural programming language, the modeler generally "hard codes" many choices, such as programming language, spatiotemporal representation, model control and input/output (I/O) interfaces, and computing paradigm (e.g., serial or parallel message passing). These fixed aspects are extremely limiting and irrelevant to the essential dynamics of the model. To improve flexibility, it is useful to develop a formalism for coding archivable modules that allows maximum generality and applicability of the modules. This formalism can be accomplished through declarative module specifications containing only enough information to specify the essential dynamics of the module and allowing a wide range of customized procedural implementations (Maxwell 1999; Maxwell and Costanza 1997*a*,*b*). This approach provides the high level of abstraction necessary for maximum generality, yet provides enough detail to allow a dynamic simulation to be produced automatically. The approach separates general specifications from site-specific specifications. Because only the universal blueprints are included in the module specification, the site-specific specializations can be delegated to a separate model-configuration phase. Examples of declarative-modeling formalisms include the Simulation Module Markup Language (SMML) (Maxwell 1999; Maxwell and Costanza 1997*b*), the Integrated Modeling Architecture being developed at the University of Maryland, and the Modelica modeling language being developed by EUROSIM (Federation of European Simulation Societies; http://ws3.atv.tuwien.ac.at/eurosim/).

As an example of a declarative module specification, consider the following SMML declaration representing a deer-population state variable. The specification defines a set of input ports that will be linked to the output ports of other modules with "link" statements and an equation that is used to update the value of DEER_POPULATION in response to event notifications. An SMML-model declaration does not specify I/O configuration, memory allocation, temporal dynamics, and spatial-grid configuration. The code describing these aspects of the model is generated automatically at the initiation of a simulation run based upon site-specific configuration information.

```
⟨atom name="DEER_POPULATION" type="state"⟩
⟨port type="input" name="DEER_BIRTHS" /⟩
⟨port type="input" name="DEER_STARVATION" /⟩
⟨port type="input" name="DEATHS_FROM_PREDATION" /⟩
⟨dynamic event="integrate" type="code" ⟩
⟨code⟩ ((DEER_BIRTHS-DEER_STARVATION)-DEATHS_FROM_
  PREDATION) ⟨/code⟩
```

8.3.1.5 Control Theory Models and Spatial Optimization Models

Spatial dynamics present difficult challenges to ecological modelers. A central issue in computational ecology is linking the demand for biological resources with the dynamics of those resources (Gross and DeAngelis 2001). These resources do not occur uniformly in space, and managers seek some control over this heterogeneity (Hof and Bevers 1998). Given a variety of criteria for managing a system, how should the "control" of the system be applied spatially in order to optimize the objective?

A large body of literature deals with optimization of outputs that vary as components of the system are controlled (Clark 1976). A comparable body of literature for spatial problems is only beginning to be developed (Hof and Bevers 1998; Jager and Gross 2000). Hof and Bevers (1998) provide examples of spatial optimization on a spatial grid through the use of limited state variables and mixed-integer programming methods to develop management solutions. Management objectives include designing species reserves, maximizing biological diversity, and maintaining population sizes above specific thresholds in stochastic environments. The computational limitations in solving optimization problems are both discouraging and encouraging. The size of feasible problems is severely restricted, but the computational limitations have prompted the development of new analytical and computational methods (particularly on parallel processors) that are discussed later in this chapter.

Other approaches to spatial optimization include the combinatorial interchange technique to minimize spatial fragmentation (Loehle 1999) that extends the stochastic search algorithms of Bettinger et al. (1997). This approach cannot readily link to dynamic models to predict population responses to fragmentation, but it is computationally efficient compared to mixed-integer programming methods. A Markov-decision approach can be applied to optimize landscapes for metapopulations (Tuck and Possingham 2000). This method allows simple dynamics of localized patches to be included, but the size of the problem increases exponentially with the number of states allowed. Other algorithms have been applied to attempt to specify optimal spatial-reserve patterns for biodiversity conservation (Csuti et al. 1997; Pressey et al. 1997), although they ignore population dynamics.

8.3.1.6 New Methods for Developing Statistical Models

New techniques are also being developed to improve our ability to produce ecological statistical models and to handle increasingly large data sets. Traditional multivariate linear-regression tools are useful for finding global effects, especially with sparse data sets. For data mining (finding previously unknown, significant relationships between variables in large data sets), there is no need to assume global structure. Local data can refine global rules by adding conditions to global rules. The resulting regression is thereby determined by local conditions. Classification and regression tree analysis (RTA) uses iterative splitting of the data to develop empirical relationships between response and predictor variables without the restrictive distribution assumptions of classical regression analysis. This approach creates models that are fitted by binary recursive partitioning, in which a data set is successively split into increasingly homogeneous subsets (Clark and Pregibon 1992). Regression tree analysis is much more flexible than classic statistical methods in uncovering structure in data with variables that are hierarchical, nonlinear, nonadditive, or categorical in nature. Regression tree analysis is useful as a means of devising prediction rules for rapid and repeated evaluation, as a screening method for variables, as a diagnostic technique to assess the adequacy of linear models, and for summarizing large multivariate data sets (Clark and Pregibon 1992; Iverson et al. 1999).

Multivariate adaptive-regression splines (MARS) is a multivariate, nonparametric regression procedure that builds flexible regression models by fitting separate splines (or basis functions) to distinct intervals of the predictor variables (Friedman 1991). The variables and interactions to use and the endpoints of the intervals for each variable are optimized simultaneously by evaluating a "loss-of-fit" criterion. Multivariate adaptive-regression splines also search for interactions between variables, allowing any degree of interaction to be considered. It uses adaptive regression, guiding the function being estimated by the local nature of the data. Where RTA excels at detecting local data structure and marginal interaction effects between predictor variables, MARS excels at detecting global and linear local data structure, flexibly modeling relationships that are additive or that involve interactions between predictor variables (Prasad and Iverson 2001). The discontinuous branching of RTA is replaced with a continuous, smooth response surface. Multivariate adaptive-regression splines provide an automatic, nonlinear stepwise regression tool that is particularly useful where variables need transformation and where interaction effects are likely to be relevant.

8.3.1.7 Providing Improved User Interfaces to Make Models Accessible

Ease of use is a key criterion for the acceptance or rejection of a model by managers, and the user interface provides the biggest opportunity for the modeler to improve ease of use. Most users of computer software now expect a graphical user interface (GUI). When the GUI is designed to be intuitive, consistent, and not redundant and to have a logical flow, potential users will be more likely to explore the utility of the model (Jacucci et al. 1996). A large number of GUI-development software packages are available to aid the construction of GUIs for models coded in almost any high-level language. A model GUI may also feature sophisticated graphical or animated output of model results, making them more readily interpreted and allowing more efficient evaluation of multiple model runs (e.g., see Figure 8.4). Object linking and embedding (OLE) and dynamic data exchange (DDE) are capabilities to embed or link data from one application software within a file of another software package. Dynamic data exchange might be used to link a spreadsheet model to a simulation model, for example. Hypertext markup language (HTML) and other Web-oriented code can be used to allow distributed modeling over the Internet. Spatial models are often constructed with a custom user interface (e.g., ArcView extensions). A common result of an enhanced user interface is an improved likelihood that decision makers will apply the model.

8.3.1.8 New Computational Technologies

Our discussion has alluded to the limits of computational technology on the development of ecological models. Computational science has combined elements of computer science, information technology, scientific modeling, and numerical analysis to allow new approaches to old problems previously handled by approximations and to deal with new problems previously considered intractable. Distributed computing combines the computing resources of separate machines that may be collocated or physically distant from each other. An example is a Monte Carlo simulation in which many repeated stochastic evaluations are distributed to several machines and returned to a single machine for collating and analysis. Any resource analysis problem involving multiple independent simulations can be conducted in this manner, with the main constraints being the control of the distribution of tasks to various machines and the load balancing required so that the final compilation of results is not delayed by machines that are slower than others. This method is appropriate to problems like the evaluation of multiple alternative scenarios.

Grid computing is somewhat more complex, involving not just simultaneous use of processing power, but the heterogeneity of resources available across a grid of machines (Foster and Kesselman 1999). An example would be the activation of and downloading of real-time data from a remote sensor, the automated processing of a query to a database for related data located on one machine, providing all of the assembled data as input to a simulation on a second machine, and processing the output of the simulation for visualization and analysis on a third machine. The major challenge in grid computing is the development of a software interface (middleware) to allow a user to analyze a problem without having to know the details of where the software, databases, available central processing unit (CPU) cycles, and other resources are located on the grid. The ideal system would allow a resource manager to pose a question (with appropriate constraints) and the middleware to assign appropriate components to different machines on the grid, automatically handling load balancing, error checking, collating, and returning of the results to the user. For example, a question might be posed regarding the effects of different land-use patterns in the future of water demands in a region. The middleware would request land-use history maps from a GIS database, send these to a machine for spatial analysis, and conduct a simulation to project alternative futures [as is done in the LUCAS system; see Hazen and Berry (1997)]. The middleware would concurrently obtain information on water-use history from a different database, correlate this information with land-use patterns, combine the water-use and land-use simulations, and provide the results to the user. Such middleware is well beyond current capabilities, but the software technology needed is developing rapidly (see the GLOBUS project at http://www.globus.org).

Alternatively, parallelization methods speed processing by breaking the problem into pieces that can be processed separately. Many ecological modeling problems clearly fit within this framework, including problems involving repeated simulations with alternative inputs, sensitivity analyses obtained by varying simulation parameters, and uncertainty analyses obtained by including or excluding certain model components or assumptions. Another benefit of parallel architectures is an improved ability to model situations that are essentially parallel in reality. Ecological systems are inherently parallel because many components vary concurrently in time and space, and interact at numerous scales. Developing appropriate parallel implementations to model these interactions is quite difficult, and only limited research has been conducted. However, the availability of parallel architectures for ecological modeling allows one to conceptualize models that may be considerably more realistic than strictly serial implementations would be. For example, Mellott et al. (1999) investigated parallel methods for an individual-based predator–prey model and point out that the parallel implementation involved quite different assumptions about individual movements and interactions than were necessary in a prior serial implementation.

8.3.2 Relevance of Advances in Model Implementation for Decision Making

The advances in model implementation outlined above will enhance decision making in the long term by allowing modelers to improve the sophistication and relevance of models. Public expectations of resource managers are steadily increasing, requiring more-definitive abilities to predict the consequences of management actions. Much of the information currently needed by managers is not available because the models have not yet been developed or provide inadequate information. This void exists, at least partly, because of limitations in computing power or analytical and conceptual-modeling capabilities. A combination of technological advances and improved dialogue between modelers and managers is needed to fully realize the potential of ecological models to enhance environmental decision making.

8.4 Communicating Model Structure and Output

Managers are reluctant to use model results for making decisions unless they are confident that they understand how the model works and that the model, in fact, accurately produces the information they require. Models that are perceived as an incomprehensible black box will not be widely used by managers. Consequently, it is critical that an implemented modeling system be adequately explained and communicated both to managers and to stakeholders affected by management decisions. A number of techniques are available to enhance the communication of models to decision makers, making their structure and function more transparent.

8.4.1 Approaches and Technologies

8.4.1.1 Artificial Intelligence

Artificial intelligence (AI) refers to a branch of computer science focused on problems associated with the acquisition, representation, and utilization of knowledge (Schmoldt and Rauscher 1996). One goal of AI research is to program computers to produce seemingly "intelligent" behavior, and this ability has several applications in ecological modeling. AI can provide an "intelligent" interface with a model, providing context-sensitive help and direction in using the model, and it can provide guidance in interpreting the results. Communication of model characteristics can be aided by interfaces that allow users to click on icons of model modules to delve deeper into the structure and assumptions behind each piece of the model. Each icon can be expanded to show the underlying knowledge used to describe the associated process and the interactions between processes. Examples of this kind of representation are the STELLA-based models (Hannon and Roth 1997) and the logic-based models mentioned in Section 8.2.2.

8.4.1.2 Gaming

Communication of model results can also be enhanced when simulation models are used in a gaming environment to determine strategies that are optimal for achieving goals. Game theory involves the mathematical analysis of abstract models of strategic competition. Such models are often used in military and economic planning and more recently in land-use decision making. In these games, the rules are clearly set forward, but the ramifications of these rules are not always apparent even though (or perhaps because) they are determined by feedback loops within the system. Sometimes unexpected or random events (such as storms) are simulated in the models. It is critical that the permissible actions, information available to each participant, and criteria for termination of the game be made clear. Typically, there is no single way to win such a game. Optimal strategies depend upon the goals of the player, and developing a variety of potential actions may help determine appropriate strategies to attain the desired outcome. The advantage of using a gaming approach in environmental decision making is that the options of decision makers can be set forward without the expense or time involved in actually implementing such options. The engaging nature of these games causes the user to become more involved in thinking about the process and interactions than they would without the gaming tool.

8.4.1.3 Dealing with Uncertainty

A key element of model communication involves appropriate attention to the uncertainties in the data, model structure, and model projections. Models always contain some errors and inaccuracies because they are simplifications of reality. One of the critical tasks in the use of models is to identify sources of uncertainty and describe the effects of these uncertainties on model predictions so that the output of the model can reliably support decision making.

Two strategies are available for dealing with model uncertainty. Many population models embrace and acknowledge uncertainty by selecting model parameters from a distribution of values instead of choosing a single value for a parameter. With this strategy, a relatively simple model is run numerous times (hundreds or thousands), producing a distribution of possible model outputs. The modeler acknowledges uncertainty because the multiple model outputs are generally presented in a statistical form (e.g., 20% of the possible outcomes result in a 10% decrease in population size). In this context, the modeler presents the results in terms of the risk of a certain event occurring. Unfortunately, probabilistic formulations of model outputs may be confusing for decision makers because clear, unequivocal answers are not provided.

An alternative to model-based risk assessment is the use of large, comprehensive models that attempt to duplicate critical natural processes. These models typically have lengthy run times, so that running them hundreds or thousands of times is not feasible. Additionally, these models are typically used for regulatory purposes, where relative answers may be insufficient. These models typically use engineering methods to optimize model parameters and to confirm the performance of the simulation. While it is not possible to remove all sources of error and uncertainty from these models, efforts are generally made to optimize model performance, to identify model sensitivity to key parameters through Monte Carlo simulation (in which certain model parameters are randomly changed), and to describe the error structure of the model by comparing model predictions to observed data. Error analysis helps the modeler identify weaknesses of the model or biases (particular scenarios in which certain state variables may be systematically underestimated or overestimated). This explicit representation of uncertainties tends to enhance communication only for modelers who are comfortable with large, comprehensive models (and not necessarily for decision makers).

8.4.1.4 Model Standards

Effective communication of model results depends upon adherence to certain standards in model development. Ecological models are used in at least two ways, conceptual exploration (research) and projection (decision making). Exploratory models are used to better understand complex natural processes so that the driving variables and relationships between variables can be studied. Exploratory models are often highly specialized, and their accuracy is evaluated in terms of the statistical variation explained by a model. Alternatively, models used in a regulatory context to support decisions and determine policies are often developed and applied by the engineering profession. Development of engineering models is usually founded on a mathematical description of conservation of mass and momentum principles. Model documentation and confirmation are critical elements in establishing the credibility of a model and its application. It is important that models, particularly those used in a regulatory context, be described in detail and that important steps in the development of a model be referenced. This specification allows users of the model to trace the development of its mathematical formulations and conceptual underpinnings to ensure that the model is properly applied. Such documentation allows models to be categorized by application, dimensionality, spatial discretization strategy, solution scheme, and temporal strategy. Within each category, efforts should be made to standardize ecological models to increase their ease of use and to increase their reliability. All model applications should undergo a rigorous, documented confirmation process involving parameterization (estimating optimum values for model parameters), calibration (adjusting model parameters and model formulation to match observed data with model predictions), and validation (verifying that the model works correctly on a data set different from the data set used for model calibration).

8.4.1.5 Visual Output

Visualization is a very powerful form of communication, as epitomized in the adage that "a picture is worth a thousand words." For models with a spatial component, GIS provides tremendous communication potential by placing model inputs and intermediate and final results in a spatial context. A good example is a model predicting gray wolf habitat in the northern lake states (Mladenoff et al. 1995). By showing the spatial distribution of input variable values and the results of model calculations, the authors make a compelling case for the utility and validity of their model.

The GIS also provides a framework for integrating information from different modeling paradigms. An example is the development of integrated forest management models, where a GIS provides the integration for timber optimization models and process models predicting wildlife habitat and biological diversity (Naesset 1997). The optimization model produces treatment schedules for forest stands, the locations of which are tracked in the GIS. A spatial model that can access the GIS can assess the potential effects on wildlife when those specific stands are harvested. Finally, GIS can act as a catalyst for stakeholder involvement (Cornett 1994). People find it much easier to relate to visualizations of data and concepts than to text and numbers. Because "seeing is believing," spatial representations of model results can lower skepticism and increase the involvement of stakeholders in the decision-making process. Maps, animations, or virtual reality pictures are understood by most users (Shepard 2000). For example, FORSYS (a cooperative for forest systems engineering) is developing graphical systems to represent the data gathered by the national forests to visually demonstrate alternative management practices (McGaughy 2001).

While model and data visualizations may be very useful, there are limitations. Just as graphs can be constructed in ways that are misleading, the huge variety of color schemes available can cause the same data to be interpreted quite differently. Visualizations of results should take account of the limitations and variations in human sight (Agoston 1987). Up to 8% of some human groups are partially color-blind (color-deficient or dyschromatopic). Ecological model applications should use color schemes that allow major results to be appropriately interpreted by these individuals (Curnutt et al. 2000).

8.4.2 Communicating Model Assumptions and Results for Decision Making

The development of high-quality ecological models will not contribute to decision making unless they provide the information that managers want. To build relevant models, the modeler must consult with managers or stakeholders from the conceptualization stage through validation and use. This level of communication will develop an understanding and trust in the model by the users, giving them a full knowledge of its strengths and weaknesses, what assumptions were made, what shortcuts were taken, and how all of these affect the validity of the model. If the managers are uncomfortable with some of the assumptions, they may collect the data needed to fill in the knowledge gaps highlighted by the modeling process. This involvement will instill a sense of ownership and trust in the model output.

8.5 Case Studies Using New Modeling Approaches for Decision Making

Two case studies illustrate how intractable resource management problems can become manageable through the use of ecological models.

8.5.1 Computational Fluid Dynamics Model for Fish Movement

Detailed fish swim-path selection at small scales can be simulated by coupling a computational fluid dynamics (CFD) model with a fish movement model (NFS) to design fish passages around turbines in a hydroelectric dam. The CFD model (the Eulerian-reference framework) describes the physical domain as a fine-scale grid composed of multiple cells. The CFD module provides discrete representations of the flow field (data are presented at cell nodes or cell faces only), and the Lagrangian module provides the framework necessary for depicting movement of individual fish (Figure 8.5).

The linkage between the CFD model and the NFS model is built with a common engineering tool known as a particle tracker (described earlier). With the coupled framework, a fish track can be envisioned as a sequence

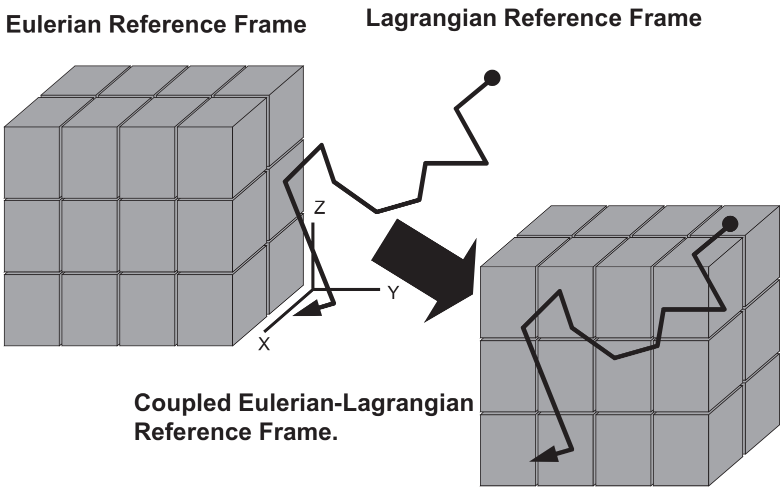

FIGURE 8.5. Merging CFD output data that uses a Eulerian reference frame with fish-track data that use a Lagrangian reference frame onto a single geospatial framework creates a coupled Eulerian–Lagrangian frame of reference.

of position pairs comprising an initial and sequential position, with the change in position determined by the sum of two different vector processes, passive transport and volitional swimming. Over short time steps (a second or less), a fish must be swimming headfirst into the current if its displacement is less than what would be predicted by passive transport because fish generally do not swim backwards. Conversely, if its displacement was greater than would be predicted by passive transport alone, it must be swimming with the current (Figure 8.6).

The simple logical progression presented by Figures 8.5 and 8.6 can become the basis of an analytical or statistical procedure to unravel how fish respond to hydraulic fields. Hydraulic information at nodes from the CFD output can be interpolated to the initial position of each position pair. With this information, it is reasonable to pose the two fundamental questions of fish swim-path selection presented in Figure 8.7: (1) What hydraulic conditions determine whether a fish is oriented with or against the current? (2) What hydraulic conditions determine the magnitude of volition swimming once the fish's orientation is known? Of course, the same logic applies to each of the vector directions.

The swim-path behavior of the virtual fish can be summarized in various ways to support decision making. For example, exit pathways of virtual fish can be summarized as the proportion using a preferred pathway, such as bypass system, versus a less-desirable passage, such as through the turbines. Such predictive simulations can be used to select optimum fish passage or fish protection designs or operations.

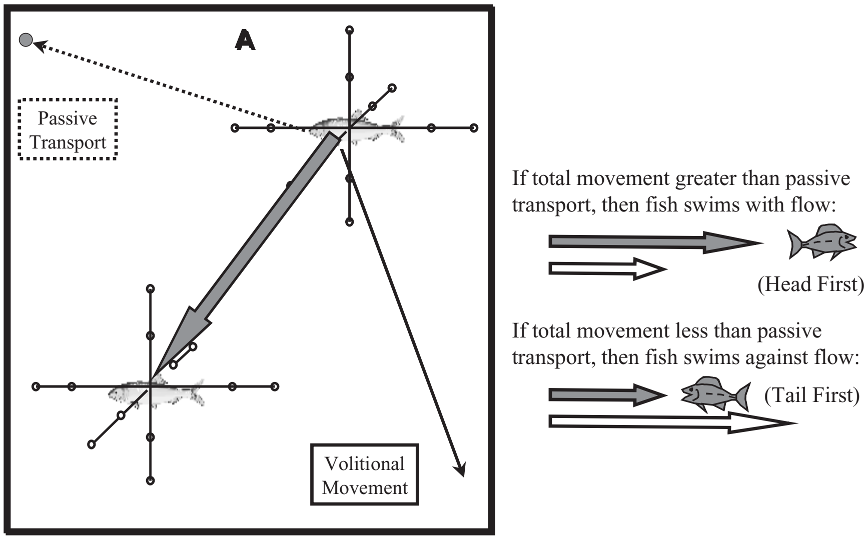

FIGURE 8.6. Hydraulic conditions interpolated to the position of the fish can be used to transport the fish through the CFD grid as though it were a neutrally buoyant, passive particle. The predicted location of the fish under passive transport can be subtracted from the known position of the fish at the next time step. The difference between the two distances represents the direction and extent of volitional swimming by and the random velocity component of the fish.

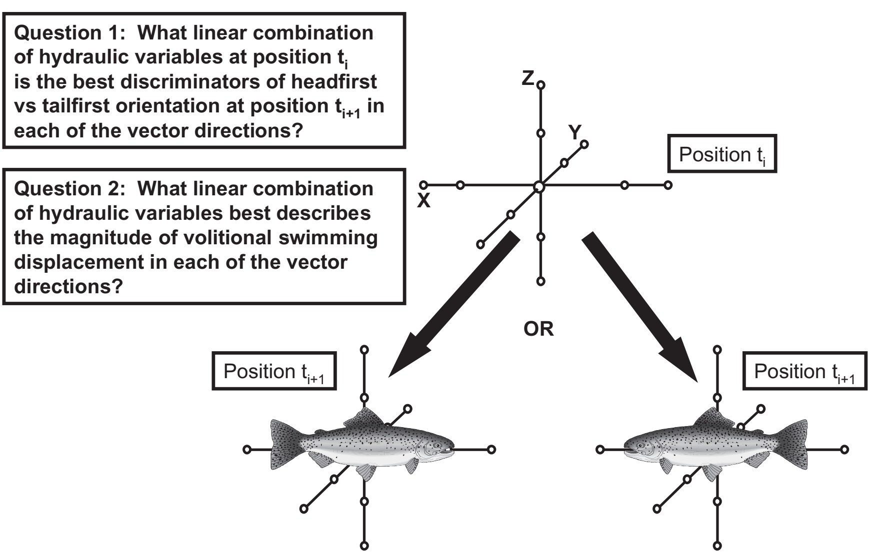

FIGURE 8.7. By comparing fish total displacement to passive transport, it then becomes possible to ask two fundamental questions.

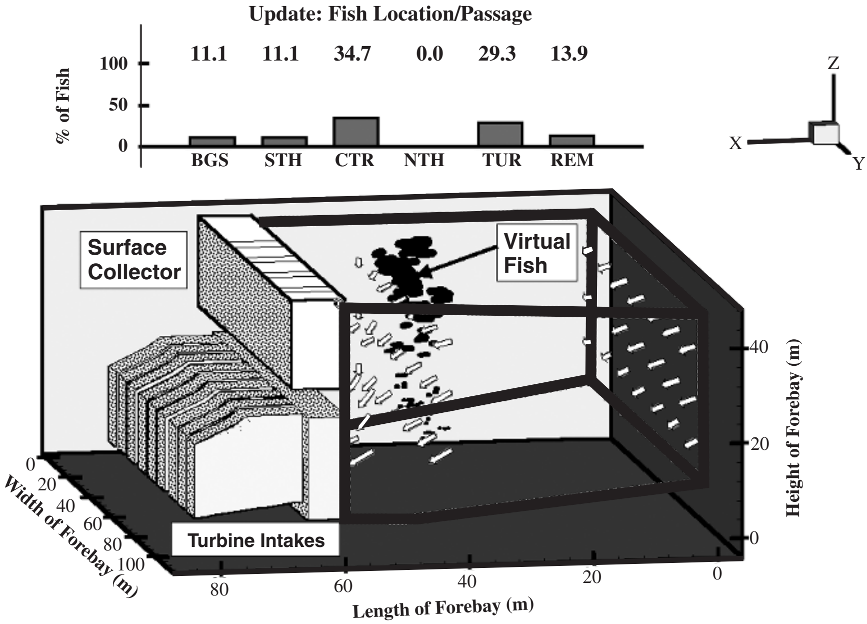

FIGURE 8.8. Example of one frame from an animation based on CFD output (represented by arrows) coupled to a swim-path-selection model for a Columbia River dam to assess the performance of a surface bypass collector. The collector attracts forebay fish to four entrances (BGS, STH, CTR, and NTH) so that outmigrating fish have an alternative passageway around the dam instead of passing through the turbines (TUR). The decision-support module (histogram at top of figure) tracks how many simulated fish exit the dam by each possible route and how many remain in the forebay (REM). The CFD was provided by Iowa Institute of Hydraulic Research and was produced with the U^2RANS model.

The use of CFD model output coupled to fish swim-behavior models is relatively new, and methods are still evolving. Extensive model calibration and verification must be made before the results of such analyses can be used for natural resources management. However, in spite of challenges, coupled models have the power to address major fishery resource management issues that currently are intractable (e.g., Figure 8.8).

8.5.2 Linked Multihierarchical Models for Decision Support

A second case study shows a new approach to integrating models to provide decision support. All natural systems have numerous interacting components operating at a variety of temporal and spatial extents. The historical approach to modeling such systems has been to break the system down into interacting subcomponents described by a dynamical system (typically ordinary differential equations) and to connect these compartments by flows of material among them (e.g., biomass and nutrients). However, this method forces the modeler to use only one mathematical approach to structure the system. New methods are developing to allow linkages among system components that take into account differing levels of detail to describe the interactions between them. Advocates of this multimodeling methodology argue that the use of a single modeling approach is inappropriate for problems spanning a wide variety of temporal, spatial, and organismal scales. Multimodeling does not refer to multiple models representing the same components of a system to determine the importance of additional detail. Rather, it refers to using different modeling approaches for different components of the system and linking these different models to study the interactions among the components.

One example of such a multimodel is the ATLSS (Across Trophic Level System Simulation) project, constructed to aid analysis of the ecological impacts of planning for the hydrologic restoration of the Everglades of South Florida (DeAngelis et al. 1998). The ATLSS uses a mixture of approaches based upon the inherent temporal and spatial resolution and extent of various trophic components, linked together by spatially explicit information on the underlying environmental (e.g., water and soil-structure), biotic (e.g., vegetation), and anthropogenic (e.g., land-use) factors. The linked components include spatially explicit indices (Curnutt et al. 2000), compartment models, differential equations for structured populations and communities (Gaff et al. 2000), and individual-based models (DeAngelis et al. 2000). Linking models that operate at very different spatial and temporal extents is a major challenge, requiring a variety of spatial interpolation methods (Luh et al. 1997) and careful design of model interfaces (Duke-Sylvester and Gross 2002). The multimodeling approach can readily be expanded to include economic, land-use, and human-population impacts, although this will require careful error-propagation analysis.

8.6 Lessons Learned from Earlier Modeling Approaches

The application of ecological models by managers has sometimes fallen short of expectations. An analysis of two examples may be instructive for ecological modelers in general.

8.6.1 FORPLAN

The FORPLAN linear-programming (LP) model was the primary analytical tool used by the U.S. Department of Agriculture (USDA) Forest Service for natural resource analysis and forest planning in the 1980s (Iverson and Alston 1986). However, FORPLAN fell from favor by the mid-1990s because three interacting factors collectively undermined the acceptability of FORPLAN solutions.

The first factor was the rapidly increasing public interest and participation in natural resource management decision making (Behan 1990; Knopp and Caldbeck 1988; Wondolleck 1988). The second factor was the agency's strategic mistake of reducing all major aspects of the problem to a single LP solution, making the models very large and often requiring dubious transformations of information in the process. But the third factor, the difficulty of explaining the derivations of FORPLAN solutions, was perhaps the most problematic (O'Toole 1983). With enormous public interest in the management implications of model solutions, this final factor was a fatal flaw. The lesson for modelers with a stake in resource management is simple: scientifically sound models are a necessary, but not sufficient, condition for successful model application in the modern public arena of resource management. Increasingly, models are expected to explain themselves in convincing and intuitive ways.

8.6.2 Habitat Suitability Index Models

Another example of a modeling approach that fell short of expectations is Habitat Suitability Index (HSI) modeling. Such models have been developed for a wide variety of wildlife species as part of a formal habitat-evaluation procedure that was extensively applied by the U.S. Fish and Wildlife Service (Verner et al. 1986). These models focus on providing a simple, formalized method for assessing impacts on wildlife habitat. The HSI models attempt to provide information useful to managers on the site characteristics that affect the use of particular habitats by a species. The models typically consist of simple relationships among habitat quality and multiple characteristics, such as canopy cover, diameter classes of trees and shrubs, tree stem densities, area of open water, and distance to forest cover. The objective is to combine these variables to provide an overall index of suitability.

The HSIs are based on local habitat variables, ignoring species interactions except those caused by the indirect effects of related habitat variables. Early HSI models ignored most landscape characteristics, making the models inappropriate for situations where the sizes, shapes, edge effects, and neighborhood relationships of habitats have a greater effect on habitat preference than local forest composition and structure. Because they are based only upon habitat variables, they cannot take account of historical factors driving local abundances, such as demography. Nor can they deal with the absence of species resulting from interactions not described by the given habitat variables, such as restrictions caused by pathogens. Considerable effort to develop new methods to ameliorate some of these limitations have been developed recently, making extensive use of remote-sensing methods (Scott et al. 2001). Though inherently static entities, HSIs can also be extended to include the dynamics of underlying environmental factors, taking account of different scales of species response both temporally and spatially (Curnutt et al. 2000).

8.7 Recommendations and Conclusions

What do these evolving approaches mean for ecological modelers? Advances in technology have progressively allowed ecological modelers to focus more of their creativity and intellect on the formulation of models (design and structure) and less on the mechanics of modeling (computer coding and debugging). Furthermore, advances in the sophistication and reliability of ecological models have attracted the attention of decision makers, who hope that models may provide critical understanding that is currently lacking. However, a gap remains between the models developed by researchers to answer research questions and the predictive tools needed by managers for sound natural resource management decisions. The questions of interest to researchers may not be directly relevant to resource managers. Our strongest recommendation for ecological modelers who wish to be relevant to managers is to talk to managers! Modelers often fail to build relevant models primarily because their perception of the needs of managers is flawed.

However, new technologies have the potential to revolutionize the field of ecological modeling. Technology is beginning to overcome many of the traditional barriers to linking models and dealing with the thorny scale issues of the past. Technology provides tremendous efficiencies by making collaborative model development easier and allowing model components to be used in multiple ways. However, to fully exploit this potential, modelers must constantly strive to think in new ways. It is now possible to consider how technology can be used to model systems as they are understood rather than to struggle to represent the system within the limits of the technology. This possibility presents great opportunity.

Ecological models will be increasingly scrutinized in the public arena. They must be defensible (perhaps in court), transparent (in assumptions and structure), and thoroughly documented and tested. Consequently, modelers must give more attention to communicating with users, decision makers, and stakeholders. The risks are high, but the needs for solid ecological models to provide decision support are growing and are critical. The payoff will come in the form of better resource management decisions and increased public support for ecological modeling research.

References

Agoston, G.A. 1987. Color Theory and Its Application in Art and Design. 2d edition. Springer-Verlag, Berlin, Germany.

Behan, R.W. 1990. RPA/NFMA: Solution to a nonexistent problem. Journal of Forestry **88**:20–25.

Bettinger P., J. Sessions, and K. Boston. 1997. Using Tabu search to schedule timber harvests subject to spatial wildlife goals for big game. Ecological Modelling **94**: 11–123.

Boggs, W. and M. Boggs. 1999. Mastering UML with Rational Rose. Sybex, San Francisco, California, USA.

Booch, G. 1994. Object-Oriented Analysis and Design with Applications. Benjamin/Cummings Publishing Company, New York, New York, USA.

Bormann, B.T., M.H. Brookes, E.D. Ford, A.R. Kiester, C.D. Oliver, and J.F. Weigand. 1994. Volume V: A Framework for Sustainable-Ecosystem Management. USDA Forest Service General Technical Report PNW-GTR-331. USDA Forest Service, Pacific Northwest Research Station, Portland, Oregon, USA.

Clark, C.W. 1976. Mathematical Bioeconomics: The Optimal Management of Renewable Resources. John Wiley & Sons, New York, New York, USA.

Clark, L.A. and D. Pregibon. 1992. Tree-based models. Pages 377–419 *in* J.M. Chambers and T.J. Hastie, editors. Statistical Models. S. Wadsworth & Brooks/Cole Advanced Books & Software, Pacific Grove, California, USA.

Cornett, Z.J. 1994. GIS as a catalyst for effective public involvement in ecosystem management decision-making. Pages 337–345 *in* V.A. Sample, editor. Remote Sensing and GIS in Ecosystem Management. Island Press, Washington, Distract of Columbia, USA.

Csuti, B., S. Polasky, P.H. Williams, R.L. Pressey, J.D. Camm, M. Kershaw, A.R. Kiester, B. Downs, R. Hamilton, M. Huso, and K. Sahr. 1997. A comparison of reserve selection algorithms using data on terrestrial vertebrates in Oregon. Biological Conservation **80**:83–97.

Curnutt, J.L., E.J. Comiskey, M.P. Nott, and L.J. Gross. 2000. Landscape-based spatially explicit species index models for Everglades restoration. Ecological Applications **10**:1849–1860.

Davis, L., K.N. Johnson, P. Bettinger, and T. Howard. 2001. Forest management. 4th edition. McGraw-Hill, New York, New York, USA.

DeAngelis, D.L. and L.J. Gross, editors. 1992. Individual-Based Models and Approaches in Ecology. Routledge, Chapman and Hall, New York, New York, USA.

DeAngelis, D.L., L.J. Gross, M.A. Huston, W.F. Wolff, D.M. Fleming, E.J. Comiskey, and S.M. Sylvester. 1998. Landscape modeling for everglades ecosystem restoration. Ecosystems **1**:64–75.

DeAngelis, D.L., L.J. Gross, W.F. Wolff, D.M. Fleming, M.P. Nott, and E.J. Comiskey. 2000. Individual-based models on the landscape: Applications to the Everglades. Pages 199–211 *in* J. Sanderson and L.D. Harris, editors. Landscape Ecology: A Top-Down Approach. Lewis Publishers, Boca Raton, Florida, USA.

Duke-Sylvester, S. and L.J. Gross. 2002. Integrating spatial data into an agent-based modeling system: Ideas and lessons from the development of the Across Trophic Level System Simulation (ATLSS). Chapter 6 *in* H.R. Gimblett, editor. Integrating Geographical Information Systems and Agent-Based Modeling Techniques for Understanding Social and Ecological Processes. Oxford University Press, Oxford, UK.

Ellison, A.M. 1996. An introduction to Bayesian inference for ecological research and environmental decision-making. Ecological Applications **6**:1036–1046.

Foster, I. and C. Kesselman, editors. 1999. The Grid: Blueprint for a New Computing Infrastructure. Morgan Kaufmann, San Francisco, California, USA.

Friedman, J.H. 1991. Multivariate adaptive regression splines (with discussion). Annals of Statistics **19**:1–141.

Gaff, H., D.L. DeAngelis, L.J. Gross, R. Salinas, and M. Shorrosh. 2000. A dynamic landscape model for fish in the Everglades and its application to restoration. Ecological Modelling **127**:33–52.

Gardner, R.H. and E.J. Gustafson. Simulating dispersal of juvenile American martens in heterogeneous landscapes. Ecological Modelling (submitted).

Goodwin, R.A., J.M. Nestler, D.P. Loucks, and R.S. Chapman. 2001. Method for simulating mobile populations in aquatic ecosystems. ASCE Journal of Water Resources Planning and Management **127**:386–393.

Gross, L.J., and D.L. DeAngelis. 2001. Multimodeling: New approaches for linking ecological models. Pages 467–474 *in* J.M. Scott, P.J. Heglund, M. Morrison, M. Raphael, J. Haufler, and B. Wall, editors. Predicting Species Occurrences: Issues of Scale and Accuracy. Island Press, Covello, California, USA.

Halpern, D.F. 1989. Thought and Knowledge: An Introduction to Critical Thinking. Lawrence Erlbaum Associates, Hillsdale, New Jersey, USA.

Hannon, B.M. and M. Roth. 1997. Modeling Dynamic Biological Systems. Springer-Verlag, New York, New York, USA.

Hazen, B.C. and M.W. Berry. 1997. The simulation of land-cover change using a distributed computing environment. Simulation Practice and Theory **5**:489–514.

Hof, J. and M. Bevers. 1998. Spatial Optimization for Managed Ecosystems. Columbia University Press, Chichester, New York, USA.

Holling, C.S. 1992. Cross-scale morphology, geometry, and dynamics of ecosystems. Ecological Monographs **62**:447–502.

Iverson, D.C. and R.M. Alston. 1986. The Genesis of FORPLAN: A Historical and Analytical Review of Forest Service Planning Models. USDA Forest Service General Technical Report INT-214. USDA Forest Service, Intermountain Forest and Range Experiment Station, Ogden, Utah, USA.

Iverson, L.R., A.M. Prasad, B.J. Hale, and E.K. Sutherland. 1999. An Atlas of Current and Potential Future Distributions of Common Trees of the Eastern United States. USDA Forest Service General Technical Report NE-265. USDA Forest Service, Northeastern Research Station, Radnor, Pennsylvania, USA.

Jacucci, G., M. Foy, and C. Uhrik. 1996. Developing transportable agricultural decision support systems: Part 1. A conceptual framework. Computers and Electronics in Agriculture **14**:291–300.

Jager, H.I. and L.J. Gross. 2000. Spatial control: The final frontier in applied ecology. Review of J.G. Hof and M. Bevers. Spatial Optimization for Managed Ecosystems. Ecology **81**:1473–1474.

Knopp, T.B. and E.S. Caldbeck. 1988. The role of participatory democracy in forest management. Journal of Forestry **88**:13–18.

Kolasa, J. 1989. Ecological systems in hierarchical perspective: Breaks in community structure and other consequences. Ecology **70**:36–47.

Levin, S.A. 1992. The problem of pattern and scale in ecology. Ecology **73**:1943–1967.

Loehle, C. 1999. Optimizing wildlife habitat mitigation with a habitat defragmentation algorithm. Forest Ecology and Management **120**:245–251.

Luh, H.-K., C. Abbott, M. Berry, E.J. Comiskey, J. Dempsey, and L.J. Gross. 1997. Parallelization in a spatially-explicit individual-based model. 1. Spatial data interpolation. Computers & Geosciences **23**:293–304.

Martin, J.L. and S.C. McCutcheon. 1999. Hydrodynamics and Transport for Water Quality Modeling. Lewis Publishers, Boca Raton, Florida, USA.

Maxwell, T. 1999. A Parsi-model approach to modular simulation. Environmental Modeling and Software **14**:511–517.

Maxwell, T. and R. Costanza. 1997*a*. A language for modular spatio-temporal simulation. Ecological Modelling **103**:105–113.

Maxwell, T. and R. Costanza. 1997*b*. An open geographic modelling environment. Simulation Journal **68**:175–185.

McGaughy, R.J. 2001. EnVision Environmental Visualization System. Miscellaneous brochure. USDA Forest Service, Pacific Northwest Research Station, Portland, Oregon, USA.

Mellott, L.E., M.W. Berry, E.J. Comiskey, and L.J. Gross. 1999. The design and implementation of an individual-based predator-prey model for a distributed computing environment. Simulation Theory and Practice **7**:47–70.

Mladenoff, D.J., T.A. Sickley, R.G. Haight, and A.P. Wydeven. 1995. A regional landscape analysis and prediction of favorable gray wolf habitat in the northern Great Lakes region. Conservation Biology **9**:279–294.

Naesset, E. 1997. Geographical information systems in long-term forest management and planning with special reference to preservation of biological diversity: A review. Forest Ecology and Management **93**:121–136.

Nestler, J.M. and V.K. Sutton. 2000. Describing scales of features in river channels using fractal geometry concepts. Regulated Rivers: Research and Management **16**:1–22.

Nestler, J.M., R.A. Goodwin, D. Degan, and D. Dennerline. 2002. Simulating movement of Blueback herring in a southern impoundment using a CEL hybrid ecological model: Application and evaluation. Transactions of the American Fisheries Society **13**:155–169.

O'Neill, R.V., A.R. Johnson, and A.W. King. 1989. A hierarchical framework for the analysis of scale. Landscape Ecology **3**:193–205.

O'Toole, R. 1983. A Citizens' Guide to FORPLAN. Cascade Holistic Economy Consultants, Eugene, Oregon, USA.

Prasad, A.M. and L.R. Iverson. 2001. Predictive vegetation mapping using a custom built model-chooser: Comparison of regression tree analysis and multivariate adaptive regression splines. Proceedings of the Fourth International Conference on Integrating GIS and Environmental Modeling (GIS/EM4): Problems, Prospects and Research needs (Banff, Alberta, Canada, 2–8 September 2000). CD-ROM. GIS/EM4, Boulder, Colorado, USA.

Pressey, R.L., H.P. Possingham, and J.R. Day. 1997. Effectiveness of alternative heuristic algorithms for identifying indicative minimum requirements for conservation reserves. Biological Conservation **80**:207–219.

Rahel, F.J. 1990. The hierarchical nature of community persistence: A problem of scale. The American Naturalist **136**:328–344.

Reynolds, K.M. 1999. NetWeaver for EMDS Version 2.0 User Guide: A Knowledge Based Development System. USDA Forest Service General Technical Report PNW 471. USDA Forest Service, Pacific Northwest Research Station, Portland, Oregon, USA.

Reynolds, K.M. 2001. A logic framework for biological assessment of forest ecosystem sustainability. Journal of Forestry **99**:26–30.

Reynolds, K., M. Jensen, J. Andreasen, and I. Goodman. 2000. Knowledge-based assessment of watershed condition. Computers and Electronics in Agriculture **27**: 315–333.

Schmoldt, D.L. and H.M. Rauscher. 1996. Building knowledge-based systems for natural resources management. Chapman and Hall, New York, New York, USA.

Scott, J.M., P.J. Heglund, M. Morrison, M. Raphael, J. Haufler, and B. Wall, editors. 2001. Predicting Species Occurrences: Issues of Scale and Accuracy. Island Press, Covello, California, USA.

Shepard, S.R.J. 2000. Visualization as a decision-support tool in managing forest ecosystems. The Compiler **16**:25–40.

Stillings, N.A., M.H. Feinstein, J.L. Garfield, E.L. Rissland, D.A. Rosenbaum, S.E. Weisler, and W.L. Baker. 1987. Cognitive Science, An Introduction. MIT Press, Cambridge, Massachusetts, USA.

Tuck, G.N. and H.P. Possingham. 2000. Marine protected areas for spatially structured exploited stocks. Marine Ecology Progress Series **192**:89–101.

Verner, J., M.L. Morrison, and C.J. Ralph, editors. 1986. Wildlife 2000: Modeling Habitat Relationships of Terrestrial Vertebrates. University of Wisconsin Press, Madison, Wisconsin, USA.

Walters, J.R. and N.R. Nielsen. 1988. Crafting Knowledge-Based Systems. John Wiley & Sons, New York, New York, USA.

Warburton, K. 1997. Social forces in animal congregations: interactive, motivational, and sensory aspects. Pages 313–336 *in* J.K. Parrish and W.M. Hamner, editors. Animal Groups in Three Dimensions. Cambridge University Press, New York, New York, USA.

Wondolleck, J.M. 1988. Public Lands Conflict and Resolution: Managing National Forest Disputes. Plenum Press, New York, New York, USA.

Zadeh, L.A. and J. Kacprzyk 1992. Fuzzy Logic for the Management of Uncertainty. John Wiley & Sons, New York, New York, USA.

Part 3

Key Issues

Section III: Data

9
Data and Information Issues in Modeling for Resource Management Decision Making: Communication Is the Key

John R. Richardson and Cory W. Berish

9.1 Introduction

Environmental decision making can be viewed as a process that is based on scientific data, with data and information flowing from the bottom up and decisions coming from the top down. The data are synthesized into information that can be used to make informed decisions (Figure 9.1). At each step there is a transformation of data to information. Any gaps or inconsistencies in this data flow degrade the foundation on which this process is based. A smooth and integrated flow from data to decisions is essential if informed decisions are to be effective and efficient. The theory is that the more informed a decision is, the more likely it will be correct and will produce the greatest benefit. The key to ensuring this smooth and integrated flow is good communication among those who produce the data, use the data in models, and analyze and apply the results of the models in making decisions (Schiller et al. 2001).

Decision implementation can be viewed as a top-down procedure, where the decisions are made at the top of an information hierarchy and flow down, often through a different pathway than the information followed on the way up and to different people than originated the information/data-flow process. This decision-making process is subject to influence by political factors that may or may not be based on sound science. The knowledge and abilities of the individuals at each stage of the process can be quite different (see Figure 9.1). For this whole process to work effectively, information and data must be relative, succinct, and comprehensible by all of those involved. A breakdown of this communication process can inhibit resource managers from making effective decisions based on sound science.

The flow of data and information from the bottom up is often based on a particular model of the working environment and varies by source. Basic data may often be collected to answer specific questions, such as what the level of dioxin is around a facility. This type of sampling takes place based

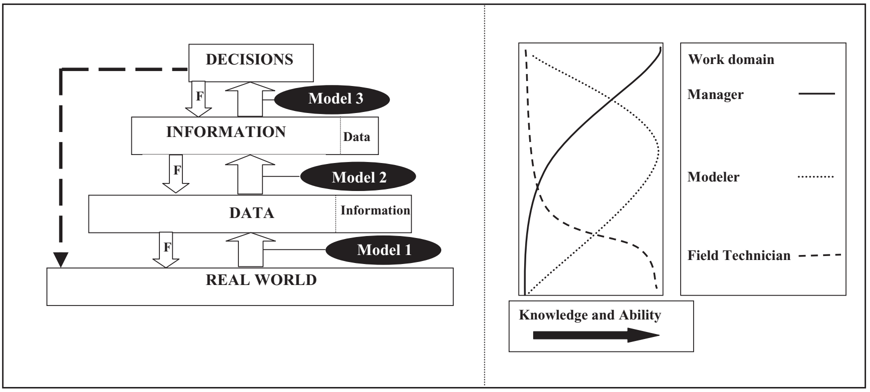

FIGURE 9.1. Hypothetical flow of data, information, and decisions in a decision-making process. At each level in the hierarchy of information flow, different models are often used to filter the data into information. Feedbacks occur at each step (F), while the decisions made by resource managers have direct effects on the real world (→). The knowledge and experience of each person involved in a decision process differ widely depending on where in the hierarchy the person works.

on a priori decisions and the spatial and temporal relevance of the sampling regime. Because field sampling is often expensive, there is usually some optimization of the regime to be economically efficient. The field data are then passed on to modelers, who build a representation of the real world that is used in the decision-making process. Unfortunately, the models that define and frame this information may or may not be built specifically for the needs of the decision makers and managers. Unsatisfactory decisions and outcomes can result from information and models not directly applicable to the problem.

Environmental assessment questions are often developed from existing data (Berish et al. 1999). Using existing data may lead to poorly developed questions, and developing environmental management decisions based on these questions, existing data, and political subjectivity can lead to poor decisions. Rarely are environmental management decisions made without political considerations and inputs from the public (Walters 1986). As discussed by Dale (in press), the development of relevant questions, with appropriate data feeding into the model, is a crucial first step.

Environmental managers often have a different background or experience than modelers do and are unable to help define explicitly useful models. Modelers often do not have the political insight or desire to include the decision-making process in an ecological process model. Sometimes the difference in technical expertise that separates the environmental decision makers from modelers is not the problem but a failure to communicate for a number of reasons. For example, at the U.S. Environmental Protection Agency (USEPA), administrators in Washington, District of Columbia, are miles away from the regional offices that collect data and implement management decisions. The individual regions are fairly autonomous, and solutions to problems used in one region may not adequately diffuse to the other regions. The research done by USEPA through the Office of Research and Development (ORD) provides a firm foundation for regulatory decisions made by the agency, but the time frame for the development of information through the research process sometimes lags behind the needs of the regional programs to make decisions regarding resource management.

The technical expertise, background, and jargon at each decision level may be so different that communication may not be optimal. Even though the same language is used, the areas of expertise may not overlap enough to provide for the best understanding of the problems and issues. This leads to the requirement that some degree of communication and participation is required at all levels of the information-flow hierarchy (Walters 1997; Rogers 1998).

Data must be acquired that fit the modeling process. Models must be developed that not only use appropriate data but also are designed to answer the appropriate questions. Options for the decision-making process should be included in the model. Ecological models often do not have appropriate links to the decision-making process to develop scenarios that aid in making resource-based decisions. Given that decision makers often do not know the limitations of models and data, the quality and quantity of data and information must be well documented for environmental resource managers to make informed decisions.

9.2 Data and Modeling Issues

One example of a successful environmental management decision-making process that included modeling was developed by a multiagency Regional Ecosystem Office (REO). The REO assembled a six-sequence procedure on how to address environmental conditions at the watershed scale (REO 1995). The REO analysis procedure is similar to USEPA's Watershed Assessment approach (USEPA 1996). The REO analysis procedures include:

- Characterization of the watershed area to be studied
- Definition of key questions
- Data collection on existing environmental conditions in the watershed relative to the key question
- Data analyses and making information available on baseline conditions

- Interpretation and refinement of the information
- Development of recommendations for watershed protection for decision makers

The process whereby questions are asked, data are collected and analyzed, and decisions made can go askew at many junctions. At the USEPA, we have experienced several common pitfalls and see several common areas to be addressed:

- Misguided conceptualization can result in imperfect or wrong questions, and therefore appropriate models are not developed.
- Existing data may be used in place of appropriate data.
- Data are misused.
- Scale and statistical validity are ignored.
- Inadequate communication is practiced.

9.3 Model Conceptualization

The question and model-conceptualization phase becomes imperfect for numerous reasons. The basic definition of a model is a simple representation of the relationship of items in the real world (see Chapter 1, this volume). Models are used to simplify the real world and make it easier to understand. The endpoint of many models is not the support of decision making but clarifying complex relationships. Models often neglect major parts of systems (basically linearizing them in the time–space domain of the model) to achieve this simplification.

Solutions to environmental problems depend on the questions being asked, available data for developing the model, and conceptual framework built into the model. Conversely, existing data often frame the model and the questions that can be asked (Figure 9.2). Often, a mismatch occurs between the questions that need to be answered and the data that exist to answer the question. Often the data that are available to the modeling process do not directly fit the model. It may be temporally irrelevant, spatially inappropriate, or acquired for a different purpose. The existing data may be able to answer other questions than the desired ones. The solutions are to (1) reframe the questions to fit existing data, (2) acquire more data that are relevant to the questions, (3) reframe the questions and acquire more data, and (4) find other tools or models that can integrate the needed questions and existing data. It is often necessary to iterate through this process to develop optimum solutions to the questions being asked. In a recent volume edited by Peine (1999) several authors discuss how existing data were used to conduct an environmental assessment, including limitations dealt with, models used, and potential applications of the information that was developed. In times of receding budgets for data gathering, the use of existing data may become even more important.

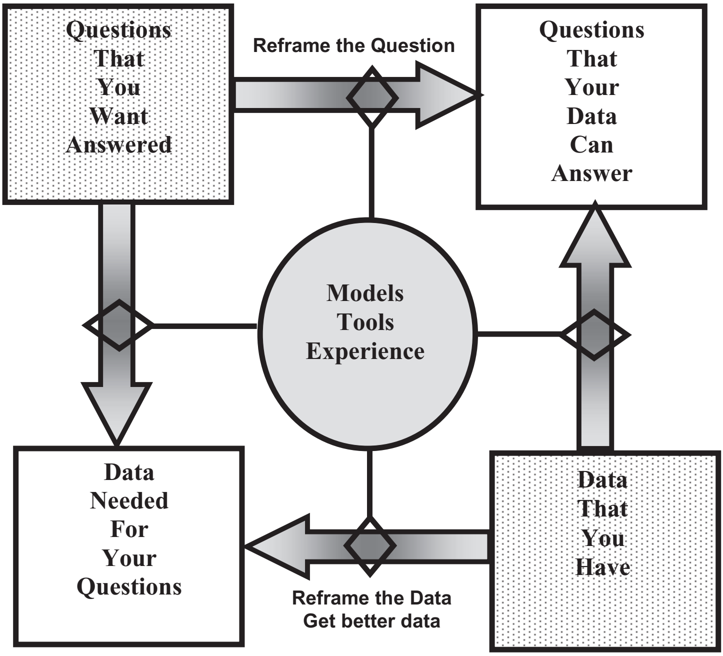

FIGURE 9.2. The process of developing questions and the data sets that can answer the questions is often iterative and cyclical. The answer that comes from this process is dependent on the question; the available data; and the models, tools, and experience of those asking the questions.

9.4 Existing Data and Misuse

Data can be misused or misinterpreted in a number of ways. Ecosystems are complex with many interactions at various levels that vary spatially and temporally. The complexity of interactions in ecosystems goes far beyond that of genetic coding, but the interaction of the four base types in deoxyribonucleic acid (DNA) provides an example of complex relationships than can be developed from only four separate entities (see Sidebar 9.1). Usually, field data or experimentally acquired data do not go beyond first-order interactions. This simplicity can make it very difficult to interpret the multiinteraction processes that occur in the real world. Often, the sampling regime is designed to linearize any other interactive effects in order to study one process at a time in an isolated manner. Optimization of this type for statistical analysis can reduce the information content and eliminate interesting nonlinear effects that might occur. It is important to understand that data acquired in this manner will often affect the development and parameterization of the models being used. Models based on these data may not have all of the appropriate interaction in the model structure. The

Sidebar 9.1
Definitions

Data and Information
Data exist as first-order information. This level represents unrelated facts. Information is developed as data are related. The combination of data and their relationships is information. Information flow up the hierarchical chain to ecosystem managers must be focused into the scope of things that the managers understand or the information will be useless.

Communications theory
Claude Shannon of Bell Laboratories (1949) came up with a way of measuring information that was based on the bandwidth needed to transmit nonredundant data. Ecologists have adapted a form of this measure (the Shannon–Weaver index) to measure diversity. This index represents the most basic structure of data, namely the presence or absence of a given entity and the amount relative to the whole of the entities measured. Information content is a representation of data that has relationships to other data. This relationship can be in time, space, or category.

Information content
The most basic information content of DNA expressed with the Shannon-Weaver (SW) index is the representation of individual nucleotides in DNA. This value is the sum of the logarithms of the probability of four separate nucleotide bases (guanine, adenine, tyrosine, and cytosine, or GATC). The contextual informational content of DNA is not just this simple index of the amount of GATC (first-order information), but base-pair SW indices (second-order information) and triplicate SW indices (third-order information) give further informational content to DNA. Because triplicates of nucleotides code for amino acids, the triplicate–triplicate SW indices give information about protein coding. The informational content thus quickly becomes a multiorder (interaction) phenomenon that can be difficult to understand at much above the protein coding level. Higher-level combinations of nucleotide sequences code for enzymes and other complex biological compounds.

In the natural world, field measurements are often only first order (quantity) because higher-order data measurements are usually difficult to make. Measuring all of the complex interactions in a swamp or other natural system is out of the range of most biological studies. By collecting pertinent and applicable data, models can be developed that represent the complex nonlinear interactions that exist in the natural world. Data collection must be able to support the level of detail and interactions in the model.

development of models is also based on ecological theory and systems principles, which may help to account for interactions and multivariate relationships that may be hidden in linear representations of field data. Model coefficients based solely on linear field data may force the model to behave in regimes for which it was not initially designed. At a minimum, the time, space, and characterization of the data must be understood in the context in which the data were acquired. This placing of the data in a contextual setting will provide a beginning to understand the caveats of the data/model/decision information flow. Know your data, know your model!

In addition, at USEPA we find that more data are not necessarily better data. With the Internet, we can easily become saturated with data and information. Web sites abound with access to databases that can easily be downloaded to an individual's computer. With such an abundance of data, determination of the applicability of individual data sets to the modeling and decision-making process can be difficult. It is important to understand the ramifications of making decisions without good data. Is such a situation any better than making wrong decisions with good data?

In the flow of data from field measurements to the resource manager or decision maker, it is imperative that contextual meaning is carried along with the flow of data. Many databases that have been in existence for a long period of time may appear to be useful for things other than that for which they were developed. An example is the STORET database that the USEPA maintains. At first glance, the data would appear to be useful in a geographic information system (GIS) context and could be used to display water-quality information spatially. The database has locational information in the attributes of sites where water-quality measurements have been made. The accuracy of the locational information is often not well documented. This drawback, however, is not the major problem of using databases like this in a GIS framework. The major problem is that the data do not always fit any rational sampling model that would allow them to be spatially mapped. The data are representative of individual sites with no spatially integrated sampling scheme. Data are often measured to fulfill permit requirements, enforcement activities, background sampling, and other ad hoc schemes. Thus, it would be very easy for uninformed GIS modelers to use STORET data in a manner that would give undesirable results. Other legacy databases have similar problems.

The necessity of metadata cannot be overemphasized. At each step in the data-gathering and modeling process, adequate documentation must be recorded to provide a firm foundation for the data processing and the following decision-making process. Metadata can be streamlined by using a form-based structure to record pertinent information at each step. The metadata should always be carried with the data. These data about data are often at least as important as the base data because they provide the context of the base data.

At USEPA, a model being used daily to determine the impact of various factors on water quality is Total Maximum Daily Loads (TMDLs). This model process is being used to help resource managers determine appropriate resource management decisions: "How much of a pollutant like nitrogen can enter a specific watershed on an annual basis?" The TMDL model then helps guide regulators to develop permit limits for future nitrogen point sources to the watershed. The TMDL model is not necessarily a prescriptive-type model because management decisions are not built into the model. It is an informational model that is used to prioritize and clarify the water-quality impacts in a watershed. In this particular case, some existing water-quality data (such as STORET) are appropriate to use based on the developed questions. Thus, the reliability of field data is a key issue for the environmental modeler because the statistical significance of the sampling point(s) may never be known to the decision maker.

9.5 Scale and Variability

Natural systems contain hierarchies of scale in time and space. Events that control ecosystems often occur as pulse events from the next higher system (Odum 1988). These control pulses organize the ecosystem in a way that maximizes energy flow and builds structure that can integrate these pulses over time and space (Holling 1992). Models that incorporate these features of differing scales in time and space and account for natural hierarchical control processes are best suited for use in developing resource management decisions. This type of model may be difficult to conceptualize and parameterize. The data needed to support these models may also be difficult to acquire.

Often, real-world data measurements that do not conform to the normal sampling distribution may be difficult to validate in a standard statistical analysis. These data represent events or processes that exist on a different time or spatial scale than the rest of the data. Linear (first-order) sampling schemes tend to disregard or throw out data that is far from the median or outside the normal distribution. Outlier data may not fit the standard statistical model, but their importance is hard to neglect. Oftentimes, the events that do not fit within the normal 95% confidence interval are the kinds of events that may control the rest of the system. Disturbance regimes often fit into a hierarchical time and spatial scale that may be difficult to measure within the time frame and spatial scale of field sampling. When they do happen, they are sometimes overlooked or discarded because their effect is far outside the 95% confidence interval of the sampling regime. Understanding the relationship of "outliers" or other nonnormal data may be very important in building a model to support resource decisions in an environment controlled by disturbance.

9.6 An Example

We would like to conclude this chapter with a condensed example of a successful environment modeling process currently underway in USEPA's Region 4.

Where are the best natural areas remaining in the southeastern United States? In response to this question, which came from the recent USEPA Region 4 administrator, John Hankinson, the USEPA began a project with the University of Florida to develop a GIS model to identify potential greenspace areas. The spatially explicit GIS model identifies areas of conservation significance and landscape linkages best suited for protecting a regionwide ecological network. The project team had previously developed the modeling protocol and the expertise for designing landscape linkages and prioritizing ecological hubs at a statewide scale for the Florida Greenways and Trails model (Hoctor et al. 2000). This particular model underwent significant public participation, comment, and peer review before being finalized and is being used to help direct $300 million per year for greenspace protection in the state of Florida. The USEPA Region 4 awarded a cooperative-agreement grant to the University of Florida Department of Landscape Architecture to develop an ecological connectivity model for the eight states in the southeast region. The purpose of the regional project is to identify lands that would aid in the protection of water resources, wetlands, and other natural areas. The following is a generalization of the individual modeling procedures that were used to develop the Southeastern Ecological Framework (SEF). Individual model steps more closely follow the model development scheme than the generalization presented here (Sidebar 9.2).

Sidebar 9.2
Basic steps in model development and data needs and inputs

Conceptualization defines the structure of the model. This is the stage where state variables and processes are defined. Interactions between the variables and the types of processes are developed from data and information from field studies, general knowledge and understanding of ecological systems, and decisions about the level of detail in the model interactions. Data requirements for this step can often be fairly general.

Calibration determines the coefficients for the state variables and flow processes. Data requirements for this and the next step are usually the most stringent. To calibrate flows and storages, the data must be relevant and accurate. There is a need to know more than just zero-order flow information. Flow values relative to the interacting processes are needed to develop models that are nonlinear. Usually, the bounds of all of the flows are not well known. Events that occur on longer time scales and at larger spatial extents than those measured may have significant consequences on the model. Generalized information or modeled data from a larger domain can be used to help set the bounds of the model.

Verification checks that the model behaves correctly with the calibration data. This analysis may require time-series data to adequately verify that the model performs as it was designed. The data set used to verify the model is usually the same as the data used to calibrate it. This practice is used to ensure that the model structure is correct and behaves in the same manner as the system being modeled.

Validation determines that the model behaves in the same manner with an independent data set. It is bad modeling practice to validate the model with the same data used to calibrate and verify the model. A second, parallel data set is required to independently validate the model. Often, when data are collected, the data set is split, and half is used to calibrate and verify, and the other half is used to validate. Validation data sets can also come from other studies of similar systems. Ensuring that the temporal and spatial characteristics of the validation data set match the model and the previously used data may be important to prevent domain errors. Validation is not always required for a model to be used.

Prediction/analysis develops data and information that can be used to support management decisions. The data derived from the model must meet the same temporal and spatial conditions as the calibration data. Validation requires that the data be within the same data frame as the input data; predictive results often go beyond the sampling area or time. As long as the model and calibration data reflect the appropriate temporal and spatial domain, the predictions with the model will have relevance. Predictions outside the time and spatial domain of the input data may not accurately reflect conditions in the real world.

GIS maps are models!

Rarely does GIS information reflect a direct relationship to what is on the ground. It is mapped through a model and has uncertainty in its spatial representation and uncertainty in its categorical data. Maps have a powerful visual impact even though they may not accurately represent the reality of what is on the ground.

9.6.1 Model Development: Calibration/Verification

The SEF incorporates the first uniform National Land Cover Data (NLCD) set to be developed at a 30-m resolution for the entire United States (Vogelmann et al. 1998). The original ecological greenways model for the state of Florida was done at a resolution of 147 m. The SEF model was developed for USEPA Region 4 (eight states: Alabama, Florida, Georgia, Kentucky, Mississippi, North Carolina, South Carolina, and Tennessee) at a 90-m resolution with a reintegration of the original land cover at 30 m. Fifteen additional data layers, such as significant ecological areas, important habitats for focal species, federally and state-managed lands, priority ecological communities, wetlands, roadless areas, floodplains, and important aquatic systems at regional and statewide scales were used to identify areas of potential conservation. Upland and riparian landscape linkages were then incorporated at a regional scale to integrate the larger areas of ecological significance into a regional network. Hubs with areas greater than 5000 acres were linked through an ecological-cost surface. The connecting pathway among the hubs represents the lowest ecological cost in going from one hub to the next.

9.6.2 Validation/Prediction

The validation of the model and GIS data layers has been primarily by peer review of the model and inputs from various workshops and presentations. The output of the model predicts where major landscape linkages could be protected or preserved to maintain the optimal connectivity between existing natural areas in the southeastern United States.

The SEF represents the area in the southeastern United States that preserves the best available land for a connected, large-scale ecosystem. The inherent ecological processes that would be preserved within this network provide a basis for watershed protection, biodiversity and wildlife conservation, wetlands mitigation, land-use planning, road right-of-way planning, wellhead protection, and many similar activities. The final ecological framework provides a basic regional landscape and natural resource planning tool (Durbrow et al. 2001).

The SEF only has value if it is used in natural resource planning and other efforts to protect greenspace and natural systems. These decisions are often at a local scale, such as county or watershed. Currently, efforts are under way to engage various federal, state, and local partners, both governmental and nongovernmental, to integrate the data and information developed in this project for resource management and protection efforts. For many planning efforts, the multitude of data layers could be of little use without a skilled GIS analyst to incorporate the data into the existing planning. So resource decision makers can use the data and information more efficiently, a simple GIS browser is being developed that will allow any user or resource manager to view the maps along with pertinent information related to the ecological framework. This combination of resource-based data and simple map interface will allow all levels of users to use the information.

The information flow in this example begins with many large data sets acquired from a variety of sources. Each of the data sets was determined to be spatially explicit enough to be included in the model. Raw field data were processed at least once to derive the data layers used in the model, although most of the data sets were acquired in a processed form. The models were developed with input from resource managers and the general public to get significant approval in the final product. As a result, the final SEF product will be packaged to facilitate its use by all interested parties.

In many natural-resource-planning projects, the real work is done at a local level. One of the important aspects of the SEF is that it was developed at a scale (30 to 90m) that could be used by local planners and resource managers. Several significant pilot projects using the data are under way and promise to provide excellent feedback for the final product.

9.7 Conclusions

To have optimum choices for environmental decision making, managers need information that is relevant and timely. Ecological/environmental models are well suited for developing the information needed to make good decisions affecting the environment. The essence of models is that they distill the important processes and variables into a simple form that can be used to understand the system being modeled and to provide insight about choices that might affect that system. The flow of data and information from real-world situations to resource managers requires that all of the people involved in the process communicate information in a timely and relevant manner. It may not be necessary for each person in the hierarchy of information flow and decision making to have a complete knowledge of all the processes, but it is imperative that they understand the overall flow of information and the caveats surrounding each step in the information hierarchy.

Resource management decisions will be made even in the absence of data, models, or relevant information. To achieve the maximum effectiveness, decisions should be made with enough information to understand the possible ramifications of those decisions. The best decision-making process will have a clear definition of the problem and issues, pertinent and adequate data, well-documented data flow, simple models with links to the environmental decisions, clear communication between modelers and resource managers, and stakeholder involvement in the process.

References

Berish, C.W., B.R. Durbrow, J.E. Harrison, W.A. Jackson and K.H. Ritters, 1999. Conducting regional environmental assessments: the southern appalachian experience. Pages 117–166 in J.D. Piene, editor, *Ecosystem management for sustainability: principles and practices illustrated by a regional biosphere reserve cooperative.* Lewis Publishers, Boca Raton.

Dale, V.H., D.T. Fortes, and T.L. Ashwood. A landscape transition matrix approach for land management. *In* J. Liu and W. Taylor, editors. Integrating Landscape Ecology into Natural Resource Management. Cambridge University Press, New York, New York, USA (in press).

Durbrow, B.R., N.B. Burns, J.R. Richardson, and C.W. Berish. 2001. Southeastern ecological framework: A planning tool for managing ecosystem integrity. Pages 352–357 *in* K.J. Hatcher, editor. Proceedings of the 2001 Georgia Water Resources Conference. University of Georgia, Athens, Georgia, USA.

EPA, 1996. Watershed Approach Framework, EPA Publication: 840S96001, June, 1966. 18pp.

Hoctor, T.S., M.H. Carr, and P.D. Zwick. 2000. Identifying a linked reserve system using a regional landscape approach: The Florida ecological network. Conservation Biology **14**:984–1000.

Holling, C.S. 1992. Cross-scale morphology, geometry, and dynamics of ecosystems. Ecological Monographs **62**:447–502.

Odum, H.T. 1988. Self-organization, transformity and information. Science **242**: 1132–1139.

Peine, J.D. 1999. *Ecosystem Management for Sustainability: Principles and Practices Illustrated by a Regional Biosphere Reserve Cooperative.* Lewis Publishers, Boca Raton.

Regional Interagency Executive Committee, 1995. Ecosystem Analysis at the watershed scale (V21) The Revised Federal Guide for Watershed Analysis, Portland, OR., p. 187.

Rogers, K. 1998. Managing science/management partnerships: A challenge of adaptive management. Conservation Ecology [online] **2**:R1. http://www.consecol.org/vol2/iss2/resp1.

Schiller, A., C.T. Hunsaker, M.A. Kane, A.K. Wolfe, V.H. Dale, G.W. Suter, C.S. Russell, G. Pion, M.H. Jensen, and V.C. Konar. 2001. Communicating ecological indicators to decision makers and the public. Conservation Ecology [online] **5**:19. http://www.consecol.org/vol5/iss1/art19.

Shannon, C.E. and W. Weaver. 1949. Mathematical Theory of Communication. University of Illinois Press, Urbana, Illinois, USA.

U.S. Environmental Protection Agency (USEPA). 1993.

Vogelmann, J.E., T. Sohl, and S.M. Howard. 1998. Regional characterization of land cover using multiple sources of data. Photogrammetric Engineering and Remote Sensing **64**:1:45–47.

Walters, C.J. 1986. Adaptive Management of Renewable Resources. Mcmillan, New York, New York, USA.

Walters, C. 1997. Challenges in adaptive management of riparian and coastal ecosystems. Conservation Ecology [online] **1**:1. http://www.consecol.org/vol1/iss2/art1.

DISCLAIMER:
The views and opinions expressed in this chapter are solely those of the authors and do not reflect the policy of the Evironmental Protection Agency.

10
Effective Ecological Modeling for Use in Management Decisions: Data Issues

David Hohler, Tom Ashwood, John R. Richardson, Lisa Mai Olsen, Noble Hendrix, and Alison Williams

10.1 Introduction: How Data Are Used in Models

Data are used throughout the modeling process, from initial identification of the question(s) to model testing and refinement. Although the nature of a specific model or set of models will determine the data required and the manner in which data are used, the following discussion provides general insights into the fundamental role of data in the modeling process. Our purpose here is to describe the different roles of data, discuss criteria to judge the appropriateness of data for a model, suggest that the process of data collection and use is iterative, and emphasize the necessity of disclosing the limitations of the data and models (Figure 10.1).

Brooks (1997) suggests a process for developing habitat-suitability-index models that may be generalized to virtually all resource models. He identifies four primary phases: development, calibration, verification, and validation. More recently, Guisan and Zimmerman (2000) suggest a similar process for habitat distribution models. Their four steps include: conceptual model, statistical formulation, calibration, and predictions that are tested against an evaluation data set. Similarly, we suggest there are five fundamental ways in which data are used in the modeling process:

1. formulation of the initial questions
2. development of the conceptual model
3. construction of the model
4. calibration/verification of the model
5. testing of the model.

10.1.1 What Is the Question?

The first question that a manager should ask before beginning a modeling exercise is "What are the specific science and management questions that are to be answered?" Clarity regarding the kind of information needed to assist the decision-making process will improve the decisions and should

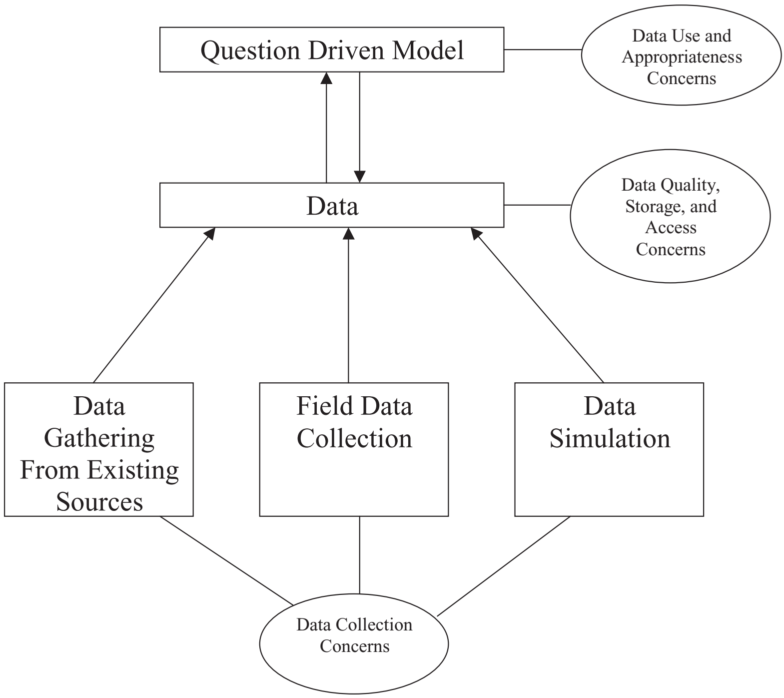

FIGURE 10.1. The fundamental concerns for the effective use of data in ecological modeling.

be first and foremost in the modeler's mind (Quigley and Cole 1997). Often, data, perhaps from a monitoring program, drive the question. The question to be answered will determine the level of detail necessary in the model. Some high-level questions may require multiple models to answer. For each of these models, it is imperative that an answerable question be defined.

10.1.2 The Conceptual Model

Once the question is defined, every ecological model should begin with a solid conceptual framework (Guisan and Zimmerman 2000). Without an adequate conceptual framework, no amount of data will provide the understanding necessary to guide management decisions (Johnson et al. 1999). To identify ecological-monitoring indicators that reflect underlying ecological structure and function requires well-developed conceptual models of the resources of concern (Barber 1994; National Research Council 1990, 1995). The conceptual model outlines the interconnections among ecosystem resources (key system components), the strength and direction of those links, and the attributes that characterize the state of the resources. The model should demonstrate how the system works, with particular emphasis on anticipated system responses to stressor input. The model also should indicate the pathways by which the system accommodates natural disturbances and how the system may acquire resilience to disturbance. These processes could be portrayed by illustrating the acceptable bounds of variation of system components and the normal patterns of variation in input and output among the model elements (Noon et al. 1999). Typically, that framework is grounded in existing data from either direct observation, extrapolation from similar studies, or ecologically sound assumptions. These data may include biological data about the organism and/or remotely sensed data about the habitat as well as other biological and abiotic data specific to the question. The conceptual model must address the question while recognizing data needs and availability to construct, verify/calibrate, test, and run the model. Once the conceptual model has been formulated, data needs can be identified and prioritized, and the process of data collection and model construction can begin.

10.1.3 Model Formulation and Construction

The conceptual model is then formalized into a set of mathematical expressions or fuzzy logic and algorithmic steps. The data required for this process typically pertain to parameter values for the mathematical expressions and related geographic information system (GIS) data.

The growing use of spatially explicit models, usually based on GIS, has led to a profusion of models in which observations of existing populations and communities are used to infer relationships among various geographic data sets and habitat requirements [e.g., Akcakaya and Atwood (1997); Gerrard et al. (2001); Knick and Dyer (1997)]. Other spatially explicit models, [e.g., Mann et al. (2000)] make predictions based on parameters that are determined from the biology of the organisms or communities. Parameterization of these models is typically based on data from literature surveys or assumptions from ecological theory. Construction and use of GIS-based models, of course, requires geographic data sets. While the use of spatially explicit models may complicate model building, it can lead to breakthroughs in large-scale understanding or the incorporation of social and economic factors into previously limited analyses (D'Erchia 1997).

10.1.4 Model Verification and Calibration

Verification is the process of confirming that the model performs as expected. The data required to verify the model must include a reasonable sample of input data and an associated set of experimental results or observations to compare with the model output. Calibration can generally be thought of as adjusting the model's parameters to improve its ability to predict the verification data set. If sufficient data are available, it is possible and common practice to use a portion of them to parameterize the model and a second portion reserved to validate the model. This verification is not a formal test of the model, merely an attempt to ensure that the model output fits the observations of the input used to construct the model.

10.1.5 Model Testing

The purpose of model testing is to determine how well the model can be extrapolated to conditions beyond those limited data under which it was constructed. The data required for model testing are similar to those required for verification/calibration. Whereas the verification data set may be small, the purposes of testing are best served by larger data sets or multiple data sets that challenge the model over a broad range of conditions. Generally, extrapolation is one of the motivations for using models to begin with. For example, Mann et al. (2000) developed a deductive, GIS-based model of threatened calcareous ecosystems (sometimes called cedar barrens or slope glades), which was verified and calibrated against small geographic data sets at Oak Ridge, Tennessee, and Fort Knox, Kentucky. The model was then extrapolated to predict the distribution of these rare communities across all of Fort Knox and across a much larger region (Missouri and Tennessee). Model testing compared the model's predicted distributions against known occurrences in these larger areas. As with most analytical procedures, it is important to examine the limits of extrapolation that result from the various components of the model, make appropriate decisions about which model components give the greatest power, and disclose the limits of extrapolation to users of the model.

10.1.6 Model Limitations

Understanding the fundamental ways that data are used, as described above, can inform the documentation of how the model may be limited. In addition, assumptions and best professional judgments are frequently substituted for field data throughout the modeling process. It is incumbent upon users to understand these assumptions as well as the strengths and limitations of the underlying data. Clearly, any limitations on the accuracy or extent of the data will affect the output of the model, so such limitations must be addressed throughout the modeling process and should be understood by and disclosed to those who use the models or their results. This documentation should accompany the model in reports, metadata, and meetings with managers to explain the modeling process and results.

10.2 Data Appropriateness Concerns

Data appropriateness does not ask the question *can* these data be used for this purpose, but instead asks the question *should* these data be used for this purpose. To determine whether data should be used for a model, it is necessary to understand the original purpose of data collection. There are no cookbooks for determining when to use a certain data set except to say that the data must not violate the assumptions of the model. The objectives for collecting the data may not have been clearly articulated even if they seemed clear to the project managers at initiation (Conquest et al. 1993). Knowing whether a particular data set is appropriate for a given model is based upon a clear understanding of the assumptions underlying both the data and the model. The key to this understanding is achieved by evaluating the metadata, or "data about data."

Metadata describe the "what, who, when, why, and how" of the data. The importance of providing and using complete metadata with models and data cannot be overestimated. Metadata are used to match up the assumptions and limitations of the data with those same factors for the model. For spatial data, the Federal Geographic Data Committee (FGDC; http://www.fgdc.gov) has developed minimum standards defining metadata. Good metadata should contain a clear definition of source, units, underlying assumptions, variability, scale, and resolution. Data limitations and qualifiers should be clearly stated or easily inferred from the metadata or supplemental "README" documentation and should be visible to the data user when accessing the data.

10.2.1 Source

Metadata should address the following questions: Who created the data? For what purpose were the data created? Were the data recorded in the field? If recorded in the field, how were the data collected? Were the data derived from remotely sensed imagery or other GIS data? Were the data simulated output from a model? These questions help determine the appropriateness of a data set for a specific use, with the purpose of data creation being the key constraint on wise data use. For example, the U.S. Environmental Protection Agency's (USEPA's) EPA 303d (Impaired Water Quality streams) data provide national coverage but were not designed to be a nationally consistent data set. Individual states were not required to use the same protocols and methods for identifying impaired waters, and so the resulting data set is a mix of different reporting methods and different criteria for classifying stream reaches. Analysis of these data, therefore, should not be used to describe national trends, and even summary information could be very misleading. Furthermore, data with a spatial component (e.g., latitude and longitude coordinates) may not have been created for pinpoint location mapping. The locations of the points may not be very accurate. Complete metadata will include information on whom to contact if there are questions about the collection, processing, and packaging of the data.

10.2.2 Units

A clear definition of units used in data measurements and representation is essential to proper data interpretation and use. Descriptive units may include units of measurement including area, volume, temperature, etc., as well as time-step definitions, such as minutes, hours, and days.

10.2.3 Assumptions

Assumptions underlying data dictate reasonable use. What has been done to the data? What has not been done to the data? Were the data collected under normal conditions? Are these data representative of a certain place or phenomenon? An understanding of the limitations of data and models is essential to good analysis.

10.2.4 Variability

Data variability, both inherent and that resulting from a sampling scheme, should be clearly documented and quantified. It includes both spatial and temporal variability. Knowledge of variability should guide the choice of sampling scheme and direct the use and interpretation of existing data.

10.2.5 Consistency in Sampling

Changes in the data collection may compromise the use of the data or change the underlying assumptions of the data. For example, if collection of data on fish species was initially obtained by trapping or netting and later by electrofishing, then assumptions about changes in population from the initial to later times may be invalid (Cairns and Smith 1993).

10.2.6 Scale/Resolution

A complete description of spatial and temporal scales and resolution are necessary to determine the appropriate use of data. Scale refers to a defined dimensional relationship between reality and the representation of reality, while resolution is a measure of the ability of a device to differentiate a value (Robinson et al. 1984). For example, a map depicting the world would be a small-scale map, while a similarly sized map depicting a county would be a large-scale map. Resolution is positively related to differentiating fine detail at a given scale. Once a data set has been formulated, changing the scale and resolution of data results in a loss of information. As a general rule, one should only compile data from larger cartographic scales to smaller cartographic scales, except in special instances, such as using field-collected data to validate remotely sensed data. In other words, one cannot add detail to data, whether it is spatial, temporal, or spectral. This is especially true with remotely sensed data (Lachowski et al. 2000).

With the proliferation of desktop GIS applications, a wealth of spatial data has become available at our fingertips. This abundance of data may, however, be a mixed blessing: "The great advantage of map data—that they are prepackaged and ready for use—is also their chief disadvantage" (Fosnight et al. 2000). Data can be obtained and used quite easily; however, the scale and classification might not be suited to a particular project. The most frequent misuse of map data "is to incorporate them into databases at scales for which they are not designed" (Fosnight et al. 2000). It is necessary to remember that digital data have accuracies that are no better than their source maps. For example, a 1:1,000,000-scale digital elevation model (DEM) is not appropriate for use at a 1:5,000 scale.

10.2.7 Projections

The geographic projections of spatial data should be described in detail within data documentation. Making assumptions regarding geographic projection can lead to inappropriate use of data and incorrect results. Spatial data that are to be used together within the context of a GIS should be of the same projection. Changing projections involves a resampling of data, and information can be lost. Therefore, it is useful to know how many times data have been reprojected and what methods were used.

10.2.8 Attribute Definitions

Good metadata should include concise definitions of data attributes. A complete understanding of attributes is critical to determining the wise use of data and the credibility of the results. Definition of variables can range from simply a full name for a field that has been abbreviated, for example, m = meters, to describing the criteria used for assigning a certain value, such as, burn = parcel has burned for more than x amount of the time within the y time period.

10.2.9 Data Limitations

Users must be made aware of data limitations. Some limitations on appropriate use may be inferred from the characteristics described above, while others must be explicitly outlined within the documentation. While data providers have the responsibility of disclosing information regarding the known limitations of their data, the ultimate responsibility lies with the user to make educated decisions regarding the appropriate use of data. As Arnold et al. (2000) point out, "Researchers and educators must sometimes walk a fine line between explaining such limitations, and undermining the perceived value of the information by detailing a long list of technical caveats."

In addition to dangers associated with the wide availability of digital data, new dangers have arisen with the advent of sophisticated software packages, including desktop GIS, models, and statistical packages. These packages allow users who may be unfamiliar with the underlying algorithms to execute complicated analyses with the click of a mouse, often leading to inappropriate results, which could lead to poor decision making. To fully understand the results, users must not only be aware of the limitations of the data, but must also determine what is being done by the software and the underlying assumptions.

10.3 Data Collection/Acquisition Concerns

The primary constraints on gathering appropriate, high-quality data are the time and resources available for data collection and acquisition efforts. In many cases, ecological models are constructed to guide management and policy decisions that must be made quickly. However, the ecological data required for the construction of models needs to be collected over a longer time scale. Available resources, such as money, equipment, and experienced personnel, can be a deciding factor as to whether data are collected by the modelers, contracted to another organization for collection, or acquired from an existing source. Often, to meet time constraints, data are obtained from existing sources, incurring a serious tradeoff among data availability, appropriateness, and quality.

The time, resources, and existing data available for a modeling project can influence decisions about the structure and function of the ecological model being constructed. All models are generalizations of the target ecological system. It is hoped that they retain the key factors that drive the system dynamics. However, the level of generalization can be constrained by the time, resources, and existing data for the modeling effort. In cases where management decisions must be made quickly, resources for data collection are limited, or the existing data are at a coarse temporal or spatial scale, the ecological model that is constructed must be very simple. Simple models that greatly generalize the system are useful as learning tools to explore the ecological system and potential management actions, but should not be relied upon for strict quantitative predictions of ecological performance. Simple models can also help focus future data collection efforts. When additional time and resources are available for data collection or the existing data closely match the desired extent and resolution, increasingly rigorous models can be built to provide quantitative predictions. Remember that even a well-parameterized model based on high-quality data can give volatile results, especially if it is based on parameters programmed to vary randomly in time and space or if it incorporates nonlinear process functions with chaotic properties. The following sections discuss methods of obtaining data and the issues that should be considered when using each type of data collection.

10.3.1 Previous Data Collection Efforts

Obtaining data from existing sources can be a cost- and time-efficient method, provided that the data are appropriate for the ecological model being constructed. With the advances in Internet and file-sharing technology and increases in monitoring programs (Beard et al. 1999), existing data from a variety of sources have become increasingly available and inexpensive. However, available data are not always appropriate data. The following concerns should be considered when obtaining data from an existing source: species appropriateness, temporal and spatial scale appropriateness, previous manipulations or analysis of the data, and measurement error.

10.3.1.1 Species Appropriateness

Are the existing data representative of the species being modeled? Existing data may be available for the same or a similar species as the one being modeled. A surrogate indicator species has characteristics, such as population density or demographic parameters, that can be used, with caution, as an index of attributes for the species of interest (Landres et al. 1988). However, as models increase in complexity, it is more difficult to find surrogate species that will accurately represent all of the characteristics of the species of interest. Species that are close in taxonomy to the species of interest are generally the best candidates for surrogate species. Even if the existing data were collected for the species of interest, intraspecific variability is a concern. Species characteristics, such as habitat and forage preferences, can vary across the geographic range of the species. For species with a large geographic range or large variation within their range, the similarity of the ecosystem's and species' traits between the existing data and those of the species being modeled should be particularly examined.

10.3.1.2 Temporal and Spatial Scale Appropriateness

Care regarding temporal and spatial variability is particularly advised when the variability is large. Two factors to consider when deciding whether to use existing data for the model are the extent and resolution of the data. Extent of the data is determined by the total spatial area of the data collection and the total length of time over which the data were collected. Resolution of the data is measured by the smallest spatial area for which data were collected and the temporal frequency of the data collection efforts. Ideally, both the extent and resolution of the existing data should match the extent and resolution of the model. Increasingly, modelers are taking into account spatial variation in ecological models. However, the variation or heterogeneity of data collected in relatively pristine areas may be different from that of more impacted systems (Stewart and Loar 1994). Further, the heterogeneity of the area of data collection will influence the relative importance of extent or resolution as the determining factor of appropriateness. In areas with broad-scale homogeneity or large patches of similar habitat, the extent of the existing data is more important than resolution to capture the existing variability. However, when fine-scale heterogeneity or small, interspersed patches pervade the area of data collection, the resolution of the existing data is more important than extent for characterizing the variability.

10.3.1.3 Degree of Manipulation

It is important to be aware of the additional assumptions that are added to the ecological model when data are obtained from an existing source. If raw field data are available, the additional assumptions added to the model are related to the sampling design and protocol for the data collection. In many situations, raw field data are not available from existing sources, and the available data have been summarized or manipulated from their raw form. Outliers may have been eliminated; data may have been smoothed, averaged, or normalized; or only ranges of particular interest may have been presented. Each of these processes would have been carried out on the basis of some assumptions, routines, or preferences. The available data may also be the output result of a previous ecological model. These characteristics do not inherently make the existing data a poor choice for a model, but it is necessary to know how the data were summarized or manipulated because the effects of these processes may affect the model and its results.

10.3.1.4 Measurement Error

Measurement error occurs when the measured sample does not accurately represent the true value in the population. This error can result from either lack of precision or bias in the data collection. With sufficient metadata, an estimate of the measurement error distribution should be included or able to be estimated. If the measurement error is known, it can be accounted for in the model, or the sensitivity of the model to the measurement error can be determined.

Overall, the decision to use existing data sources when constructing an ecological model rests on an evaluation of sufficient and accurate metadata associated with the existing data. Without metadata, it is not possible to evaluate the tradeoff between using the existing data versus investing the time and resources necessary to obtain the new data. If existing data are selected for use, the key to their success in a modeling project is the documentation and testing of the assumptions that are introduced to the model by the data.

10.3.2 Spatial Data

Whether searching for spatial data for use as direct model input, calibration data, or ancillary data, one needs to keep the specific purposes of the modeling effort in mind when selecting data. Generally, one will want to start simple and add complexity as confidence is developed that the model and data are a good fit. Using an additive process will help reduce or manage uncertainty.

In addition to intended use, time and resources will also dictate data availability. When time and resources are constrained, it is necessary to work with data that are readily available; however, the danger exists that scientific questions will then be guided by available data. There is, however, a plethora of digital spatial data available for minimal or no cost. Valuable sources of data include the literature (especially the methods sections) as well as commercial, educational, and governmental data repositories. Many of these sources are available on the World Wide Web. For example, government sources have satellite data dating back three decades and aerial photography dating back six decades for much of the United States. Most data available through federal agencies are free of charge or may carry a small cost associated with reproduction and media. In addition, many states offer impressive GIS collections. Good examples include the states of Utah, Wisconsin, and Illinois. All of the federal land and resource agencies have websites and offer data for sale or free of charge via the Internet. Web addresses have not been listed here because of their dynamic and ephemeral nature.

Good metadata are of special importance with spatial data. The FGDC was created to develop standards for data collection, analysis and dissemination. Specifically, they have been charged with "developing procedures, infrastructure, and implementation for a national digital geospatial database" (Lachowski et al. 2000). Further emphasizing the importance of spatial data standards is the National Spatial Data Infrastructure (NSDI), the role of which is to coordinate activities regarding spatial data standards among federal agencies, state and local governments, and the private sector.

10.3.3 Remotely Sensed Data

The increased accessibility of remotely sensed data raises new data issues. For example, the first major platform of the Earth Observing System (EOS), the Terra satellite, has five sensors, including the Moderate Resolution Imaging Spectroradiometer (MODIS). The MODIS receives information in 36 spectral bands (in contrast to 5 on the Advanced Very High Resolution Radiometer and 7 on the Landsat Thematic Mapper Plus) in three nested spatial resolutions (250, 500, and 1,000 m, depending on the product) and images the entire globe daily (Running et al. 2000). Large data sets with short time steps, such as MODIS data, require more effort in terms of data management. Storage and access must be considered before acquiring the data.

Plentiful data can be considered a mixed blessing because they allow for more powerful analysis but demand more planning for delivery, use, and translation for the audience (Arnold et al. 2000). As a rule, it is wise to keep a copy of all original data because important information may be lost through processing and subsetting throughout the analysis.

10.3.4 Field Data Collection

If a review of existing data reveals a lack of applicable data for the model, new data need to be collected, or the model structure needs to be modified. With the appropriate sampling methods and design, field data collection can obtain specific data for a modeling project. Although field data collection can be more expensive and time consuming than using existing data, being able to collect current species- or site-specific data at a relevant spatial scale can reduce limitations of the data for use in the model. In addition, the expense and time length of the field data collection can significantly vary, depending upon the data needed and the sampling design. The following discussion represents some of the considerations for field data collection. Sample design is an extensive topic in the ecological literature, so only a brief overview is presented here. Generally, these important topics should be considered with a statistician during the modeling process.

10.3.4.1 A Priori Concepts

A priori knowledge or beliefs about the functioning of the ecological system influence the structure of the model, the data that are perceived as necessary for the model, and the design of the data collection methods. A model reflects the modeler's perception of the system and the factors that are perceived to influence ecosystem dynamics. Although these a priori ideas may not be explicitly acknowledged, they are assumptions in the model-building process, and the modeler should be aware of potential biases.

10.3.4.2 Choice of Designs

The choice of design, whether sampling design or experimental design, is an intricate topic that involves multiple decisions and tradeoffs. The decision between conducting an experimental design or a sampling design must take into consideration data-collection objectives, the spatial and temporal scales of the required data, the populations from which data are needed, and the feasibility of the alternatives. A statistician should be consulted when making these decisions.

An experimental design, if done properly, can provide a defensible scientific approach with controls for extraneous factors, and can hence be used to test for cause–effect relationships among variables of interest (Platt 1964). However, experimental designs have their drawbacks: properly controlling for external factors may be complicated, expensive, or simply impossible given the experimental situation; replication of the experiment can be problematic in ecological situations, particularly when the spatial scale is at the landscape level; and extending an experimental design to a synoptic scope may not be feasible. On the other hand, sampling designs are common in a wide spectrum of the sciences, and can provide information on the populations of interest, as well as the distributions of and correlations between key variables.

While data observed in sampling designs can provide insights into important patterns and relationships in the ecological systems, these data cannot be used to test cause–effect relationships. Sampling designs provide observational information on target populations, not cause–effect structures with complete control for all auxiliary variables. Typically, it is too costly to analyze for all auxiliary variables at all sampling sites. Lack of information on these auxiliary variables may lead to incorrect conclusions because the missing information can lead the investigator to spurious correlations, apparent relationships that are really artifacts caused by the lack of information on underlying factors. In general, consultation with an experienced statistician is strongly recommended.

10.3.4.3 Sample Size and Sample Sites

Additional design choices must be made, whether the decision is for a sampling design or an experimental design. The investigator must determine what is an appropriate size and shape for the sampling unit. The sampling unit may be the size of a quadrat or an individual tree or a plot or a part of a landscape. The choice of the size must be based on the design requirements. Usually, the size of the sampling unit is driven by such factors as the variables to be measured, the desired resolution of the data, the scope of the study, and the existence of standard protocols that meet the data needs. By using established protocols for data collection, data are more likely to be comparable across different studies, the variability and/or distribution of the data is easier to assess from previous studies, and variability between field crews or laboratories can be easier to control. The necessary number of sampling units depends not only on the time and expense of data collection at each sample site and on the variability of the features of interest but also on the type of design selected. Optimal sampling designs and optimal experimental designs can reduce the number of samples needed to achieve the desired reliability, thus significantly reducing the cost of data collection (while at the same time possibly increasing the complexity of the analysis). For any specified experimental design, the optimum number of samples is a function of the variability of the measurements, the minimum effect size to be detected, the alpha level that is considered significant, and the power of the test (the ability of the test to determine when there are no significant effects) (Kirk 1995). However, different designs will be better able to control for effects like external variables, differing target populations, spatial autocorrelation, and treatment effects (Cressie 1993). If the variability is not available from previous studies, pilot studies, iterative sampling, or test sampling can provide estimates of the variability of the features of interest. Once the number of samples has been decided, the actual samples must be selected probabilistically from the populations of interest. The randomization method will already be determined based on the design selected.

10.3.4.4 Protocols

Following standard protocols for field sampling can enhance the applicability of the data to multiple modeling projects and can allow the estimation of measurement error. By maintaining consistency in field methods, data from multiple studies can be readily compared and combined in a model. Although measurement error is inevitable in field data collection, standard sampling protocols have generally been designed to minimize measurement error. In many cases, previous studies have been conducted on standard sampling methods to characterize the quantity and variability of the measurement error.

Overall, the collection of field data is a necessary method of obtaining data for modeling when sufficient and appropriate data are not available. The expense and time can vary significantly depending on the data needed. The key to successful field data collection is having a clear objective of what data are necessary for the model. With specific data in mind, and with the help of an experienced statistician, an experimental or observational study can be designed that will efficiently obtain the data with minimal measurement error. In this case fewer assumptions are passed along to the ecological model.

10.3.5 Data Simulation

Another method of obtaining data for ecological models is through the use of computer simulation. Data sets with known parameter values make it possible to test the accuracy of model outputs. Simulated landscapes have been used to develop generalized ecological models of landscape processes (e.g., With 1997). Simulated data are also useful for testing the sensitivity of the model to assumptions related to the model structure or the data used in the model-building process, such as assumptions regarding measurement error (Stoms et al. 1992). Like the previously discussed data collection methods, simulating data introduces assumptions into the model. Choices of parameters and data ranges to simulate, as well as the algorithms used for simulation, are important assumptions and considerations. In situations where there is not time for data collection and the ecological model is going to be used as a decision tool, simulated data for a reasonable range of model parameters can be used in a modeling process to gain insight about the system. Although quantitative predictions of realistic system behavior may not be possible, the relative importance of model parameters can be determined. This type of modeling process can then lead to improved data collection of the key model parameters (Starfield 1997).

Sensitivity analysis (SA) is the study of how the variation in the output of a model can be apportioned, qualitatively or quantitatively, to different sources of variation. A large number of sensitivity analysis methods are available in the literature (Beck 1987; Bedford 1998; Fürbinger and Roulet 1994). Each method has its advantages and disadvantages. The choice of the method to adopt to perform an SA experiment on a model is, therefore, a very delicate step that depends on a number of factors: the properties of the model under study (linearity, additivity, monotonicity, etc.); the number of input factors involved in the analysis; the computational time needed to evaluate the model; and, last but not least, the objective of the analysis (Saltelli et al. 2000).

10.4 Data Quality Concerns

Because data fundamentally influence the model through all steps of the modeling process, it is critical to identify and quantify sources of error in the data. Identifying the source of the error allows a modeler or manager to correct or manage the data appropriately. In some cases, the target population for extrapolation can be adjusted to reflect problems with the data.

10.4.1 Sources of Error in the Data

Errors in the data can be of two kinds: sampling and nonsampling errors. Sampling error is the topic of many sampling-theory texts [e.g., Cochran (1977); Kish (1995)]. These errors are based on sampling only a portion of the population rather than the entire population and on the fact that we are not certain of the relationship between the sample data and the population of interest. In addition, modeling errors, including incorrect specification of the probability distribution of the population and incorrect assumption of homogeneity of variance, can affect the model results.

Sampling errors include such issues as field measurement error, analytical errors, recording errors, coding errors, field-crew variability or drift, temporal variability of sample measurements at a field site, and spatial variability of quantities to be measured in the field. Sampling error can sometimes be estimated, most commonly by the use of properly designed quality-control programs with duplicate samples and/or replicate measurements. For example, the Forest Health Monitoring Program has successfully used quality-control data in pilot and demonstration projects to estimate the comparative magnitude of measurement error and hence to assess whether specific measurements were reliable enough to use in further program fieldwork. (Riiters et al. 1991.)

Nonsampling errors are all errors that are not sampling errors, generally attributable to the manner in which observations are made and encompassing many of the practical problems of implementing a sample design. Sources of nonsampling error include nonobservation, exclusion of certain groups or subgroups, inclusion of inappropriate sites, difficulties with definitions, and differing interpretations of class information. Quantifying nonsampling errors can be difficult and expensive because it requires multiple observations of the same phenomena. For this reason, nonsampling errors often go unnoticed. The most reasonable approach to nonsampling errors is to employ a good statistician to design the experiment or sample frame and to use an experienced researcher as an auditor. The Environmental Monitoring and Assessment Program (EMAP) and the Forest Health Monitoring Program are good examples of the careful use of a well-designed sample-site selection method based on rigorous probability-sampling techniques, and both have demonstrated the ability to adjust sample weights to handle nonsampling errors (Overton et al. 1990; Palmer et al. 1992). When using other people's data, it is imperative to have good metadata to assist in determining whether the source of the data is considered to be reliable. Quality-control data can provide information on the reliability of the data set, but are often difficult to acquire, even when they exist. Statisticians may sometimes be able to use such metadata to evaluate the data or (in rare cases) assess the validity of data points. As one example, the USEPA's Direct Delayed Response Project (DDRP) had a quality-control component sufficient to allow evaluation of individual data points so that each point in its soil chemistry database has a quality assurance (QA) flag indicating the quality of that data point (Van Remortel et al. 1988).

If no QA data or metadata are available, it may be impossible to determine the validity of any point, even apparent outliers. Still, in some cases, the data may be determined from the metadata to be from a single well-defined population. In such a case, standard statistical techniques may be of use for checking the data and assessing outliers. However, such is generally not the case with synoptic data or data collected over long time spans. Plots of the raw data can also be extremely useful. However, care must be taken because the data may represent a mixture of distributions, so that simple assessments based on normality (or other common distributions) may lead to problems.

When only summary statistics are available, one must be acutely aware of how the data were collected. Hilborn and Mangel (1997) provide an example of using summary data while assuming a normal distribution. In their example, when the raw data were correctly fit to a negative binomial distribution, a very large change in management action was recommended.

Additionally, calculating descriptive statistics may provide quantitative parameters to describe the observed patterns in plots of data. It may be useful to know how the sample mean and variance are related. Some inference of the underlying probability distribution of the data can be gleaned by calculating the coefficient of variation (CV), which is sometimes a useful measurement for displaying the variance-to-mean ratio. If the variance increases as the mean increases but the CV does not, this can indicate that the distribution may be log-normal rather than normal. The CV may become unstable when data are near the detection limit.

10.4.2 Outliers

One benefit of plotting the data is that outliers may become more evident. In descriptive statistics, the univariate descriptions of mean, mode, standard deviation, etc., may also help identify outliers. Once identified, outliers can be removed from the data set. However this must be done with caution, because outliers sometimes indicate real properties of the data, such as distributional asymmetry, or can be an "exception to the rule," which, upon further investigation, leads to new information or deeper understanding of the phenomena under study. It is always best if removal of the outlier can be justified on a basis other than its simply being an outlier. The existence of good metadata can greatly assist in this decision process. While there are quantitative methods to deal with outliers, there is always some subjectivity involved with the process (Little and Rubin 1983). In the multivariate case, some care must be taken to identify outliers because the outliers may not be identified with univariate methods over a series of variables. Robust methods to deal with outliers may use other statistics besides the mean and variance, such as the median and median deviation (Cressie 1993). In any case, managers should employ professional statisticians in developing models and particularly in the identification and removal of outliers in multivariate analysis.

10.4.3 Missing Data and Imputation

If outliers were removed or observations were simply not recorded, there will be missing data. There are several approaches to dealing with missing data: delete the record, with some loss in the quantity of information; delete the point while preserving the remaining information in the record; use a weighted estimate from a subsample of observations in which the data are present are used; adjust the definition of the target population; impute the missing or removed data points; and explicitly model the missing data (Little and Rubin 1983). The third and fourth methods approach the problem from a sampling-theoretic paradigm, while the fifth and sixth approach the problem from a modeling perspective. A statistician familiar with the data-gathering method should be consulted for recommendations and analysis if missing values are an issue. The last two methods attempt to model the missing data, and one or more assumptions must be made as to the underlying probability distribution of the data. Simple imputation has subtle problems, which are not apparent at first glance. For instance, in the simplest case of imputation, a mean value may be estimated. Although this process may not appear to affect the sample mean, it may still affect the estimate for the population and may bias the sample variance (Chernick 1983). Little and Rubin (1983) provide several situations under which data may be missing and suggest imputation techniques to deal with them. In some cases, multiple imputation methods (Little and Rubin 1987) provide better ways of modeling the data without directly imputing individual missing data points. Note that some statistical analysis techniques are relatively robust to missing data. For example, the mixed models methodology, such as is incorporated in SAS PROC MIXED, is robust to random missing observations in a multivariate, repeated measures context (Littell et al. 1996).

10.4.4 Autocorrelation

Autocorrelation occurs when samples (in either time or space) are more like neighboring samples than distant samples. In such a case, the unit of measurement (either time or distance) between sampling events is an important predictor variable. In the temporal sense, this variation in similarity may be caused by an autoregressive process, where the data are correlated but the correlation decreases as the time between observations increases. Autoregressive processes in environmental data can be even subtler because they may have seasonal patterns embedded within them. Time plots can sometimes help to show such features. Assuming that data are normally independently and identically distributed, when in fact they are not, can cause serious errors in hypothesis testing and extrapolation. The existence of spatial dependence acts to reduce the degrees of freedom, in effect decreasing the number of independent observations (Cressie 1993). This loss in degrees of freedom will increase the confidence intervals of a prediction and reduce the ability to extrapolate model results. Metadata may reveal whether autocorrelation is a problem. For example, the pilot data of the Forest Health Monitoring Program showed researchers how far apart to place subplots and measurement points within subplots for measurement categories, such as PAR (photosynthetically active radiation) and understory diversity, so that implementation plots could avoid spatial autocorrelation problems (Riitters et al. 1991).

10.4.5 Extrapolation: Information versus Data

Extrapolation requires that the structure and the variability in the data have been modeled by an understandable set of relationships, and that these relationships will be valid for the population as well as the sample. In short, we are attempting to convert data into information. For example, one use of the modeling effort may be to calculate the results of what-if scenarios. Models implicitly assume that the conditions under which the model was constructed will be the same as those under which the what-if results will be obtained. While this assumption is common and necessary for decision making, some aspects of the data quality may make such extrapolations more difficult. Instead of attempting a treatise on extrapolation, we attempt to describe particular qualities of data that may compromise a manager's ability to make decisions based on model results.

Uncertainty in both the model structure and parameter values may inhibit the ability to extract information from the modeling effort. During an analysis of the effects of parameter uncertainty on model output results, it is advisable, if possible, to separate the variation in the data caused by process (e.g., temporal variation in survival rate) from its uncertainty to other causes (e.g., sampling variation caused by finite sample size). Some techniques for accomplishing this, and the rationale behind it, are given in Gould and Nichols (1998), Steward-Oaten et al. (1995), and White (2000). Multiple working hypotheses are encouraged (Hilborn and Mangel 1997), yet some circumstances require a single modeling approach. In such instances of single model formulations or when a final model formulation has been selected, sensitivity analyses, propagation-of-error studies, or similar methods of parameter checking are a necessity. If maximum likelihood methods are being used, a profile of the parameter likelihood can also describe the amount of information present in the model structure. In a Bayesian framework, both the prior distribution and the likelihood profile should be compared to the posterior distribution to determine what effect the data have had in shaping the parameter profile. One concern in Bayesian analyses is that the prior may dominate the posterior, suggesting that no new information has been added by the data. With the above methods to obtain parameter ranges and by varying parameter values in Monte Carlo simulations, probabilistic statements can be made about specific outcomes. While this level of information may make results less clear and therefore more difficult for decision making, these types of results effectively describe the role that the data have played in forming the prediction. The USEPA's DDRP program successfully used Monte Carlo simulations to make probabilistic statements about long-term model projections (Church et al. 1989). So this technique merely introduces a manageable complication to what was already going to be a probability-based statement.

Correlated independent variables in statistical models may also present a difficulty to extrapolation. During model-fitting procedures, such as stepwise regression, correlated independent variables are typically not retained because little additional variation is explained by adding either correlated variable when the other is present. However, in instances where the two variables are likely to be targeted for management actions, there may be political, economic, or social reasons for including confounded independent variables. In cases where large numbers of interrelated variables are involved, more complex analytical techniques, such as partial least squares or principal component regression, may be used to build models without creating a list of the key variables involved.

A case study from the Pacific Northwest demonstrates that problems associated with including confounding variables and attempting to make management recommendations from the statistical model. In the arid regions of the Pacific Northwest (i.e., east of the Cascade Range), water diversions for irrigation are common. Water diversions affect salmon (*Oncorhynchus* spp.) by reducing (or removing) flows, and unscreened water diversions may intercept juvenile salmon and divert them to agricultural fields. Diversions are located primarily on the east side of the Cascades because the climate there dictates this type of irrigation. In response to growing fears over salmon declines, estimating the impact of these structures and the number of salmon that could be saved by removing the diversions was a restoration goal. Because the spatial distribution of diversions was confounded with (i.e., not homogenous or randomly distributed with respect to) various other climate, habitat, and land-use variables, the data could not support a calculation of the number of salmon that would be saved by removing the diversions (Feist et al. submitted) despite all attempts by managers to do that.

10.5 Data Storage and Management

10.5.1 Database Design

Database design is a significant topic in and of itself. The design of the database and normalization of the tables in the database need to be decided before data collection begins. Data sheets and form design are separate from database design. Most database management systems allow the database structure to be changed at any time. The problem is that, for data elements that are added, the cells of records already entered will be null. As a result, the structure of the database should not be substantially changed after data have been entered, and this structure influences how data can be retrieved (i.e., what queries are possible). Database design starts before data collection begins. Without an adequately designed database, the data that have been acquired at a large cost may not be usable to effectively address the problem. Forms should be an integral part of the design of the database and should accommodate transcription or import into the database (Conquest et al. 1993). With a good design, field sampling can often be improved with preformatted data sheets or integrated digital data collectors. Field crews can be a source of considerable error if data forms are not designed to limit errors (Conquest et al. 1993). Database design has to consider the final uses to efficiently serve the data to users.

10.5.2 Data Input

During data input, it is imperative to check and cross-check the data as they go into the database and again after data entry is complete to ensure the accuracy of the data. Handheld computers, personal digital assistants (PDAs), and forms that can be optically read on a computer are becoming common for data input. Regardless of the type of input, quality assurance/quality control (QA/QC) measures are required to ensure data accuracy.

10.5.3 Data Standards

The development of standards sometimes requires more effort than data collection and storage. There are many efforts from federal and state government agencies along with private industry to promulgate standards for data collection, measurement, QA/QC, archiving, and metadata.

The use of standards is important in developing databases that may be shared outside the realm of the initial data developer. While individual researchers have intimate knowledge of how, what, when, where, and why the data were collected and developed, other users may not be able to use the data unless adequate standards are used and the data are well documented.

10.5.4 Hardware and Software Concerns

Data storage technology seems to be growing as fast or faster than Moore's law (that computer power doubles every 18 months). Computers on the individual desktop now have more power and storage capacity than whole data centers of the recent past. Data centers have progressed to the point that the storage and manipulation of terabytes of data is currently feasible. The integration of data servers, operating systems, and server software now requires full-time support to keep the data available. The complexity of maintaining a software-based server requires a significant investment.

10.5.5 Data Backup

The only way to ensure data integrity is to have adequate backup strategies and methods. Types of data backup include

- Online mirrored backup. This type of backup requires an identical amount of online storage that the databases are backed up to on a frequent basis (often several times a day), preferably on a separate server located at a different site than the original. Data libraries that have high use and frequent updates should have this type of backup.
- Several disk drives on a single server that provide enough redundancy so, if a hardware failure occurs, they can be reconfigured quickly to restore the database. While they are technically not a backup system, they provide a type of data security.
- Tape-archive hardware and software can be automated so the backup occurs unattended. Various schemes for full and partial backups can be integrated to provide for the needs of the user. Adequate documentation about the backup process is required. Some portion of the data backups should be stored in a different place than the original database in case of fire or other catastrophic event.
- High-capacity removable storage media (such as compact disk [CD] or digital video disk [DVD]) provide the ability to store and back up data in a form that is easily restored or accessed. They can often be accessed and used more easily than tape backups but may require more operator intervention during their production than do tape backups.

10.5.6 Data Stewardship and Warehousing Groups

Historically, data were acquired, analyzed, interpreted, and reported by the individual user. After publication, the data would be archived with little or no use. With more modern technology for the storage of large quantities of data, it is possible to warehouse the data in a database that can be easily accessed by the user or shared with other users. Today, a great deal of data is held by federal and state agencies, and much of it is available over the Internet. The USEPA, U.S. Geological Survey (USGS), and other agencies have hundreds of data sets, many of which are available for downloading or accessible through direct database connectivity. In the future, users will be able to access most data sets directly and may not even have a need to keep local copies of widely available data except when more rapid access is needed. A structured-query-language (SQL) database that is available over the Internet is preferable in many ways to local copies of a database. The primary data holder can maintain and update the files and access to the data can occur when needed. Mirroring data from the primary holder is useful because it can allow faster and easier access in many cases. Mirrored data sets also act as a type of backup.

10.5.7 Network Access

In today's world, data access across a network or the Internet is becoming an important issue. Providing access to databases for a large number of users requires building databases that are well documented, easy to understand, and protected. Many software solutions exist for serving data to users across a network. The setup of these data servers should provide good service but should also protect the data from unintentional changes. Data managers should be the only ones able to modify the data. Edits or additions to the database should have well-documented procedures.

Providing full access to a database may not be what is always needed. In some cases, databases should be protected with passwords or user privileges that would prevent full-read access to all of the data. When providing network access, the bandwidth of the provider should be considered. The server must be able to provide the data to users at a rate that is satisfactory and economical.

10.6 Data Access Concerns

Access to data is an important concern when gathering data for a modeling project and deciding which outputs and data from the model to publish. Data access is a contentious issue in ecological modeling and many other scientific fields, such as medicine and engineering (Fayerweather et al. 1991; Walter and Richards 2000). Mandatory data sharing for regulatory compliance, for example with the Freedom of Information Act, and grant or funding-source requirements also play a role in determining which data are made available to the public. No sharing, voluntary sharing, and selective sharing are also choices available to the modeler (Fayerweather et al. 1991). For an ecological modeler, the type of data sharing, choice of which data to publish, and the format in which the data are published are important concerns.

10.6.1 Information versus Data

The term "data" can apply to many inputs and outputs of the modeling process. Raw field data, remote-sensing data, and processed data from the output of a model can all be inputs into an ecological model. Therefore, in terms of data access, it is important to consider what data from the modeling process should be made available. Sharing information produced from the modeling process does not necessarily include sharing raw data. Publishing raw data may be overwhelming, especially with large quantities of remote-sensing data, and provides little information to users accessing the data if they are unable to recreate the model. Publishing model outputs or analyses of the outputs provides users with more understandable information but may not convey the assumptions or uncertainties of the model, which could lead to the misuse of the model outputs.

10.6.2 Presentation of Data and Limitations Including Model and Analysis

Just as intended use and goals dictate model development and criteria for data selection, different strategies of data presentation should be used for different audiences. "Simply providing maps is not enough. Land-use decision makers need both improved [remote-sensing-]derived information and meaningful access to this information" (Arnold et al. 2000). The presentation of data, like data access, should be targeted to specific audiences, and the presentation strategies used should reflect the original goals of the project and meet the needs and expectations of the users. Never underestimate the power of models, maps, and statistics; they are a very effective way to manipulate information and can be easily misinterpreted.

10.6.3 Limiting the Sharing of Data

There are a number of arguments for limiting the sharing of data used in ecological modeling. The data or model outputs may be misused by other scientists or modelers, producing a liability to the modeler that may lead the modeler to maintain control over which data to publish and when to publish the data. The modeler has a personal claim to any plans for future projects, and publishing data increases the possibility of others stealing ideas and competing for peer recognition and future funding. Perhaps more importantly, resource protection may become an issue because the integrity of natural resources may be compromised by publishing the location and other information about the resources. For the safety of individual species, particularly endangered species, and sensitive habitats, limiting access to data on their whereabouts may lessen poaching, collecting, or other adverse ecological impacts. A final argument against the open sharing of data is the cost that is incurred by the modeler. Sharing data incurs time and resource costs to the modeler that may deplete limited funds and distract the modeler from current modeling projects. The costs can be passed along to the individuals or agencies requesting the data, but this action in effect limits access to the data and sets a precedent for restriction of data access (Macilwain 1996). So, although many public agencies are providing more access to data via the World Wide Web, personal-privacy, resource-protection, and administrative-cost issues must be considered before adopting a voluntary data-sharing policy.

10.6.4 Voluntary Data Sharing

In general, the voluntary sharing of data is encouraged and has many benefits for modelers and model users. Openness and sharing of scientific information promotes model quality and integrity. Obtaining a broader view of the system by providing data to other modelers with different backgrounds for an independent analysis of the data can enhance the credibility of the modelers and lead to improved models (Fayerweather et al. 1991). Providing access to model data also allows different modelers to gain new insights into the system and furthers the use of models in resource management. In many cases, public awareness and engagement are desired by the modelers throughout the modeling process, and free access to the data and information provides the opportunity. Providing free access to data also eliminates the duplication of data collection efforts and can decrease model development costs. In addition to voluntary data sharing, there are federal regulations that influence public agencies and researchers who obtain funds from public agencies. In a rule passed by the White House Office of Management and Budget, the Freedom of Information act applies to the access of raw data from public agencies and private researchers who receive governmental grants if the data were used as the basis for governmental regulations (Macilwain 1999). So, in some cases, public access to raw data included in the modeling process is necessary for regulatory compliance.

10.6.5 Access Policy Recommendations

Recommendations for data access policy should be made on a case-by-case basis, but several recommendations can be made for modelers. First, consider which data should be provided. Providing information and analysis of the outputs of the model does not have to include the publication of the raw data used in the modeling process. Secondly, the format in which the data are presented and the method of access to the data should be considered. If outputs from a model are published, as much information as possible about the structure, assumptions, and limitations of the model should be conveyed to the person accessing the data. Also, the method of data access is an important consideration when estimating the costs of having a voluntary data-sharing policy. For example, the publication of data via the World Wide Web may involve higher costs at the initiation of the project but is likely to be more cost effective than having to personally respond to individual requests for data over a long term. In general, for ecological modelers, a voluntary data-sharing policy would seem to be the best option for promoting openness, model credibility, and reduced model development costs, provided that possible negative consequences to resource protection are taken into consideration.

10.7 Summary Guidelines or Recommendations

To properly use data in developing ecological models,

- *Refine the management question*. What do you want or expect to learn?
- *Develop a conceptual model*. Framework without data is better than data without a framework.

- *Understand and disclose the limitations*. Understanding the limitations of the data is as important as any other aspect of the modeling process and is critical to the credibility of the project.
- *Provide and use metadata*. Reveal "where you got the data"; it is critical to understanding the limitations of the data.
- *Determine data access*. Determine who gets access to the data and in what form.

References

Akcakaya, H.R. and J.L. Atwood. 1997. A habitat-based metapopulation model of the California gnatcatcher. Conservation Biology **11**:422–434.

Arnold, C., Jr., D.L. Civco, M.P. Prisloe, Jr., J.D. Hurd, and J.W. Stocker. 2000. Remote sensing-enhanced outreach education as a decision support system for local land-use officials. Photogrammetric Engineering and Remote Sensing **66**:1251–1260.

Barber, M.C., editor. 1994. Environmental Monitoring and Assessment Program Indicator Development Strategy. EPA/620/R-94/022. U.S. Environmental Protection Agency, Office of Research and Development, Environmental Research Laboratory, Athens, Georgia, USA.

Beard, K., H.N. Hengartner, and D.K. Skelly. 1999. Effectiveness of predicting breeding bird distributions using probabilistic models. Conservation Biology **13**:1108–1116.

Beck, M.B. 1987. Water quality modeling: A review of the analysis of uncertainty. Water Resources Research **23**:1393–1442.

Bedford, T. 1998. Sensitivity indices for (tree-) dependent variables. Pages 17–20 *in* K. Chan, S. Tarantola, and F. Campolongo, editors. Proceedings of the Second International Symposium on Sensitivity Analysis of Model Output (SAMO98). EUR report 17758 EN. European Commission, Luxembourg.

Brooks, R.P. 1997. Improving habitat suitability index models. Wildlife Society Bulletin **25**:163–167.

Cairns, J. and E.P. Smith. 1993. The statistical validity of biomonitoring data. Pages 49–68 *in* S.L. Loeb and A. Spacie, editors. Biological Monitoring of Aquatic Systems. Lewis Publishers, Boca Raton, Florida, USA.

Cochran, W.G. 1977. Sampling Techniques. John Wiley & Sons, New York, New York, USA.

Conquest, L.L., S.C. Ralph, and R.J. Naiman. 1993. Implementation of large-scale monitoring efforts: Sampling design and data analysis issues. Pages 69–90 *in* S.L. Loeb and A. Spacie, editors. Biological Monitoring of Aquatic Systems. Lewis Publishers, Boca Raton, Florida, USA.

Chernick, M.R. 1983. Influence functions, outlier detection, and data editing. Pages 167–176 *in* T. Wright, editor. Statistical Methods and the Improvement of Data Quality. Academic Press, London, UK.

Church, M.R., K.W. Thornton, P.W. Shaffer, D.L. Stevens, B.P. Rochelle, G.R. Holdren, M.G. Johnson, J.J. Lee, R.S. Turner, D.L. Cassell, D.A. Lammers, W.G. Campbell, C.I. Liff, C.C. Brandt, L.H. Liegel, G.D. Bishop, D.C. Mortenson, S.M. Pierson, and D.D. Schmoyer. 1989. Direct/Delayed Response Project: Future Effects of Long-Term Sulfur Deposition on Surface Water Chemistry in the Northeast and Southern Blue Ridge Province. 1989. EPA/600/3-89/061a-d. U.S. Environmental Protection Agency, Washington, District of Columbia, USA.

Cressie, N.A.C. 1993. Statistics for Spatial Data. John Wiley & Sons, New York, New York, USA.

D'Erchia, F. 1997. Geographic information systems and remote sensing applications for ecosystem management. Pages 201–225 *in* M.S. Boyce and A. Haney, editors. Ecosystem Management: Applications for Sustainable Forest and Wildlife Resources. Yale University Press, New Haven, Connecticut, USA.

Fayerweather, W.E., S.L. Tirey, J.K. Baldwin, and B.K. Hoover. 1991. Issues in data sharing and access: An industry perspective. Journal of Occupational Medicine **33**:1253–1256.

Feist, B.E., E.A. Steel, G.R. Pess, and R.E. Bilby. What is the correct scale for habitat analyses aimed at prioritizing restoration efforts for salmon? Conservation Biology (submitted).

Forman, R.T.T. and M. Godron. 1986. Landscape Ecology. John Wiley & Sons, New York, New York, USA.

Fosnight, E.A. and D. Greenlee. 2000. Map data in support of forest management. Journal of Forestry **98**:50–52.

Fürbinger, J.M. and A.C. Roulet. 1994. Sensitivity analysis, an unavoidable step in the evaluation of simulation program. Presented at European Conference on Energy Performance and Indoor Climate in Building, Lyon, France, 24–26 November, 1994.

Gerrard, R., P. Stine, R. Church, and M. Gilpin. 2001. Habitat evaluation using GIS: A case study applied to the San Joaquin kit fox. Landscape and Urban Planning **52**:239–255.

Gould, W.R. and J.D. Nichols. 1998. Estimation of temporal variability of survival in animal populations. Ecology **79**:2531–2538.

Green, K. 2000. Selecting and interpreting high-resolution images. Journal of Forestry **98**:37–39.

Guisan, A. and N.E. Zimmerman. 2000. Predictive habitat distribution models in ecology. Ecological Modeling **135**:147–186.

Hilborn, R. and M. Mangel. 1997. The Ecological Detective: Confronting Models with Data. Princeton University Press, Princeton, New Jersey, USA.

Johnson, K.N., F. Swanson, M. Herring, and S. Greene. 1999. Bioregional Assessments. Island Press, Washington, District of Columbia, USA.

Kirk, R.E. 1995. Experimental Design: Procedures for the Behavioral Sciences. Brooks/Cole, Pacific Grove, California, USA.

Kish, L. 1995. Survey Sampling. John Wiley & Sons, New York, New York, USA.

Knick, S.T. and D.L. Dyer. 1997. Distribution of black-tailed jackrabbit habitat determined by GIS in southwestern Idaho. Journal of Wildlife Management **61**:75–85.

Lachowski, H., P. Maus, and N. Roller. 2000. From pixels to decisions: Digital remote sensing technologies for public land managers. Journal of Forestry **98**:13–15.

Landres, P.B., J. Verner, and J.W. Thomas. 1988. Ecological uses of vertebrate indicator species: A critique. Conservation Biology **2**:316–327.

Littell, R.C., G.A. Milliken, W.W. Stroup, and R.D. Wolfinger. 1996. SAS System for Mixed models. SAS Institute, Cary, North Carolina, USA.

Little, R.J.A. and D.B. Rubin. 1983. Missing data in large data sets. Pages 73–82 *in* T. Wright, editor. Statistical methods and the improvement of data quality. Academic Press, London, UK.

Little, R.J.A. and D.B. Rubin. 1987. Statistical Analysis with Missing Data. John Wiley & Sons, New York, New York, USA.

Mann, L.K., A.W. King, V.H. Dale, W.W. Hargrove, R.A. Washington-Allen, L.R. Pounds, and T.L. Ashwood. 1999. The role of soil classification in GIS modeling of habitat pattern: Threatened calcareous ecosystems. Ecosystems **2**:524–538.

Macilwain, C. 1996. Researchers resist copyright laws that could endanger data access. Nature **383**:653.

Macilwain, C. 1999. US university fears allayed over access to research data. Nature **401**:732.

National Research Council (NRC). 1990. Managing Troubled Waters: Role of Marine Environmental Monitoring. National Academy Press, Washington, District of Columbia, USA.

National Research Council (NRC). 1995. Review of EPA's Environmental Monitoring and Assessment Program: Overall Evaluation. National Academy Press, Washington, District of Columbia, USA.

Noon, B.R., T.A. Spies, and M.G. Raphael. 1999. Conceptual basis for designing an effectiveness monitoring program in the strategy and design of the effectiveness monitoring program for the Northwest Forest Plan. Pages 21–48 *in* B.S. Mulder, B.R. Noon, T.A. Spies, M.G. Raphael, C.J. Craig, A.R. Olsen, G.H. Reeves, and H.H. Welsh, editors. The Strategy and Design of the Effectiveness Monitoring Program for the Northwest Forest Plan. General Technical Report PNW-GTR-437. U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station, Portland, Oregon, USA.

Overton, W.S., D. White, and D.L. Stevens. 1990. Design report for EMAP–Environmental Monitoring and Assessment Program. EPA/600/3-91/053. U.S. Environmental Protection Agency, Washington, District of Columbia, USA.

Palmer, C.J., K.H. Riitters, T. Strickland, D.L. Cassell, and G.E. Byers. 1992. Monitoring and Research Strategy for Forests—Environmental Monitoring and Assessment Program (EMAP), volume 1. EPA/600/4-91/012. U.S. Environmental Protection Agency, Environmental Monitoring Systems Laboratory, Las Vegas, Nevada, USA.

Platt, J.R. 1964. Strong inference. Science **146**:347–353.

Quigley, T.M. and H.B. Cole. 1997. Highlighted Scientific Findings of the Interior Columbia Basin Ecosystem Management Project. General Technical Report PNW-GTR-404. U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station, Portland, Oregon, USA.

Riitters, K., M. Papp, D. Cassell, and J. Hazard, editors. 1991. Forest Health Monitoring Plot Design and Logistics Study. EPA/600/S3-91/051. U.S. Environmental Protection Agency, Office of Research and Development, Research Triangle Park, North Carolina, USA.

Robinson, A.H., R.D. Sale, J.L. Morrison, and P.C. Muehrcke. 1984. Elements of Cartography. 5th edition. John Wiley & Sons, New York, New York, USA.

Running, S.W., L. Queen, and M. Thornton. 2000. The Earth Observing System and forest management. Journal of Forestry **98**:29–31.

Saltelli, A., K. Chan, M. Scott, editors. 2000. Sensitivity Analysis. John Wiley & Sons, New York, New York, USA.

Scheaffer, R.L., W. Mendenhall, and L. Ott. 1990. Elementary Survey Sampling. 4th edition. Duxbury Press, Belmont, California, USA.

Starfield, A.M. 1997. A pragmatic approach to modeling for wildlife management. Journal of Wildlife Management **61**:261–270.

Stewart, A.J. and J.M. Loar. 1994. Spatial and temporal variation in biomonitoring data. Pages 91–124 *in* S.L. Loeb and A. Spacie, editors. Biological Monitoring of Aquatic Systems. Lewis Publishers, Boca Raton, Florida, USA.

Stewart-Oaten, A., W.W. Murdoch, and S.J. Walde. 1995. Estimation of temporal variability in populations. American Naturalist **146**:519–535.

Stoms, D.M., F.W. Davis, and C.B. Cogan. 1992. Sensitivity of wildlife habitat models to uncertainties in GIS data. Photogrammetric Engineering and Remote Sensing **58**:843–850.

Van Remortel, R.D., G.E. Byers, J.E. Teberg, M.J. Miah, C.J. Palmer, M.L. Papp, M.H. Bartling, A.D. Tansey, D.L. Cassell, and P.W. Shaffer. 1988. Direct/Delayed Response Project: Quality Assurance Report for Physical and Chemical Analyses of Soils from the Southern Blue Ridge Province of the United States. EPA/600/8-88/100. U.S. Environmental Protection Agency, Washington, District of Columbia, USA.

Walter, C. and E.P. Richards III. 2000. When does the Freedom of Information Act apply to privately held data produced under a federal grant? IEEE Engineering in Medicine and Biology **19**:121–125.

White, G.C. 2000. Population viability analysis: Data requirements and essential analyses. Pages 288–331 *in* L. Boitani and T.K. Fuller, editors. Research Techniques in Animal Ecology: Controversies and Consequences. Columbia University Press, New York, New York, USA.

With, K.A. 1997. The application of neutral landscape models in conservation biology. Conservation Biology **11**:1069–1080.

Part 3

Key Issues

Section IV: Toolkits

11 Effective Use of Ecological Modeling in Management: The Toolkit Concept

Steven M. Bartell

11.1 Introduction

The incorporation of ecological and environmental models into the process of environmental management may be facilitated through the development of a "toolkit." Such a toolkit would identify existing ecological and environmental models relevant to environmental management and provide for the effective and efficient implementation of these models in a management decision-making framework. In this discussion, ecological models refer to those constructs that explicitly describe the dynamics of individual organisms, populations, communities, or ecosystems. Environmental models describe the spatial or temporal dynamics of physical, chemical, and other habitat features, but might not directly consider biological or ecological properties or their dynamics. For example, models that describe the transport and distribution of chemicals in air, soils, sediments, or surface waters without addressing bioaccumulation would be environmental models but not necessarily ecological models. Clearly, both categories of models can contribute importantly to environmental management.

This chapter briefly outlines alternative structures of an ecological modeling toolkit in support of environmental management and decision making. The toolkit is considered from the perspective of "model makers" and "model users." Issues important to both communities are highlighted. The chapter tabulates several examples of modeling approaches that have proven useful in environmental management. Finally, conclusions and recommendations are made concerning the development of an environmental manager's modeling toolkit.

11.2 The Toolkit Concept

Alternative concepts for an environmental modeling toolkit may describe a continuum between simple collections or organized libraries of models to highly interactive, dynamic, and self-designing systems (Figure 11.1). One

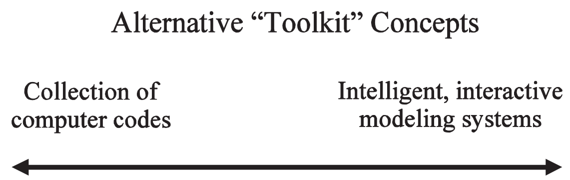

FIGURE 11.1. A gradient of alternative toolkit designs.

concept of the toolkit embraces the idea that a collection of scientifically credible, generally accepted, and reliable resource management models can and should be made available to assist decision makers. These models could become the "tools of the trade" for environmental managers. The emphasis is on using existing models to assist in the management decision-making process; the model results will not directly determine environmental management decisions.

Alternatively, the toolkit can be envisioned as more than a collection of models: the toolkit can become a highly integrated, operational decision support system that is interactive with the environmental or resource manager [e.g., Garcia and Armbruster (1997)]. Under this concept, future environmental managers will be able to invoke a toolkit that will interactively guide them in selecting an appropriate model from a distributed, global library (or assist the manager in developing the necessary model), link in the needed data sets, perform the model calculations, assist in the analysis and visualization of model results, and facilitate the incorporation of the model results and analyses into an operational decision-making framework. The toolkit will be virtual and dynamic and will be derived from an Internet-based, self-building process in which model makers and model users freely interact to continually build and modify the toolkit to meet their specific resource management needs. Again, this toolkit would support the decision-making process, not make decisions. Although the concept is somewhat futuristic, many of the components of such a toolkit already exist.

11.3 Toolkit Implementation

After the fundamental nature of the toolkit has been determined, the next challenge is to identify appropriate tools for inclusion. The development of the toolkit requires considerations from the viewpoint of model makers and model users. These two groups are inclined to view models from different perspectives that can be summarized in terms of whether or not a model predicts an impact and whether or not a predicted impact occurs (e.g., Figure 11.2).

		Adverse impact predicted: True	Adverse impact predicted: False
Adverse impact observed	**True**	**Model accurately predicts that an environmental effect will occur**	**Model fails to predict an environmental effect – Model maker's ruin**
	False	**Model predicts an environmental effect when none actually occurs – Model user's ruin**	**Model accurately predicts that no effect will occur**

FIGURE 11.2. Perspectives concerning the development and use of modeling tools in environmental decision making.

11.3.1 Model Makers

Model makers (and users) desire models that accurately and reliably predict the occurrence or nonoccurrence of a particular environmental impact [e.g., Burns (1986)]. Model makers strive to avoid the dissemination of models that might fail to forecast an actual impact (i.e., model maker's ruin). One problem model makers face is that of providing the management community with models that cannot be validated for all conceivable applications. It remains neither possible nor desirable to completely specify an ecological system in the form of a model. Therefore, making simplifying assumptions is an unavoidable aspect of the modeling process. Because of such simplifications, all ecological and environmental models are invalid descriptions at some level of structural and functional detail. Model validity has also been addressed from the perspective of comparing model predictions with available data. Because the results of all possible future model–data comparisons cannot be evaluated, ecological and environmental models can never be "validated" from this perspective. Under these kinds of constraints, the model maker must determine the conditions (e.g., initial conditions, regions of model parameter space, and environmental forcing functions) where the model has been demonstrated to perform with sufficient accuracy and precision to support correct and reliable decision making. These conditions define a domain of applicability for the model (Figure 11.3). The model maker works to increase the domain of applicability through continued data collection, model testing, and model refinement. From the viewpoint of the model maker, all models are by definition invalid; however, some are useful (Mankin et al. 1975).

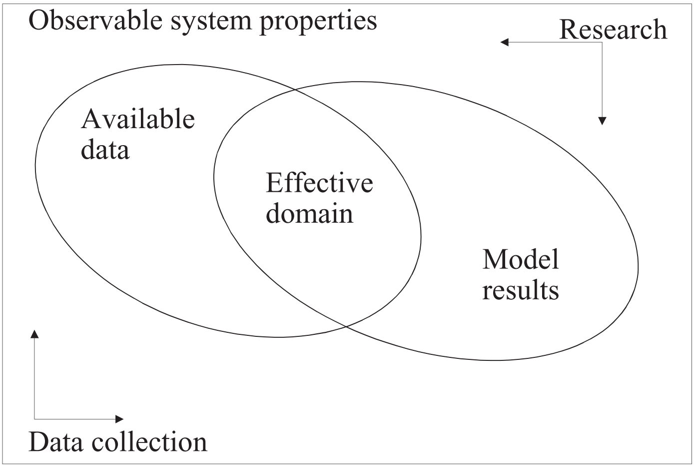

FIGURE 11.3. Defining the conditions for reliable model application in relation to model development and available data. Area of overlap refers to model results that agree with data and describes the effective domain of the model [modified from Mankin et al. (1975)].

11.3.2 Environmental and Ecological Models

If the toolkit serves mainly as a library or repository for approved models, several questions must be successfully addressed:

- What kinds of ecological and environmental models should be included in the toolkit?
- What are the criteria that should be used to qualify or disqualify models for inclusion?
- Will separate toolkits be developed to support different management objectives and organizations (e.g., fisheries, forestry, and toxic chemicals)?
- Should ecological models already used routinely in resource management (e.g., habitat suitability index models) be forced into a toolkit?
- Will each toolkit become a highly regulated and controlled software product whose distribution and use will be closely guarded and monitored by each resource agency?

Literally hundreds of ecological models have been developed and published in the peer-reviewed technical literature (Pastorok et al. 2001). Apart from narrowly defined reviews and summaries [e.g., Campbell and Bartell (1998); Jorgensen et al. (1996); Suter and Bartell (1993); Barnthouse (1992); Emlen (1989); Barnthouse et al. (1986)], the identification and collation of potentially useful models for resource management requires comprehensive and costly literature searches.

It may prove daunting to identify and examine the models in any meaningful way for inclusion in the toolkit. Nevertheless, a recent survey and evaluation of ecological models by the Chemical Manufacturers Association identified and examined more than 100 models and determined their relevance for assessing ecological risks posed by toxic chemicals (Pastorok et al. 2001). Specific criteria were defined, and each model was examined in light of those criteria. The criteria are:

- *Realism*—Accuracy and comprehensiveness of the biology, ecology, and environmental processes included in the model;
- *Relevance*—Applicability of the model objectives and outputs for assessing ecological risk;
- *Flexibility*—Feasibility of applying the model to different problems and locations;
- *Uncertainty analysis*—Whether or not the model is conducive to sensitivity and uncertainty analysis;
- *Degree of development*—General acceptance of the model by the scientific community;
- *Parameter estimation*—Number of model parameters and the feasibility of their accurate estimation;
- *Regulatory acceptance*—Adoption of the model for use by a regulatory agency;
- *Credibility*—Adequate comparisons of model results to data; and
- *Resource requirements*—Level of effort required to implement the model

These or similar criteria could be used to identify and evaluate ecological and environmental models for inclusion in the toolkit. Criteria for model evaluation and model selection might vary in relation to specific management objectives.

Ecological and environmental models have proven useful for various environmental management issues and challenges (Table 11.1). Major motivations for the toolkit concept include the desire to increase the use of models in environmental management where models are already used and to introduce models into management where models have not historically been used.

If the toolkit is conceived as becoming highly integrative and interactive in decision support, technologies that facilitate these features will have to be identified, as well (Table 11.2). Such an interactive toolkit would include state-of-the-art computer hardware and software technologies that would facilitate the design and implementation of ecological and environmental models. These tools would also provide for the presentation, analysis, and visualization of model results. This concept of the toolkit would both describe and convey the modeling results to the decision-making process. The continuing evolution of object-oriented programming and the Internet afford an opportunity for the development of the toolkit as a highly distributed network (e.g., national or international).

Table 11.1. Examples of models that have been used in environmental resource management.

Model	Description and application	Reference
AGNPS	Spatial–temporal transport of nutrients and pesticides in surface waters; examines pesticide and nutrient runoff from agricultural applications of these chemicals	Young et al. 1986
PRZM	Surface runoff, erosion, leaching, and movement of agricultural chemicals; emphasizes leaching of pesticides into groundwater	Carsel et al. 1984
BASINS	Point and nonpoint source watershed model; integration of geographic information system (GIS) and model algorithms for estimating toxic chemical loadings from watersheds into surface waters	www.epa.gov/OST/BASINS
HSPF	Watershed hydrological simulation program; simulates streams flows	Johanson et al. 1981
SEISMIC	Spatial environmental information system for managing chemical impacts	Hollis et al. 1993
QUAL2E	Riverwater-quality model; applications in assessments of nutrients, ecological production, and dissolved oxygen in surface waters	Brown and Barnwell 1987
ECoS	Water-quality model for estuarine ecosystems	Harris et al. 1984
HEP	Habitat evaluation procedures; applications in ecosystem restoration and management involving habitat improvement for selected fish and wildlife	USDI 1980
FINMAN	Decision support model used in multiobjective management of tropical grouperoid fisheries	Ault and Fox 1989
ADSS/IREM	Integration of GIS and habitat evaluation procedure models for integrated river basin environmental management; applications to Lonetree Wildlife Management Area, North Dakota	Garcia and Armbruster 1997

Table 11.2. Modeling capabilities in support of an interactive toolkit.

Multi- and parallel-processing computers
Efficient, distributed global networking and communication
High-level programming languages (Java, Visual C++, C, and Fortran-90)
Artificial-intelligence and expert-system technologies
Graphic user interfaces
Geographic information systems (GIS)
Data visualization methods
Animation (e.g., VRML)

11.4 The Toolkit and Environmental Management

Discussions of the structure of the toolkit and its contents benefit from considering the nature of specific resource management decisions and how such decisions are actually made. Such consideration further benefits from insights provided by those resource managers who participate in toolkit development.

11.4.1 Model Users

The design and construction of the toolkit must reflect the needs of the model users. The primary user group, by definition, includes those individuals charged with making decisions that potentially affect environmental resources (e.g., land use, forests, fisheries, water quality, and agricultural chemicals), including resource planners, environmental engineers, applied ecologists, resource managers, risk analysts, and environmental lawyers. The toolkit might also be of practical or academic interest to the academic community of environmental scientists, social scientists, economists, landscape architects, land owners, and risk communicators.

Model users desire to avoid situations where effects are predicted by models but do not subsequently occur (see Figure 11.2). Costly plans or actions to avoid or minimize an anticipated environmental impact may be enacted unnecessarily as the result of incorrect model forecasts (model user's ruin). Such modeling "false positives" also diminish the ability of managers to act decisively in the face of future predictions of impending impacts. That is, will the next predicted impact be another false positive?

11.4.2 Managers and Decision Makers

The management of environmental resources is fundamentally a decision-making process. Therefore, the toolkit might reasonably include decision models in addition to ecological and environmental models. Minimally, ecological and environmental models included in the toolkit should be compatible with decision-making models. For example, Figure 11.4 illustrates a hypothetical dynamic control model for evaluating the potential ecological

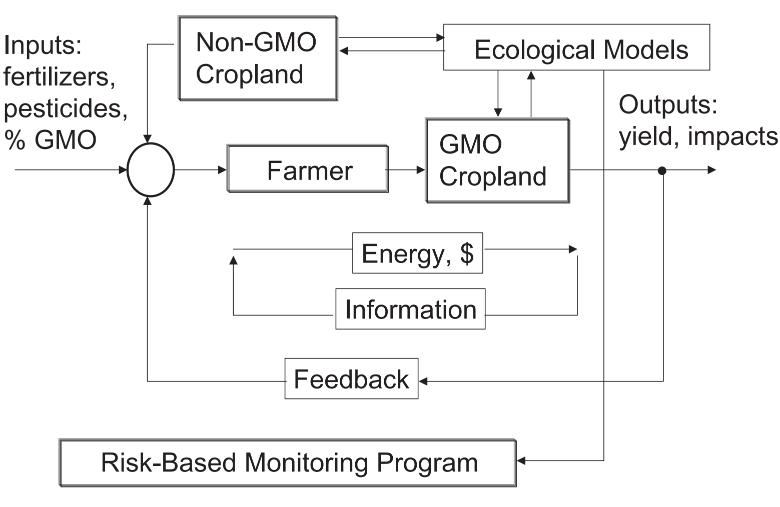

Figure 11.4. A dynamic control model for managing the use of genetically modified organisms (GMOs) in crops.

risks (e.g., gene flow to native plants and alteration of soil arthropod communities) posed by the use of genetically engineered crops. This framework indicates that the ecological model (selected from the toolkit) has become an integrated component in the decision model and contributes information concerning possible risks in conventional croplands and croplands containing genetically modified organisms in relation to decisions concerning the use of fertilizers, the application of pesticides, and the percentage of crops to be planted with genetically modified plants. The ecological model also provides input to a risk-based monitoring program as an integral part of the overall crop management model. As illustrated by this example, it may prove efficient and effective to work backwards from the set of resource management challenges faced by the agencies and decision-making processes in designing, building, and filling the toolkit.

11.5 Data Management

A toolkit that will effectively support the use of models in environmental decision making will necessarily include capabilities for data handling. Models often require large amounts of data. Data are used in the processes of (1) model development, (2) model implementation, (3) definition of initial conditions, (4) estimation of model parameter values, and (5) model verification and evaluation. The design and construction of the toolkit will have to successfully address these data issues in relation to environmental and ecological modeling. The toolkit will need the capability to operationally link models to complex, often spatially explicit data sets. As data requirements of increasingly complex environmental models expand, the toolkit may need the ability to perform sophisticated interpolations to fill in missing values in constructing model-input data files. Additionally, the toolkit should facilitate the ability to check for data errors (e.g., likely erroneous values) and either correct errors or propagate the error estimates through the model calculations (e.g., a Monte Carlo simulation).

Models can also produce large amounts of results that will require similar data-handling capabilities to extract information that will be meaningful in resource management and decision making (mason and Gurney 1993). The toolkit will necessarily address data analysis and postprocessing issues that include (1) higher-dimensional data handling and (2) data visualization. For example, current GIS methods are generally constrained to the analysis and presentation of two-dimensional data or model results. However, many environmental resource challenges involve additional dimensions, including the vertical and time dimensions. Data visualization methods will be necessary for displaying the four-dimensional output (i.e., three-dimensional results that vary through time). Ecological animation that uses the virtual reality markup language might provide one of the necessary capabilities in advanced data visualization. Whatever the technology, the objective for this aspect of toolkit development is summarization of model results in a manner that contributes to informed decision making and environmental management.

11.6 Summary and Recommendations

An environmental modeling toolkit could assume various forms and range in complexity from a localized collection of existing models to a globally distributed, interactive, intelligent decision support system. Several government agencies have already organized their modeling and data-handling capabilities. These existing capabilities should be examined in relation to developing new toolkits to support environmental management by other agencies, organizations, and managers. Criteria have been developed for the systematic evaluation of ecological and environmental models that might be included in toolkits [e.g., Pastorok et al.(2001)]. These criteria should reviewed for possible use in identifying existing models for inclusion in the toolkit.

The technical components of a toolkit envisioned as an interactive modeling and decision support system already exist. Even while technologies continue to evolve and advance, current capabilities in computer hardware and software need only be integrated into an operational environmental modeling and decision support system. The beginnings of these kinds of systems also exist (e.g., USEPA BASINS) and should be evaluated for their relevance in the design and implementation of the toolkit concept.

References

Ault, J.S. and W.W. Fox, Jr. 1989. FINMAN: Simulated decision analysis with multiple objectives. American Fisheries Society Symposium **6**:166–179.

Barnthouse, L.W. 1992. The role of models in ecological risk assessment: A 1990's perspective. Environmental Toxicology and Chemistry **11**:1751–1760.

Barnthouse, L.W., R.V. O'Neill, S.M. Bartell, and G.W. Suter II. 1986. Population and ecosystem theory in ecological risk assessment. Pages 82–96 *in* T.M. Poston and R. Purdy, editors. Aquatic Toxicology and Environmental Fate. Volume 9. Report STP 921. American Society for Testing and Materials, Philadelphia, Pennsylvania, USA.

Brown, L.C. and T.O. Barnwell. Jr. 1987. The Enhanced Stream Water Quality Model QUAL2E and QUAL-UNCAS: Documentation and User Manual. EPA/600/3-87/007. U.S. Environmental Protection Agency, Athens, Georgia, USA.

Burns, L.A. 1986. Validation methods for chemical exposure and hazard assessment models. Pages 148–172 *in* Environmental Modeling for Priority Setting Among Existing Chemicals. EcoMed, Munich, Germany.

Campbell, K.R. and S.M. Bartell. 1998. Ecological models and ecological risk assessment. Pages 69–100 *in* M.C. Newman and C.L. Strojan, editors. Risk Assessment: Logic and Management. Ann Arbor Press, Chelsea, Michigan, USA.

Carsel, R.F., C.N. Smith, J.T. Mulkey, J.D. Dean, and P. Jowise. 1984. User's Manual for the Pesticide Root Zone Model (PRZM). Release I. EPA-600/3–84–109. U.S. Environmental Protection Agency, Athens, Georgia, USA.

Emlen, J.M. 1989. Terrestrial population models for ecological risk assessment: A state-of-the-art review. Environmental Toxicology and Chemistry **8**:831–842.

Garcia, L.A. and M. Armbruster. 1997. A decision support system for evaluation of wildlife habitat. Ecological Modelling **102**:287–300.

Harris, J.R.W., A.J. Bale, B.L. Bayne, R.F.C. Mantoura, A.W. Morris, L.A. Nelson, P.J. Radford, R.J. Uncles, S.A. Weston, and J. Widdows. 1984. A preliminary model of the dispersal and biological effects of toxins in the Tamar Estuary, England. Ecological Modelling **22**:253–284.

Hollis, J.M., S.H. Hallet, and C.A. Keay. 1993. The development and application of an integrated database for modelling the environmental fate of herbicides. Paper 10B-1, pages 1355–1364 *in* Brighton Crop Protection Conference—Weeds. British Crop Protection Council, Farnham, Surrey, U.K.

Johanson, R.C., J.C. Imhof, H.H. Davis, J.L. Kittle, and A.S. Donigan. Jr. 1981. User's Manual for the Hydrologic Simulation Program—Fortran (HSPF). Release 7.0. U.S. Environmental Protection Agency, Athens, Georgia, USA.

Jorgensen, S.E., B. Halling-Sorensen, and S.N. Nielsen. 1996. Handbook of Environmental and Ecological Modeling. CRC Lewis Publishers, Boca Raton, Florida, USA.

Mankin, J.B., R.V. O'Neill, H.H. Shugart, and B.W. Rust. 1975. The importance of validation in ecosystem analysis. Pages 63–71 *in* Simulation Council Proceedings Series, La Jolla, California, USA.

Mason, D.C. and R.J. Gurney. 1993. Data handling developments for coastal modelling. Pages 32–36 *in* A.R.D. Stebbing, K. Travis, and P. Matthiessen, editors. Environmental Modeling—the Next Ten Years. Society of Environmental Toxicology and Chemistry—Europe, Brussels, Belgium.

Pastorok, R.A., S.M. Bartell, S. Ferson, and L.R. Ginzburg. 2001. Ecological Modeling in Risk Assessment. CRC Lewis Publishers, Boca Raton, Florida, USA.

Suter, G.W., II, and S.M. Bartell. 1993. Ecosystem-level effects. Pages 275–308 *in* G.W. Suter II, editor. Ecological Risk Assessment. Lewis Publishers, Chelsea, Michigan, USA.

U.S. Department of the Interior (USDI), Fish and Wildlife Service. 1980. Habitat Evaluation Procedures (HEP). ESM 102. Department of the Interior, Washington, District of Columbia, USA.

Young, R.A., C.A. Onstad, D.D. Bosch, and W.P. Anderson. 1986. Agricultural Nonpoint Source Pollution Model: A Watershed Analysis Tool. A Guide to Model Users. U.S. Department of Agriculture, Agricultural Research Service and Minnesota Pollution Control Agency, St. Paul, Minnesota, USA.

12 Role of Computational Toolkits in Environmental Management

Jeffery P. Holland, Steven M. Bartell, Thomas G. Hallam, S.T. Purucker, and Christopher J.E. Welsh

12.1 Introduction

As a component of environmental resource management, decision makers (e.g., resource managers), stakeholders (e.g., the public and nongovernmental organizations), and modelers (e.g., scientists and engineers who develop and use modeling and assessment tools to perform evaluations of alternative management practices) face pressure to accurately project and evaluate the costs, benefits, options, and potential consequences of proposed resource management actions. Current technologies offer many capabilities to help address these difficult demands. These technologies include geographic information systems (GIS), landscape ecological modeling and simulation, group collaborative forums and conferencing, expert systems, multidimensional visualization tools, decision support systems (e.g., computer-based programs that aid decision makers in evaluating differing courses of action), and web-based data-mining tools. Usage of each of these technologies is rapidly growing. The problem for many users of such technology, however, is blending these tools together into a coherent and integrated computational framework [e.g., a toolkit or toolbox; see English et al. (1999)] that is keyed to the management process.

12.1.1 The Toolkit Concept

The concept of a "toolkit" embraces the idea that a collection of scientifically credible, generally accepted, and reliable resource management models and assessment tools can and should be made available to assist modelers, decision makers, and stakeholders. Just as a master craftsman carries a comprehensive set of tools that can used to complete a project, a resource manager, modeler, or stakeholder should have a set of modeling tools available to aid the collaborative decision-making process. Note that, for any given job, the craftsman may employ only a small subset of the tools in the kit; however, given the breadth of tasks the craftsman may face, the toolkit must have a range of tools so that the craftsman can look in the kit and find the tools appropriate for the task. In this same manner, the environmental management toolkit must have the range of tools required to meet the needs of decision makers, stakeholders, and modelers.

In the context of environmental management, toolkit functionality would be most effectively cast as a highly integrated set of tools that facilitates conceptualization of problems; encourages interaction among decision makers, modelers, and other stakeholders; and empowers easy querying of databases and model results with the capability of producing clear, visually based outputs. Given that the ultimate purpose of the toolkit is to support decision making, features that aid building and running models, accessing data, building consensus, conducting alternative analyses, and presenting results are essential.

12.1.2 Why Would a Toolkit Be Useful?

The lack of familiarity with models and modeling terminology is, to a great degree, responsible for less-than-optimal use of ecological models in resource management decisions. A toolkit, or a series of interconnected toolkits, stocked with information on modeling approaches, models, and visualization tools applicable to common environmental investigations (e.g., forest planning and environmental assessments) would provide an invaluable source of information for managers regarding the effective use of such technologies as a part of resource management. The toolkit would be a resource to help make managers, stakeholders, and modelers aware of modeling and assessment options available to address different types of resource management issues.

Inherent in the toolkit approach is a degree of standardization required to facilitate the connection and use of multiple tools (models, GIS, and databases) in a seamless and integrated fashion. Such standardization would greatly increase the flexibility toolkit users would experience while employing different models and assessment tools for a given resource management scenario. As such, the models and tools contained within a toolkit would likely be used more productively (and would more often be accepted by regulatory agencies and the public) than others. Holland (1998) overviews the development of three modeling and assessment toolkits for groundwater, receiving water, and watershed analyses. Use of these toolkits has been shown to increase user productivity by a factor of 10. Further, these toolkits have received significant regulatory acceptance as exemplified by U.S. Environmental Protection Agency (USEPA) support for their development and by their use by USEPA regional offices throughout the United States (Holland et al. 2001).

12.1.3 Toolkit Types and Functionality

Just as craftsmen with different specialties may carry different sets of tools, the types and functions of toolkits will vary depending on the user and use.

A properly functioning toolkit should assist its users in their efforts to interact during problem formulation (conceptualization) and beyond. As such, the toolkit would be designed around the following four questions, as adapted from Westervelt (2001):

- *Who is the target user?* The target user will have different sets of requirements for the toolkit, as discussed below.
- *What is the user's starting point?* The user would approach the toolkit with a set of goals (e.g., management and technical objectives) and proposed management actions.
- *What does the user want to do?* The user will want to better understand the risks and tradeoffs associated with the proposed actions relative to resource management goals. This understanding will be achieved through the use of the analytical tools available in the toolkit.
- *What are the user's skills?* Users (or their staffs) should be comfortable with computers for doing word processing, performing geospatial analyses, and creating reports and presentations. These users will range from generalists who understand the system as a whole, but are typically less informed regarding its specifics, to specialists who understand the mathematics and theories associated with system details (but perhaps not the overarching issues for the system).

Given this variety of users, resource managers and decision makers may want a general set of tools geared toward conceptualizing problems (e.g., the formulation of problem geographic, socioeconomic, and political boundaries; decision variables; and alternatives), determining approaches where modeling would prove useful, interpreting model outputs, and visualizing or presenting results. Modelers will want much more detailed and specific information on available models or modules (including access to the models and their modules, themselves), site-specific data, model parameters, boundary conditions, etc. Stakeholders may be interested in some combination of these capabilities. For a toolkit to function properly, significant interaction must occur among resource managers, stakeholders, and modelers to ensure that questions are formulated in terms that can be directly addressed by modeling and assessment tools.

From the discussion above, four differing, but interwoven, functional spheres must be supported by a toolkit: those for the problem formulation/conceptualization process (which involves all three of the user classes), for the decision maker, for the stakeholder, and for the modeler/analyst. As such, one could envision the following four overlapping toolkits as shown Figure 12.1:

- *Conceptual toolkit*—Decision makers, stakeholders, and technical staff must operate from a common ground. The function of the conceptual toolkit is to facilitate finding that common ground. This toolkit should include methods to develop a common language for describing specific environmental questions and the means to analytically identify problem

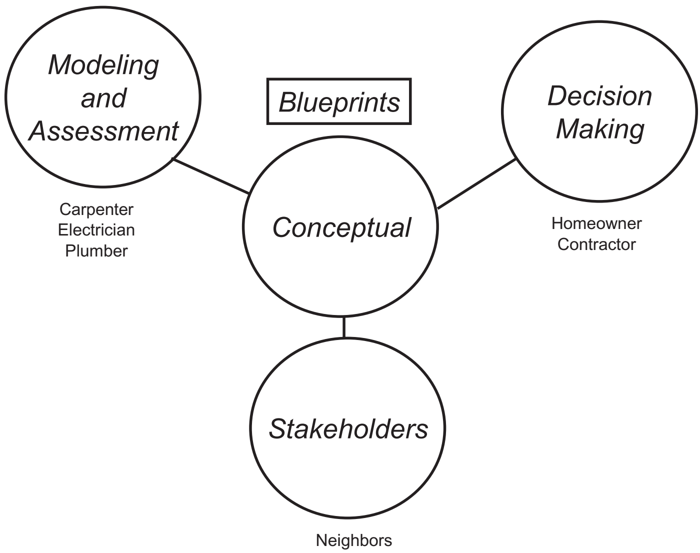

FIGURE 12.1. Relationship among the different toolkits.

components. The ecological-risk-assessment framework developed by the USEPA (USEPA 1992) is an example of this process.

- *Decision maker's toolkit*—The decision maker's toolkit is geared toward decision support. The most important aspects of decision making that would be supported by such a toolkit are alternative formulation, evaluation, and tradeoff analysis. This toolkit must include tools that facilitate interactions among resource managers, stakeholders, and technical staff to reach consensus on the problem(s) to be addressed and the validity of potential approaches to addressing said problem(s). Information regarding the types of ecological models appropriate for application to common environmental issues should be available within the toolkit.
- *Modeler's toolkit*—Model developers and users (including decision makers who wish, and have the ability, to run models themselves) should have documentation and links to available models, modules, and descriptions of modeling approaches. The modeler's toolkit would include all the tools (e.g., grid generators, parameter estimators, and setup and calibration tools) needed to develop new models or to apply existing models and assessment tools that answer specific questions. To be fully functional, this toolkit must include guidelines or standards enabling seamless communication among models, between databases and models, and between model outputs and inputs to tools in the decision maker and/or stakeholder toolkits.
- *Stakeholder's toolkit*—The set of tools needed by stakeholders (the public, nongovernmental organizations, etc.) focuses on data mining and

access to technical results that are presented in formats amenable to stakeholder use. This toolkit would include visualization capabilities similar to those provided for decision makers.

Of these four toolkit types or functions, the modeler's toolkit has experienced the most development to date (see the Sidebar 12.1 for examples of such development). The conceptual toolkit has the greatest development left to conduct, but it most likely has the greatest potential payback associated with its use in environmental management.

General issues of toolkit design and functionality are presented in the next section. More specific information for each toolkit is provided immediately thereafter. Note that these toolkits actually represent specific types of functionality required by the user. As discussed in this chapter, such functionality could be supplied by four independent, but linked, toolkits or through one master toolkit with differing levels of functionality.

12.2 General Issues of Toolkit Design and Functionality

Clearly, the potential users (and uses) determine the different purposes for developing a toolkit. Modelers may want to use a toolkit to set up a model, to calibrate and verify it, and to present model results. Stakeholders, alternatively, might wish to mine databases, to assess differing management alternatives, and to conduct tradeoff analyses. As a result, the functional requirements for a modeler's toolkit could differ greatly from the requirements for the stakeholder's or the decision maker's toolkit. It is therefore essential that any toolkit be developed with its ultimate audience in mind. The more general building blocks of toolkit development are presented in Figure 12.2, and each building block is discussed below.

12.2.1 Web Empowerment and Implementation

Among the general building blocks of any toolkit, none is perhaps more important than that of being "Web empowered." The use of the Internet and the World Wide Web is a phenomenon of increasing commercial and social significance. At present, it is common for managers, stakeholders, and modelers to use digital elevation models, contaminant fate and effects data, urban landscape data (e.g., locations of roads, population centers, and industrial complexes), land-cover and land-use data, and soil information that are obtained from Internet sources. However, the data needed by these differing groups are seldom resident on a single Web site. The ability of different decision makers, from local resource managers to planners to senior decision makers, to productively access data from decision support systems is contingent upon those systems' facilitating connectivity to remote data sources over local area networks and/or the Internet as seamlessly as one

Sidebar 12.1
Examples of toolkits

The existence of the large number of decision aids and of modeling systems from the U.S. Army Corps of Engineers (Holland, 1998; Holland et al. 2001) and the U.S. Geological Survey (Leavesley et al. 1996) is indicative of the paucity of and need for integrated decision maker's toolkits. Several U.S. federal agencies are active in the partnered development of integrated computational frameworks to support natural and cultural resource management and decision making. A partnership of the U.S. Army Corps of Engineers (USACE), USEPA, Department of Energy, and Nuclear Regulatory Agency is devel-oping a joint risk-assessment, decision-support system [e.g., Deliman et al. (2000)]. The USEPA, in conjunction with industry, has developed the BASINS software package (Lahlou et al. 1998) to support decision making regarding total maximum daily loadings. The U.S. Geological Survey in concert with the U.S. Bureau of Reclamation (Fulp and Frevert 1998) and the Tennessee Valley Authority (Zagona et al. 1998) have developed decision support systems for water resources management. Numerous journals, many online (go to http://www.iwap.co.uk and select "journals"), are specifically oriented toward decision support and knowledge management in natural resources.

While there are literally hundreds (perhaps thousands) of "decision support" systems, most of these systems are site-specific or place-based in design and function. Only recently have broad-based, integrated computational frameworks of the type envisioned herein as a "decision maker's toolkit" begun to surface. Most of these toolkits [e.g., Holland (2001); Danish Hydraulics Institute (1999)] are in their formative stages. Industry groups, such as the OGC and Nobility, Inc. (http://www.nobility.com/), are also developing products ranging from interoperability protocols to proprietary marketplace solutions. The need for such toolkits, along with descriptions of required functionality, have an ever-broadening base of support among a variety of technical organizations. As an example, a recent report from the U.S. Government's Interagency Group on Decision Support (Case et al. 2000) mirrors many of the requirements listed above for computational toolkits and frameworks that support natural resource management.

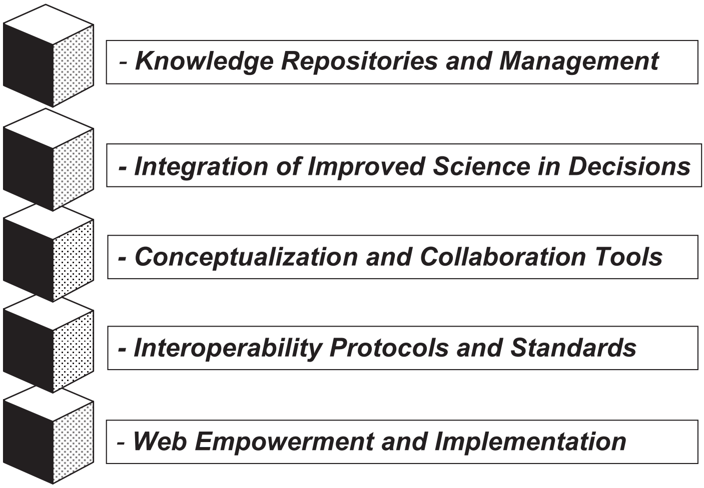

Figure 12.2. Building blocks of toolkits.

presently uses a Web browser. Equally important is the ability of modelers to access different data sources and types quickly with minimal manipulation. Ideally, toolkit users would view cyberspace as nothing more than an extension of their local computers.

12.2.2 Interoperability Protocols and Standards

Productive use of any integrated toolkit, particularly for decision makers and stakeholders, requires the establishment and use of protocols (standardized methods that connect software components and their outputs) for interoperable data archiving and retrieval, database development, metadata presentation, and tool linkage (such as GIS-to-model connectivity). Examples of protocol developments, particularly those associated with the linkage of models, analytical tools, and information technologies, are discussed by Leavesley et al. (1996), Holland and Goran (1999), and Whelan et al. (1997). Crowe (2000) discusses several modeling environments, including the Spatial Modeling Environment and the Environmental Systems Research Institute's ModelBuilder (ESRI 2000). Such products represent candidate development environments for achieving and enforcing interoperability through the use of standards and protocols.

Several other initiatives are under way, such as the development of the Hierarchical Data Format (National Center for Supercomputing Applications 2001) and the activities of the Open GIS Consortium (OGC) [see Lake (2000)], that hold the promise of providing such protocols. Several agencies of the U.S. government are partnering (Case et al. 2000) in the development and promulgation of such standards, often in collaboration with the OGC.

The use of standard protocols is necessary for the creation of standard (and stable) data management, seamless connectivity to remote servers, straightforward links between differing data sources and assessment/modeling tools, etc. Any sustainable opportunity for decision makers and stakeholders to query databases of multiple types efficiently (e.g., through just a few mouse clicks using a query language that is natural to the decision maker) and to visualize or further manipulate those data is directly related to software and hardware interoperability. Unfortunately, there are now several sets of "standards" for archiving and querying geospatial data. Clearly, the development of one set of interoperability protocols or standards would be highly beneficial.

12.2.3 Conceptualization and Collaboration Tools

Conceptualization involves the formulation of the environmental management problem(s) being tackled, the key system components (e.g., physical, biological, social, and economic) associated with the problem(s) being investigated, and the potential management alternatives to be considered as a part of problem solving. The process of conceptualizing problems, and their potential solutions, has become a highly collaborative one that involves decision makers, stakeholders, scientists and engineers, and the public. Recent activities among the U.S. federal agencies, as exemplified by those of the (U.S. Department of Agriculture (USDA) Johnson et al. 1999), illustrate the collaborative nature of future decision making.

Tools to support problem, objective, and alternative conceptualization are essential for all potential toolkit users. These tools could range from (1) a web-based decision tree that, through branched queries, leads the decision maker or stakeholder to specify the particular problem or solution alternative to (2) a fully icon- or object-based method for accomplishing the same result. Westervelt (2001) provides a review of candidate software applications that could support development of a conceptualization capability for the U.S. Army's Land Management System (Holland and Goran 1999).

Tools empowering group meetings, shared data mining and visualization, and consensus building (all on the Internet) are required. Therefore, the decision maker's toolkit, in concert with the stakeholder's and conceptual toolkits, must provide the computational means to facilitate both conceptualization and collaboration (Johnson et al. 1999).

12.2.4 Integration of Improved Science into Decision Making

The integration of advanced science and engineering, particularly for new discoveries, is a challenging task. A recent USDA report from its Committee of Scientists (Committee of Scientists 1999, p. 123) states that

> Collaborative planning rests upon a foundation of scientific information developed by scientists and other knowledgeable people in an open, public process. This 'assessment' process ensures that current scientific thinking is a part of the planning process as well as a sound foundation of credible information. Issues in planning that have a significant scientific content include: whether the temporal and spatial scales being considered are appropriate for the questions being asked, whether all relevant information is being considered, whether that information is interpreted in a manner consistent with current scientific understanding, whether the level of risk to species and ecosystems associated with the alternatives is acknowledged, and whether the uncertainty of our knowledge is recognized.

If collaborative planning is the very foundation of decision making, then appropriate and effective use of scientific data is the foundation of collaborative modeling and assessment.

Toolkits must be formulated to integrate scientific discovery and data into the decision-making process. This integration requires that the toolkit facilitate better use of existing or new scientific information in resource management. An example of how a toolkit could facilitate better use of existing technology involves improved use of modeling results in estimating likely outcomes from implementation of management alternatives. A second example involves integration of new scientific understanding from different disciplines, such as economics, ecology, biology, and hydrology. Experience of the authors in the development of the Department of Defense (DoD) Groundwater Modeling System (GMS) (Holland et al. 2001) has shown that, when a toolkit (in the case of the GMS, for subsurface modeling) with standard protocols is employed by the research community, new scientific discoveries (e.g., new subsurface remediation processes) are codified and implemented in decision making much more quickly than would happen without such a toolkit. It is likely that the economies experienced in the development of the GMS would be repeated with the development of a more generalized ecological modeling toolkit.

12.2.5 Knowledge Repositories and Management

The envisioned toolkits must provide for repositories and catalog services that document lessons learned, components of the decision process, existing technical capabilities (such as software and subject-matter experts), and the location of relevant data. Up-to-date capabilities of these types would improve decision makers' and stakeholders' abilities to be "smart buyers" in environmental management and would assist modelers in understanding model applicabilities and limitations. The establishment and maintenance of these services would require a number of technological advances. Open "wizards" would have to be developed that facilitate placing data within Web-accessible repositories. The repositories themselves would have to be defined with interoperability protocols, such as those described above, so that they can be queried and mined by decision makers and stakeholders. Advanced search engines, pattern recognition algorithms, artificial neural networks (Babovic and Bojkov 2001), and other knowledge management agents would have to be employed to make efficient use of these repositories and catalog services. Current catalogs and inventories of available models and analysis tools, along with a set of well-documented case studies, would have to be established, as well.

12.2.6 Requirements for Toolkit Functionality

For toolkit(s) to support the different user communities, they must

- Integrate predictive capabilities (modeling and simulation), data management, GIS, visualization, and heuristics into a decision support framework
- Have collaborative functions (such as multiuser viewing and manipulation of archived data) to augment multiple-stakeholder use
- Support protocols for interoperability so that modeling results will interact seamlessly with other analysis tools within the toolkit
- Provide methods to aggregate technical data to facilitate data usage
- Provide an efficient means to evaluate alternatives and propose new ones as part of the decision-making process
- Link effectively to business processes of differing, and often highly disparate, users
- Provide three-dimensional (3-D) visualization and animation capabilities
- Provide Web (Internet) accessibility and functionality
- Support the elements of the decision process (as discussed in more detail below)
- Aid the selection of appropriate modeling and analysis tools (e.g., empower "smart" buying)
- Provide a repository of lessons learned
- Facilitate completion of place-based (e.g., site-specific) decision-support-system development
- Provide a means for incorporating decision constraints and rules within the overall computational toolkit
- Provide statistical and data-mining tools for manipulating and querying potentially large databases

12.2.6.1 Documentation

The tools in any toolkit should be fully documented. The documentation should

- Describe the particular tool in detail and prescribe its correct application in relation to environmental resource management

- Provide examples of correct and inappropriate uses or applications of each tool
- Describe the types, limitations, and sources of required inputs
- Describe the kinds of results produced by the tool and their interpretation
- Discuss the relative strengths and limitations of the tool
- Present the uncertainties generally associated with implementation of the tool

The documentation should be readily accessible (e.g., in help files and online tutorials) and should include interactive tutorials that can instruct users on the appropriate applications of the toolkit contents to increase the effectiveness of their involvement in the resource management process.

12.2.6.2 Metadata Requirements

With any focus on methods for data analysis and presentation, a toolkit must address the source and quality of the information accessed by its users. That is, it needs to include "data about the data" or metadata. These metadata, as well as the data they describe, will also need to be conveniently accessed by toolkit users via an Internet-based implementation of the user's toolkit.

The metadata for any specific data set, model results, or other information relevant to environmental resource management should (1) identify the source, content, and format of the database; (2) indicate who performed the work; (3) describe the methods used to produce the results; and (4) present a general summary of the credibility and uncertainty associated with the data, results, or information. Clearly, the metadata will have to be developed in terms that are understandable to the diverse set of users who have roles in specific resource management issues.

The metadata should permit access to the data at different levels of inquiry, beginning with more generalized summaries and proceeding to more in-depth analyses and presentations of the data, model results, or other information in the particular database.

12.3 Conceptual Toolkit

The scientists and engineers who develop models, the managers who must make decisions, and the stakeholders associated with those decisions each generally have different objectives. However, all are driven by a common theme, the environmental problem that begs a solution. Problem solution requires identification of the goals and objectives of the different stakeholders and resource managers involved in the given environmental problem. In the most general case, these goals and objectives would diverge to the point that an answer deemed optimal to all parties would be the exception rather than the rule. A toolkit is therefore required that would facilitate identification of issues among all stakeholders while aiding formulation of potential alternative solutions that are the least divisive to the environment and stakeholder objectives. This toolkit is the conceptual toolkit.

12.3.1 The Glue That Binds

The focal environmental problem will have some components that are known to be fundamental and others that may not be well understood or even agreed upon as being important. The conceptual toolkit is a blueprint, a schematic of the focal issues that delineates important interactions among components and, through feedback, indicates gaps in knowledge about the scientific problem. It is also a tool to facilitate communication. This toolkit must express environmental science and engineering at levels sufficient to initiate modeling efforts and, at the same time, must be sufficiently explanatory to address issues of environmentally cognizant stakeholders and managers. The conceptual toolkit is thus both a development tool and a communication tool that is important for interactions of scientists and engineers with the stakeholders and the decision makers. As such, the conceptual toolkit should form a nucleus that relates each of the modeler, stakeholder, and decision maker toolkits to one another.

The most basic aspect of the conceptual toolkit is its graphical nature. This toolkit must be designed with icons and terminology that can be intuitively grasped by modelers, stakeholders, and decision makers if it is going to provide the common ground required to support collaboration among these communities. The conceptual toolkit should provide a hierarchy of methods, ranging from simple sketch pads to elaborate group collaborative environments, in support of problem and alternative formulation, evaluation, and feedback. This is undoubtedly the most ambitious, and the least well developed, of the four toolkits discussed in this chapter.

12.3.2 From Conceptualization to Model Development and Analysis

The conceptual toolkit, by framing the environmental problem, addressing differing stakeholder objectives, and presenting scientific components, provides the foundation for the modeling process. The first step in that process is the determination of the objectives of the model. By identifying those objectives, the conceptual toolkit would provide important input into the modeling efforts. By introducing scientific knowledge and associated uncertainty, the conceptual toolkit would set the foundation for the analysis of the problem and the evaluation of alternative management scenarios. There should be both forward and backward information exchange between problem conceptual models and mathematical science and engineering models so that each can be modified as additional information is obtained from the analysis or as the objectives of stakeholders or decision makers are modified.

12.3.3 From Conceptualization to Communication

Even after the objectives are delineated, the conceptual toolkit would be used to suggest alternative decision options. As the conceptual blueprint is modified by alternative decisions, feasible impacts are communicated to stakeholders and managers for reaction and modification. This communication is an iterative process, with exchanges occurring many times.

12.3.4 From Analysis to Decision

As the problem-solving process progresses through modeling, analysis, and decision making, additional studies will likely be formulated on the basis of stakeholder, decision maker, and modeler feedbacks to the current state of analysis. Additional management alternatives should then be formulated via the conceptual toolkit.

12.4 Stakeholder's Toolkit

Various environmental nongovernmental organizations (NGOs), such as the Sierra Club, Nature Conservancy, Environmental Defense Fund, Isaac Walton League, and the general public, constitute a set of stakeholders that have become increasingly active in the resource management decision process. Public and NGO activities related to resource management may include formulation of a particular position through public forums, involvement in the legislative process, purchase and setaside of lands for conservation, formal review of proposed resource management activities by public agencies, and the conduct of alternative technical analyses.

The diverse occupational backgrounds and technical training of stakeholders challenges the development of a toolkit that meets the needs of this group. Stakeholders include interested individuals with little or no formal training in ecology or resource management who have sincere interests and commitments (e.g., advocates) to sound environmental decisions on issues that directly influence them or future generations. Other stakeholders are highly trained and technically competent in disciplines relevant to environmental and ecosystem management, but they are not advocates of any particular decision or policy. Such trained individuals might be retained by environmental NGOs to provide technical support and consultation in relation to specific resource management decisions.

The tools needed to support the interests of stakeholders would provide a functionality similar to that needed by the decision makers. However, the technical training and proficiency of stakeholders, particularly among the general public, may well be less than the capabilities of individuals entrusted with resource management decisions. A stakeholder's toolkit has to be carefully designed to accommodate, and perhaps anticipate, the more limited technical capabilities of stakeholders, and its functionality may have to be more broadly defined than that of the toolkit developed to assist decision makers.

The stakeholder's toolkit should assist stakeholders in reviewing and understanding the technical and policy bases for decisions regarding the management of specific environmental resources. The toolkit should provide the stakeholders with the capability to readily identify, collate, examine, interpret, and evaluate the data, model results, and other information used to arrive at particular resource management decisions. The toolkit should make transparent the alternative actions and the information base used by managers to arrive at a decision.

Additionally, the stakeholder's toolkit should facilitate virtual interactions (via the Internet) between stakeholders and other participants in the resource management process (e.g., decision makers, technical support staff, and risk assessors). Similarly, the results developed with different components in the stakeholder's toolkit should be transferable to decision makers and other professional participants in the environmental management process. It is anticipated that stakeholder access to information will be mainly through the World Wide Web or advances in this communication technology. The Internet will likely increase the number and technical sophistication of stakeholder groups during the coming decades. The stakeholder's toolkit should therefore provide access to all of the technical tools (e.g., models, data, analytical techniques, and visualization) used in the resource management and decision-making process.

12.4.1 Data-Mining and Statistical Tools

Development of the stakeholder's toolkit should initially focus on identifying and selecting tools that facilitate the statistical interpretation of data and information produced by the technical support staff and decision makers. Stakeholders probably will not develop and execute complex ecological models. However, they may employ sophisticated statistical analyses of large sets of data and model results or implement intricate decision models as part of their participation in the resource management process.

Stakeholders need methods that help them interpret, understand, and evaluate these kinds of technical aspects associated with specific resource management decisions. Such methods should emphasize capabilities in recognizing, retrieving, and presenting relevant model results, data, and other information pertinent to specific resource management topics or decisions. The stakeholder's toolkit should provide the capability to query or evaluate data or results of models at several levels from general inquiries to detailed examinations.

12.4.2 Web-Based Visualization

Tools that provide information-rich, visual summaries of complex data, model results, statistical relationships and decision making should be among the first additions to the stakeholder's toolkit. Such tools could be conveniently and rapidly accessed via the Web and might reasonably include

- Two- and three-dimensional color graphic displays
- Animated displays of model results and remotely sensed data
- Complex pattern analysis and recognition algorithms
- Audio/video summaries of issues pertinent to the topic of concern
- Interactive analyses and visualization of model results and remotely sensed data

The use of Web-based visualization tools will depend upon the development of general guidelines for presenting data and the results of models.

12.4.3 Tools for Multiuser Interactions

The toolkit should also facilitate collaborative efforts among various stakeholders or among stakeholders, the technical assessment community, and decision makers in examining the information basis for specific topic areas or evaluating decisions regarding particular environmental resources. Such collaboration might take the form of real-time data sharing, simultaneous visualization and analysis of data or model results, and the interactive review and evaluation of decision alternatives and their associated information bases.

Use of this collaborative functionality will increase the transparency of the technical and policy basis underlying specific resource management decisions.

12.5 Decision Maker's Toolkit

Decision makers have multiple requirements for technology to support the decision-making process that are equally applicable to government agencies, private corporations, individuals, and a host of international organizations. These same requirements are also of an ever-increasing importance to state and local government decision makers for issues ranging from total maximum daily loadings to recreation to urban development.

12.5.1 Issues Associated with Toolkit Requirements

It is anticipated that most decision makers will be users rather than producers of data. Therefore, data mining and advanced visualization, all facilitated with Web-based collaborative accessibility, are key components of the decision maker's toolkit. Some managers will be interested in using modeling tools, and, for certain place-based decisions, these managers would be able to execute these models through connections to the modeler's toolkit. These models and tools must be cast in a fashion that facilitates their use as a part of the decision-making process.

12.5.2 Elements of the Decision Model

The decision maker's toolkit must be a part of the overall decision-making process. Five major elements are associated with the representation of the generalized environmental management decision process:

- Statement of management objectives
- Delineation of management alternatives
- Expression of the physical, biochemical, ecological, and/or socioeconomic states (existing or likely) of a given site or sites
- Evaluation of and learning from possible outcomes from different management alternatives
- Estimation of the utility (relative worth) of these possible outcomes relative to the stated management objectives

Case et al. (2000) present an analogous decision process with the following elements:

- Recognition of problem or opportunity—Raising an issue in the formal decision-making contest
- Process mapping—Deciding how an issue will be resolved and who will decide
- Problem framing—Describing the problem to be solved or the opportunity to be captured
- Defining goals and criteria—Selecting indicators and measures that guide decision making in terms of what is sought and how success will be measured
- Intelligence gathering—Collecting and integrating information that will support problem framing and evaluation of the utility of alternatives
- Evaluating and choosing alternatives—Comparing alternative courses of action on multiple, and often competing, criteria
- Learning from outcomes—Using the experience gained to refine management, goals, criteria, and the decision process

Note that, although these elements are shown in a linear order, they actually represent a continuum that cycles through multiple times. Further, one can enter this decision-making continuum at different points in the process. For example, a cycle typically occurs in situations where initial management objectives are expressed that yield a range of potential alternative management scenarios. In such cases, the best from among a set of alternatives is assessed on the basis of available data, stakeholder requirements, and the state of scientific understanding at the time. The effectiveness of the selected alternative is then monitored. Such monitoring produces new information that is used, along with any scientific advancements and changes in stakeholder requirements, to propose changes to the management alternative being employed. This cycle is then repeated in a fashion that allows management to adapt as a function of societal, ecological, and economic factors.

The decision maker's toolkit should provide an integrated suite of tools that purposefully follows and supports the elements of the decision model. As such, this toolkit should provide standard templates for data presentation and problem formulation for different decision types. For example, specific templates should be developed that would support regulatory, risk assessment, and habitat restoration decisions. Clearly, there are many other resource decisions that must be supported, and the tools within the decision-making toolkit should be developed in a modular fashion so they can be efficiently combined to support "real-world," site-specific decision making.

12.6 Modeler's Toolkit

The modeling and assessment toolkit consists of the computational components that represent the physical and biological facets of the system being managed. Of the four toolkits discussed in this chapter, more advances have been made for the modeler's toolkit than the others (see Sidebars 12.1 and 12.2). Numerous models are available that could be integrated into such a toolkit, and we will not attempt to list them or recommend a particular subset. Instead, we will discuss issues related to constructing a modeling and assessment toolkit with emphasis on its functionality, some potential future developments, and the role of standards in developing a toolkit that will maximize accessibility of the components and a degree of confidence in the results produced.

The selection and implementation of the environmental models contained within this toolkit generally fall under the responsibility of modelers rather than decision makers, managers, or stakeholders. These modelers usually find the best models and assessment tools for the job and identify the data needed to run the model. Once the model is constructed and integrated into the toolkit, the modeling results would then be exported to the other toolkits as decision variables and information. Therefore, the manager or stakeholders faced with making an environmental decision may not be

Sidebar 12.2
Example use of a modeling toolkit

The U.S. Department of Defense (through the U.S. Army Engineer Research and Development Center), in concert with the USEPA, Departments of Energy and the Interior, and more than 15 university partners, has developed a comprehensive subsurface modeling toolkit, the DoD Groundwater Modeling System. The GMS provides the ability to support requirements for modeling and assessment tools throughout the life cycle of contaminated-groundwater site restoration and cleanup (Figure 12.3).

The GMS integrates more than 10 multidimensional subsurface models and visualization, animation, parameter-estimation, grid-generation, and site-conceptualization tools within a single-point-of-access graphical environment. The GMS functionality includes:

- Pre- and postprocessing support for MODFLOW96, MODPATH, MT3DMS, FEMWATER, RT3D, SEAM3D, SEEP2D, UTCHEM, PEST, and UCODE
- Site characterization tools
- GIS/CADD import/export
- SCAPS and CPT data import
- Finite difference/finite element grid generation

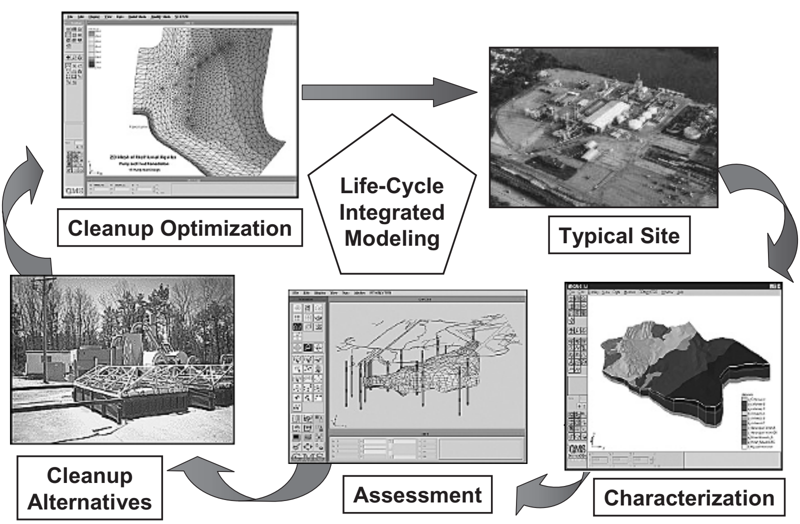

FIGURE 12.3. Five major facets of the DoD groundwater modeling system.

- Automated calibration tools
- "True layer" finite difference grid visualization
- 2-D and 3-D data interpolation and visualization
- Geostatistical library including
  Kriging (ordinary, universal, zonal, and indicator)
  Inverse distance weighting
  Natural neighbor
  Clough–Tocher
  AVI video file animation
  Conceptual modeling approach
  Regional-to-local telescoping model conversion
  Coordinate transformation

The GMS is employed to support a "typical" contaminated site cleanup in the following manner. First, geologists and hydrogeologists use the GMS's characterization tools to conceptualize the site geologic and hydrologic components (see Figure 12.3). This phase of GMS involves management and manipulation of numerous site data. The result is the development of a site conceptual model that includes geologic layering, location of all water bodies, and probable locations of contaminant source plumes. These features are then illustrated with fully 3-D visualization tools that are on board GMS.

In the second phase, GMS provides the means to set up, calibrate, verify, and execute different subsurface models to assess likely contaminant plume migration and the potential for these plumes to interact with human and ecological receptors. Tools to design, simulate, and optimize (as required) different restoration alternatives are provided to the modeler and cleanup specialist to facilitate investigating the efficacy of alternative strategies prior to the actual site implementation.

The GMS also provides a host of visualization and animation tools to allow decision makers and stakeholders to view the effectiveness of various alternatives in controlling plume movement and restoring the subsurface environment. Such visualized modeling results can be placed on the Internet or in presentation software for display to stakeholders.

Use of the GMS in site-specific cleanup and restoration activities has shown its utility in a variety of ways. The multiple technical disciplines involved in contaminated site cleanup and restoration, ranging from geologists to environmental engineers to regulators, employ the GMS toolkit for their discipline-specific requirements. However, because of the protocols and standards integrated into GMS, the products developed by one discipline or in one phase of a cleanup can be directly and seamlessly used by other disciplines and phases. Site conceptual models can, for example, be directly imported into many GMS-supported modeling tools. Results from models are output in formats that are easily viewed over the Internet or on a personal computer with standard browsers, graphical tools, and animators. Further, most data used to set up a particular subsurface model are directly transferable for use by another GMS-supported model.

The overall result of the use of the GMS toolkit is the development of streamlined and integrated computational methods that improve the productive use of subsurface models in support of contaminated groundwater restoration and cleanup. These increases in productivity have translated to reduced resources (time and money) for modeling and assessment and to optimized site cleanup and restoration designs that more completely consider site uncertainties.

expected to directly access the components that would be in this toolkit. However, the specification of the focus, extent, and goals of the problem being addressed (via the conceptual model established through dialogue between managers and modelers) should determine the scope of these components and the manner in which they will be used. Ultimately, the degree to which a site-specific implementation develops its own technical methods versus tapping the resources of existing models can significantly affect the scope of the project. Therefore, of the different toolkits considered in this chapter, the modeling and assessment toolkit may realize the most significant time and cost savings for a given place-based implementation because of the generally high cost of both the modeling development effort and conducting adequate quality assurance.

12.6.1 General Functionality

The modeling and assessment toolkit would export its results to the decision maker's and stakeholder's toolkits. The particular modeling results exported, and the input parameters used to create them, will be significantly influenced by the conceptual toolkit and by the particular decision being addressed. Because the input parameters will already have been determined via collaboration with the modeler, it may be possible to run the model to provide output to the other toolkits dynamically. If this is not possible for computational or other reasons, a data set of model results can be provided to the other toolkits for each set of assumptions. Either method for providing results must be flexible enough to provide alternative results based upon changes in these modeling assumptions. In some cases, the models themselves must also be made available because they may directly affect the outcome of any decision functions that are evaluated.

Because most environmental decisions are spatially based, results will typically be calculated and analyzed in a geospatially oriented computational environment. This environment, as a component of the modeler's toolkit, would have to provide a single point of access to grid-generation, parameter-estimation, visualization, calibration, verification, and animation techniques. In addition, it must provide access to many models and analysis tools. For example, assessment of the effects of a stressor on an exposed ecological population could require the use of the following modeling and assessment tools:

- Exposure assessment methods
- Fate and transport models
- Individual behavior models
- Methods to partition behavior between biota and media
- Chemical-toxicity-assessment methods
- Ecological population models

The selection of these tools would, in turn, require the consideration of the type of stressor, temporal scale, spatial scale, land-use history, and biotic and abiotic properties of the system being studied.

12.6.2 Enhancements/Developments Required

Clearly, numerous models in a toolkit could be applied to a given environmental decision. Therefore, it is important that the modeler's toolkit have a complete and intuitive human–computer interface that appeals to modelers. This toolkit would also provide a link to a database of model descriptions that could be queried for information regarding the set of models that are most relevant for the problem at hand.

Another need within this toolkit is for self-documentation to transfer modeling methods and assumptions to other toolkits. The ability to develop an audit trail for assessments would highlight assumptions employed in the modeling process and would export this information to other toolkits that use modeling results. Modeling equations, graphical output, and variables can be exported to a file format that can be interpreted by a number of different word processors and used to demonstrate assumptions to users of the decision maker's and stakeholder's toolkits. This information would also form the basis for the peer review of modeling and the preparation of the final report.

Modeling and assessment uncertainty analysis is another development that would provide very useful information to other toolkits. In theory, uncertainties could be propagated throughout the models that are used in order to establish an overall uncertainty or to perform a sensitivity analysis for the decision variables. In practice, these uncertainties are difficult to quantify across different models. With sufficient standardization across models, however, uncertainty estimation techniques could be employed to calculate distributions of interest.

12.6.3 Role of Standards

Each of the models contained in the toolkit must be interoperable with all other appropriate models in the toolkit as well as be able to communicate with other toolkits. The toolkit must be able to incorporate new or modified models within the system as well as to link to provided data sets. For these reasons, standards have a very important role. An explicit standardization approach provides for consistent and standardized use of ecological models with known reliability in resource management and assists in producing credible results.

Given the variety of resource decisions and the number of available tools to address them, it is advisable to develop decision-specific components within the modeler's toolkit. For example, ecological-risk-assessment modeling tools required by the USEPA may have little overlap with modeling tools that evaluate the effects of different timber-cutting strategies developed for the Forest Service.

Standards should be established to specify a minimal set of criteria for determining whether a given model would be incorporated into the toolkit. Important considerations for inclusion are transparency and accessibility of documentation. Also, accurate, efficient, scientifically defensible linkages must be made available

- To pass outside data sources to toolkit components
- To move information within models of the toolkit
- To provide results to other toolkits

The toolkit and each of its components should be upgraded periodically to ensure that state-of-the-art models are being used.

12.7 Summary and Recommendations

Numerous benefits (see Sidebar 12.2) and challenges are associated with the development of integrated computational systems, "toolkits," in support of environmental management and decision making. Decision makers, stakeholders, and modelers all require different types of toolkit functionality. It is equally clear, however, that appropriate linkages between these toolkits are required if one is to experience the most robust use of these toolkits in environmental management and problem solving.

We recommend that the four toolkits discussed in this chapter (the modeler's, decision maker's, stakeholder's, and conceptual toolkits) be adopted as the fundamental tools required for the environmental management and decision making. Of the four toolkits, the conceptual toolkit is the one that is the least well understood. However, it also represents the toolkit that may have the greatest impact on environmental management, given its nature as the "glue" between the other three toolkits.

The overarching, common requirements of the toolkits may warrant a toolkit development approach that builds and shares modules-meeting these common requirements while providing specific modules to meet the more focused requirements of the modeler, stakeholder, and decision maker. Given such commonality, especially that noted between the stakeholder's and decision maker's toolkits, we believe that one adaptive toolkit, with modules that meet the specific needs of stakeholders and decision makers, may be an effective paradigm for toolkit development.

As alluded to in Sidebar 12.1, several federal agencies in the United States and many international organizations have expressed interest in the development of such toolkits. There is significant potential for synergism between these individual initiatives, so collaboration among these differing groups in the development of toolkits should be formalized and expanded. This partnering is particularly important in developing standards and protocols (common linkages among different models, assessment tools, and databases). The ability of components within a given toolkit to communicate, the opportunity for new components to join and function within a toolkit, and the effectiveness of virtual development teams to build new tools in a distributed fashion are all directly and specifically related to the establishment and acceptance of a single set of standards and protocols in environmental management.

The utility of the toolkit concept must be more formally documented in real-world problem solving. In this regard, Case et al. (2000) recommend that a series of demonstrations be conducted that exercise and build upon the different toolkits discussed in this chapter. We strongly endorse this recommendation.

References

Babovic, V. and V.H. Bojkov. 2001. Runoff Modeling with Genetic Programming and Artificial Neural Networks. D2K Technical Report 0401-1. Danish Hydraulics Institute (DHI) Water and Environment, Copenhagen, Denmark.

Case, M.P., T. Gunther, W.D. Goran, J.P. Holland, D. Johnston, G. Lessard, and W.J. Schmidt. 2000. Decision Support Capabilities for Future Technology Requirements. ERDC TR-01-2. U.S. Army Corps of Engineers, Engineer Research and Development Center, Champaign, Illinois, USA.

Committee of Scientists. 1999. Sustaining the People's Lands: Recommendations for Stewardship of the National Forests and Grasslands into the Next Century. U.S. Department of Agriculture, Washington, District of Columbia, USA.

Crowe, S. 2000. Spatial modeling environments: Integration of GIS and conceptual modeling frameworks. Presented at the Fourth International Conference on Integrating GIS and Environmental Modeling (GIS/EM4): Problems, Prospects and Research Needs, Banff, Alberta, Canada, 2–8 September, 2000.

Danish Hydraulics Institute (DHI). 1999. MIKE SHE Water Movement User Manual. DHI Software, Copenhagen, Denmark.

Deliman, P.N., C.E. Ruiz, and J.A. Gerald. 2000. Development of a web-based risk assessment modeling system. Pages 178–191 *in* F.T. Price, K.V. Brix, and N.K. Lane, editors. Environmental Toxicology and Risk Assessment: Recent Achievements in Environmental Fate and Transport. Volume 9. ASTM STP 1381. American Society for Testing and Materials, West Conshohocken, Pennsylvania, USA.

English, M.R., V.H. Dale, C. Van Riper-Geibig, and W.H. Ramsey. 1999. Overview. Pages 1–31 *in* V. Dale, and M. English, editors. Tools to Aid Environmental Decision Making. Springer-Verlag, New York, New York, USA.

Environmental Systems Research Institute (ESRI). 2002. ModelBuilder for ArcView Spatial Analyst 2, an ESRI White Paper. ESRI, Redlands, California, USA. Also see http//ww.esri.com/.

Fulp, T.J., and D.K. Frevert. 1998. Watershed and river systems management programs: Current and future applications in the Bureau of Reclamation. Pages 5–71 to 5–78 *in* Volume 2, Section 5, Proceedings of the First Federal Interagency Hydrologic Modeling Conference, Las Vegas, Nevada, 19–23 April, 1998. Subcommittee on Hydrology of the Interagency Advisory Committee on Water Data, Las Vegas, Nevada, USA.

Holland, J.P. 1998. Hydroinformatic Advancements in Integrated Hydroenvironmental Modeling Systems. Hydroinformatics 98. International Association of Hydraulic Research, Copenhagen, Denmark.

Holland, J.P. 2001. The land management system: A framework to support future water and natural resources decision making. Hydrologic Science and Technology **17**:155–166.

Holland J.P., and W.D. Goran. 1999. Development of an Integrated Land System in Support of Department of Defense Land Management. ERDC-CERL TR-99-86. U.S. Army Corps of Engineers, Construction Engineering Research Laboratory, Champaign, Illinois, USA.

Holland, J.P., J.F. Peters, S.E. Howington, and R.S. Maier. 2001. Science and modernization in hydroenvironmental modeling systems. Pages 410–417 *in* Proceedings of the 22nd Army Science Conference, Accelerating the Pace of the Transformation to the Objective Force, Baltimore, Maryland, 11–13 December, 2000. CD-ROM. Office of the Assistant Secretary of the Army for Acquisition, Logistics, and Technology, Washington, District of Columbia, USA.

Johnson, K.N., J. Agee, R. Beschta, V. Dale, L. Hardesty, J. Long, L. Nielsen, B. Noon, R. Sedjo, M. Shannon, R. Trosper, C. Wilkinson, and J. Wondolleck. 1999. Sustaining the people's lands: Recommendations for stewardship of the national forests and grasslands into the next century. Journal of Forestry **97**:6–12.

Lahlou, M., L. Shoemaker, S. Choudhury, R. Elmer, A. Hu, H. Manguerra, A. and Parker. 1998. Better Assessment Science Integrating Point and Nonpoint Sources: BASINS, Version 2 Users Manual. EPA/823/B-98-006. U.S. Environmental Protection Agency, Office of Water, Washington, District of Columbia, USA.

Lake, R. 2001. GMS 2.0, enabling the geospatial web. Geospatial Solutions, July, 38–41.

Leavesley, G.H., P.J. Restrepo, S.L. Markstrom, M. Dixon, and L.G. Stannard. 1996. The Modular Modeling System—MMS: User's Manual. Open File Report 96–151. U.S. Geological Survey, Denver, Colorado, USA.

National Center for Supercomputing Applications. 2001. HDF5 reference manual, release 1.4.1. Hierarchical Data Format Group, University of Illinois, Urbana-Champaign, Illinois, USA.

U.S. Environmental Protection Agency (USEPA). 1992. Framework for Ecological Risk Assessment. EPA/630/R-92/001. USEPA, Washington, District of Columbia, USA.

Whelan, G, K.J. Castleton, J.W. Buck, B.L. Hoopes, M.A. Pelton, D.L. Strenge, G.M. Gelston, and R.N. Kickert. 1997. Concepts of a Framework for Risk Analysis in Multimedia Environmental Systems. PNNL-11748. Pacific Northwest National Laboratory, Richland, Washington, USA.

Westervelt, J.A. 2001. Development of the LMS Conceptualization Level. Technical report for the U.S. Army Corps of Engineers, Engineer Research and Development Center in fulfillment of Contract Number DACA88-99-0-0234, University of Illinois, Urbana-Champaign, Illinois, USA.

Zagona, E.A., T.J. Fulp, H.M. Goranflo, and R.M. Shane. 1998. Riverware: A general river and reservoir modeling environment. Pages 5–113 to 5–120 *in* Volume 2, Section 5, Proceedings of the First Federal Interagency Hydrologic Modeling Conference, Las Vegas, Nevada, 19–23 April, 1998. Subcommittee on Hydrology of the Interagency Advisory Committee on Water Data, Las Vegas, Nevada, USA.

Part 3 Key Issues

Section V: Investments Needed

13 Science and Management Investments Needed to Enhance the Use of Ecological Modeling in Decision Making

Lev Ginzburg and H. Resit Akçakaya

13.1 Introduction

Despite substantial advances in ecological modeling during the past two decades, models are rarely used in environmental decision making. In this paper, we explore the reasons for this lack of model use and discuss different types of scientific and management investment that might enhance the use of models in environmental decision making.

We believe one of the most important factors preventing widespread use of models in decision making is a lack of training. Many managers lack the experience to decide on appropriate kinds of models and the scales of resolution that are best to solve a given problem (Breininger et al. 2002). Related to this issue, we discuss the need for improved communication between managers and modelers.

Another important factor is the lack of appropriate and relevant data. We believe this deficiency is often an extension of lack of training, because managers who lack training in modeling do not know what types of data to collect to optimize the use of models.

As we will discuss below, a large number and variety of ecological models have been developed during the past decade. The lack of appropriate models is not an important factor, because many generic and specific models that already exist can be applied to practical problems and decision making.

13.2 Enhancing the Use of Models in Decision Making

Investments are needed in four areas to enhance the use of ecological modeling in decision making: training and education; application of existing models; integration of existing models; and developing new, case-specific models.

13.2.1 Training and Education

Teaching the use of existing models is the most efficient way to reach the goal of enhanced model use in the short term. Teaching can take various forms, and can be done in a variety of formats. Both the content and the format of training should depend on the audience. Here we consider two types of audience: managers and technical personnel.

Environmental managers, people who make decisions on management and research in governmental agencies and in the industry, are often unfamiliar with the potentials of modeling. The topics for educating managers in the use of ecological models could include

- Types of questions that can be addressed with ecological models
- Selecting the appropriate model
- Types of data needed for different types of models
- Interpreting the results of models
- How models incorporate variability and uncertainty
- Interpreting and communicating risk and uncertainty
- Recognizing limitations of models
- Learning to identify inappropriate uses of models
- Examples of the successful use of models

Another type of audience includes technical personnel who may be using or reviewing models developed by others. To judge the technical merits of models, they need to have a basic understanding of the fundamentals of modeling. The topics for technical personnel should include all the topics for managers. In addition, the following topics may be useful to train technical personnel:

- Components of different types of ecological models
- Tradeoffs between complexity (realism) and practicality (data availability)
- Collecting the appropriate data
- Analyzing data to estimate model parameters
- Incorporating variability and uncertainty
- Presenting model results

In addition to managers and technical personnel, modelers may also need training, for example to better understand biological aspects of the system, practical limitations to data collection, and the needs and limitations of management. However, this training is different because, unlike the topics discussed above, it is very case-specific. It is best done in workshops that aim at improving the communication among modelers, managers, and technical personnel.

13.2.2 Application of Existing Models

During the past several decades, a large number and variety of ecological models have been developed (see Table 13.1 for a list of examples). The variety of ecological models is reflected in their level of biological organization (population, metapopulation, food-chain, community, landscape, and ecosystem levels), in the way they describe time (discrete versus continuous), in their treatment of variability (deterministic versus stochastic), and in their level of detail (scalar, age-structured, stage-structured, spatially explicit, individual-based, etc.). For reviews of ecological models, see Burgman et al. (1993), Akçakaya and Sjögren-Gulve (2000), and Akçakaya (2000).

The simplest way to develop a model is to apply an existing model to a management question. "Application" means estimating parameters of the model, based on data that are specific to the location, species, and/or system in question, and using the model to address a specific management question about a particular case. This process is also often called "modeling," and it is true that analyzing case-specific data to estimate the parameters to incorporate into an existing platform is a method of building a model. However, we call this process "application" simply to differentiate it from the process of writing a computer program to create a model or a modeling platform.

There are many successful applications of existing models to address environmental issues (see Table 13.2 for a list of examples). Some of these applications have guided or determined management decisions, as we discuss below.

Decisions supported by model results have included listing a species as threatened, determining the type and schedule of management actions, and decisions on development permits. For example, in May 1995, the Oregon Department of Fish and Wildlife used RAMAS to develop an age-structured model in a report on the biological status assessment for the marbled murrelet, as a response to a petition to list the species under Oregon's Endangered Species Act (Oregon Department of Fish and

Table 13.1. Examples of existing models.

Population models
Stochastic scalar abundance models
Structured models (e.g., Leslie matrix)
Metapopulation models (e.g., RAMAS GIS and Vortex)
Landscape models
Forest landscape models (e.g., LANDIS and FORMOSAIC)
Aquatic landscape models (e.g., ATLSS)
Ecosystem models
Food-web models (e.g., RAMAS Ecosystem and Populus)
Aquatic-ecosystem models (e.g., AQUATOX, CASM, and IFEM)

Table 13.2. Examples of applications of existing models to environmental issues.

Species and population	Type of application or the purpose of the model	Reference
African elephant *Loxodonta africana* in Kenya	Harvest and reserve size	Armbruster and Lande 1993
Steller sea lion in northeastern Pacific	Harvest	Pascual and Adkinson 1994
Grey seal and ringed seal in Baltic Sea	Hunting	Kokko et al. 1997
Cottontail rabbit in New England	Habitat fragmentation and loss	Litvaitis and Villafuerte 1996
Gliding marsupial *Petaurus australi*	Determining area requirements	Goldingay and Possingham 1995
Leadbeater's possum in Southeastern Australia	Conservation and timber-management options	Lindenmayer and Possingham 1996
Golden-cheeked warbler; black-capped vireo	Viability assessment	USDOI 1996a,b
Northern spotted owl	Timber harvest in old-growth forests	Akçakaya and Raphael 1998
California spotted owl	Estimating risk of extinction	LaHaye et al. 1994
California gnatcatcher	Effects of fires and El Niños	Akçakaya and Atwood. 1997
European nuthatch in Denmark	Habitat fragmentation	Verboom et al. 1991
Helmeted honeyeater in Victoria, Australia	Translocation as a conservation measure	Akçakaya et al. 1995
Florida scrub-jay	Effects of habitat connectivity and catastrophes	Root 1998
Marbled murrelet in Oregon	Listing as threatened species	Oregon Dept. of Fish and Wildlife 1995
Pool frog in Sweden	Large-scale forestry	Sjögren-Gulve and Ray 1996
Loggerhead sea turtle *Caretta caretta*	Turtle excluder devices	Crowder et al. 1994
Yellow mud turtle and Kemp's ridley sea turtle	Headstarting as a management tool	Heppell et al. 1996
Brook trout in Appalachian streams	Multiple anthropogenic effects	Marschall and Crowder 1996
Striped bass in Santee-Cooper system, S.C.	Evaluation of management options	Bulak et al. 1995
Bluegill sunfish in North Carolina	Recovery after heavy metal impacts	Crutchfield and Ferson 2000
Butterfly *Melitaea cinxia* in Finland	Minimum viable metapopulation size	Hanski et al. 1996.
Land snail *Arianta arbustorum* in Switzerland	Effects of floods	Akçakaya and Baur 1996
Land snail *Tasmaphena lamproides* in Tasmania	Forest management	Regan et al. 1999
Pea aphid (*Acyrthosiphon pisum*)	Ecotoxicological impacts	Walthall and Start 1997
Polychaetes *Capitella* sp. and *Streblospio benedicti*	Response to pollutants	Levin et al. 1996
Banksia goodii (rhizomatous shrub) in Australia	Fire and land clearing	Drechsler et al. 1999
Mountain golden heather *Hudsonia montana* in N.C.	Controlled burning and trampling reduction	Gross et al. 1998
American ginseng and wild leek in Canada	Harvest	Nantel et al. 1996
Bradshaw's lomatinum in western Oregon	Prairie-burning treatments	Kaye et al. 1994
Sentry milk-vetch in the Grand Canyon	Protection from trampling	Maschinsky et al. 1997

Wildlife 1995). This species was later listed as threatened under Oregon's Endangered Species Act.

In another case, a metapopulation model was used to evaluate the effectiveness of translocation as a management tool for the endangered helmeted honeyeater (Akçakaya et al. 1995). An updated version of this model is currently being used to support the decision regarding timing of release. Data from a geographic information system and a RAMAS metapopulation model were used to determine the viable population size for the Florida scrub jay (Root 1998). This model was used in the context of four reserve designs developed as part of a habitat-conservation planning process focusing on scrub habitat on nonfederal lands in Brevard County, Florida (Brevard County Office of Natural Resources 1995).

A metapopulation model for a threatened land snail species (Regan et al. 1999) is contributing to planning outcomes in the Togari Forest of northwest Tasmania. Another metapopulation model was applied to the redhorse populations in the Muskingum river in Ohio (Root et al. 1997) to model the thermal impact that might result from a proposed increase in power plant operation. The proposed increase was approved by the Ohio Environmental Protection Agency.

Brook et al. (2000) applied several existing models (including RAMAS Metapop, RAMAS Stage, Vortex, Inmat, and Gapps) to 21 populations. The results both validated the predictions of these models by comparing them with observations and showed that models developed with different software gave similar results when used with the same data sets.

In summary, a large variety of existing ecological models can be applied to support or guide management decisions. Such applications require the collection of site-specific data and statistical analysis of the data to estimate model parameters. Once the model parameters have been determined (together with their uncertainties resulting from measurement error and their natural variabilities), the application of an existing model requires very little research effort. Therefore, the major scientific issues in the application of existing models involve data analysis methods. These methods include survival estimation methods based on mark–recapture data; methods for estimating spatial, temporal, and error variance components; as well as variance caused by such components as age and sex.

Most of the models considered in this paper, as well as most successful applications of modeling to management questions, are at the population level rather than the community or ecosystem levels. This selectivity reflects the state of ecological modeling: the theory of single-species dynamics is more complete than that of species interactions and community dynamics. The disadvantage of the ecosystem approach is the complexity of interactions among species and our lack of understanding of community and ecosystem dynamics. As our understanding increases, conservation and management practices will likely become more ecosystem-based. However, the contingencies and complexities involved may make it impossible to find general laws in ecosystem ecology (Lawton 1999). Currently, ecosystem-based approaches to practical ecological problems suffer from vagueness and circularity (Goldstein 1999). The single-species models are obviously not useful for all questions; models at community and ecosystem levels are often needed to address different types of questions. Nevertheless, it seems that single-species dynamics will remain one of the major practical methods for environmental conservation and management in the next decade and beyond, until the increased understanding of ecosystem dynamics allows more generic and practical models to be built.

At this point, the question of model selection, or the selection of the modeling approach appropriate for a particular case, arises. Three important factors are the question to be addressed, the quantity and quality of the data available, and the ecology of the system involved. In some cases, these criteria may point to different models. For example, the question may require a complex model, but the data may allow only a simple model. In such a case, the common approach of using a complex model and making assumptions for the parameters for which data are not available is not the most productive approach. Instead, two approaches can be taken, in many cases, simultaneously. On the one hand, a simple model can be used to explore other (more fundamental or more general or simpler) questions. On the other hand, more data can be collected, guided by sensitivity and uncertainty analyses with the more complex model.

Other factors important in model selection include generality and transportability. Other factors being equal, more generic models are easier to apply to new cases with minimal or no new programming, whereas more case-specific models often require additional programming to be applicable to a new location or species. In some cases, this additional programming can be as substantial as creating a new model.

13.2.3 Integration of Existing Models

In the recent past, significant model development has involved the integration of existing models rather than models created from scratch. Of course, in some sense, all models are created by combining basic building blocks, such as components that implement basic functions for dose–response relationships, density-dependence functions, random-variate generators, etc. However, what we mean by "integration" here is the linking of two or more fully developed models or generic modeling platforms. We will first discuss examples of such integration and then list some potential future developments that may involve the integration of existing models.

Two of the most commonly used approaches in population modeling are matrix models (Leslie 1945; Caswell 1989) and metapopulation models (Levins 1970; Gilpin and Hanski 1991). Models that integrate these two approaches have included multiregional models [e.g., Fahrig and

Merriam (1985)] and the spatially structured RAMAS Metapop (Akçakaya 1994).

Another integration involved habitat models and demographic models. Habitat models aim to predict a species' response to its environment or its habitat requirements (Verner et al. 1986), whereas demographic models aim to predict the changes in its abundance or its risks of decline and extinction (Burgman et al. 1993). Models that integrate habitat and demographic models have used different approaches, including individual-based models (Lamberson et al. 1994), grid-based models (Price and Gilpin 1996), and habitat-based metapopulation models (Akçakaya et al. 1995).

A third example of integration aims to link landscape models with metapopulation models. Landscape models predict changes in landscape and land use, based on modeling the dynamics of vegetation, natural processes [such as disturbances (fire, floods, wind, etc.) and succession], and human impacts (such as timber harvest and pollution). A new approach aims to integrate the landscape model LANDIS with the habitat-based metapopulation model RAMAS GIS. LANDIS (Mladenoff et al. 1996) predicts changes in forest stand structure, including species composition, dominant tree species, and age distribution. The RAMAS GIS (Akçakaya 1998) simulates the dynamics of species that inhabit distinct habitat patches. The integrated model will allow risk assessments for species and populations based on expected habitat changes. It will simulate the dynamics of the metapopulation in a landscape in which the underlying habitat variables (and thus the number, size, and spatial structure of the habitat patches) are changing (Akçakaya 2001). Incorporating landscape dynamics in the spatial structure of metapopulation models will allow evaluating effects of landscape management options on the viability of key species.

We believe the trend of integrating existing models will persist in the near future and that developing models through the integration of existing types will continue to be more efficient than creating entirely new models.

Existing models and approaches have several potential links. One of these possibilities involves linking simple (scalar) population models to allometric relationships. The resulting models can be used in screening assessments with minimum or no field data. An important research issue for this development is testing whether the level of conservatism (precaution) of this approach is comparable to the level required in a screening test.

Another type of integration may involve linking fate-and-transport models to ecological models. Although this approach has been used in specific cases, a general modeling platform is needed that links physical/chemical models (e.g., hydrological models), dose–response models, and population or metapopulation models (to assess ecological affects).

General models are also needed to integrate food-web and metapopulation models. Such an integration would allow modeling trophic interactions in a spatially structured habitat, with different metapopulation structures for different species. In this approach, coordinating temporal and spatial scales and resolutions will be an important research issue.

Integration may also involve several models of the same type. For example, linking habitat-based models for a set of several target species allows decision making in a multispecies context. A simple approach to such multispecies modeling involves combining habitat requirements of a set of target species and weighting the habitat suitability with ecological risk or status.

13.2.4 Developing New, Case-Specific Models

In most cases, an existing model is suitable to address the management question. In some cases, however, new model development is required. Such requirements can often be met by the integration of existing types of models, as discussed above. In rare cases, the management question may require a completely new approach to modeling.

One misconception about creating new models is that they are more transparent. In general, there is no relationship between the transparency of a model and its age. Some existing, generic models are very transparent, with detailed documentation of the equations and algorithms used and several papers describing applications of the model. New models created for a specific case can sometimes be "black boxes," because of their complexity and because resources are often not available for developing detailed manuals and other documentation.

The major advantage of developing entirely new models lies in enabling future scientific advances rather than addressing immediate management issues. Obviously, many management questions would benefit from advances in modeling in particular and ecology in general. Thus, creating new models should not be ignored. However, given a management issue, it makes sense to first review if an existing model can address the issue. Such an approach would prevent a lot of costly duplication of modeling effort.

13.3 Investment for Enhancing Model Use

Making research investments to enhance the use of ecological models involves three decisions (represented by the diamond-shaped boxes in Figure 13.1). The first decision is between research and training. We believe investment in training and education gives the most return in the short term. As discussed above, training and education may take different forms depending on the target audience. For educating managers in the use of models, we believe a one-day workshop format is the most suitable. For training technical staff and researchers, the most cost efficient is Internet-based, asynchronous teaching supplemented by two-way communication

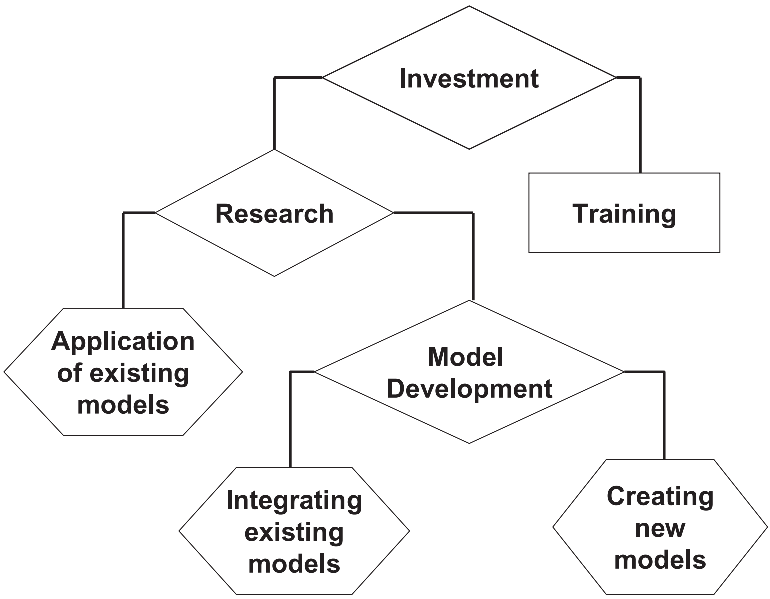

FIGURE 13.1. Series of three decisions (represented by the diamond-shaped boxes) for making research investments to enhance the use of ecological models in environmental decision making.

(e.g., by telephone). Thus, we recommend that Web-based short courses on ecological modeling be developed and offered to technical personnel in agencies involved in environmental decision making.

The second decision related to investments for enhancing model use involves the relative research investments in model development versus application (see Figure 13.1). The relative investment in applying existing models versus developing new ones depends on the time scale at which management decisions are needed. Both of these options require collecting and analyzing data to address the question. After the relevant data have been collected and analyzed, application of an existing model requires minimal additional investment in time and research effort. Therefore, for short-to-medium time horizons, the most efficient way of developing models involves using existing models with parameters based on data for the specific question at hand. In a majority of cases in which a management question can be addressed by models, the limiting ingredient is the availability of data, not the model.

The resource requirements for model application depend on the type of model that is appropriate for the available data and the question to be addressed, and on the availability of a software platform to apply that model. In general, data-intensive models (such as individual-based models) require more data and more resources to apply. Models that require programming or extensive customization require more time and resources than models that can be implemented with existing software platforms.

The third decision is about the relative investment in developing models by integrating existing models versus creating new models. The former option results in models with enhanced capabilities in a medium time horizon, whereas the latter option results in new models in the long term. The resources required for developing new models depend on the type of model, the species, and the landscape or the ecosystem being modeled.

13.4 Conclusion

In this paper, we considered four areas for making investments needed to enhance the use of ecological modeling in decision making: training and education; application of existing models; integration of existing models; and developing new, case-specific models. The relative enhancement of model use in decision making with these four types of research investments, as well as their different time horizons, are represented in Figure 13.2. The horizontal axis of this graph obviously has a very crude scale, which in reality depends on several factors. The vertical axis gives some arbitrary measure of how much the use of models is enhanced with a given amount of resources. By "enhancement," we mean an increase in the efficient and productive use of ecological models in environmental decision making.

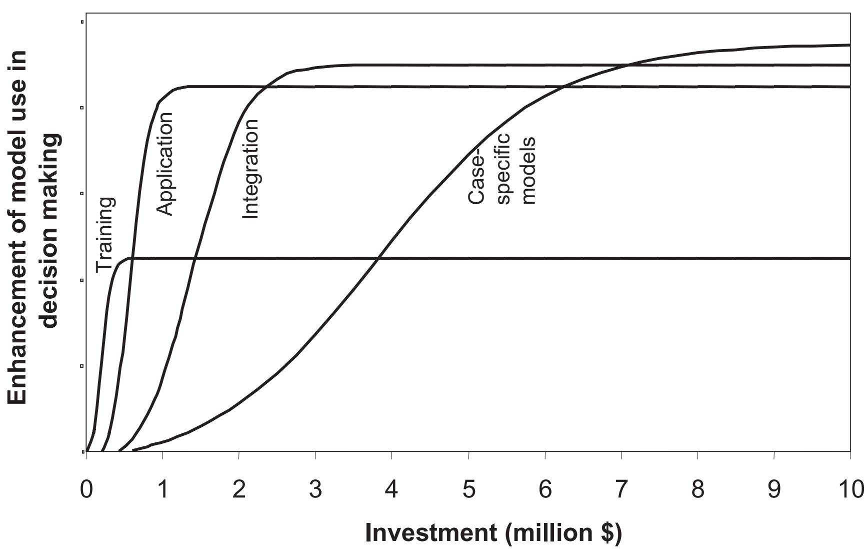

FIGURE 13.2. Efficiency of investment in the enhancement of the use of ecological models in decision making.

Thus, the figure is not meant to be predictive; it is simply a conceptual illustration of the effectiveness of various research and educational investments discussed in this paper.

In summary, we believe that, in the short term, the most efficient way to enhance the use of models in environmental decision making is through the education of environmental managers in workshops and the training of technical personnel by Web-based courses. In the medium term, model use can best be enhanced through the application of existing models to specific cases. In the long term, manifold opportunities exist for developing new modeling approaches by linking or integrating existing types of models.

References

Akçakaya, H.R. 1994. RAMAS Metapop: Viability Analysis for Stage-Structured Metapopulations. Applied Biomathematics, Setauket, New York, USA.

Akçakaya, H.R. 1998. RAMAS GIS: Linking Landscape Data with Population Viability Analysis. Applied Biomathematics, Setauket, New York, USA.

Akçakaya, H.R. 2000. Population viability analyses with demographically and spatially structured models. Ecological Bulletins **48**:23–38.

Akçakaya, H.R. 2001. Linking population-level risk assessment with landscape and habitat models. Science of the Total Environment **274**:283–291.

Akçakaya, H.R., M.A. McCarthy, and J. Pearce. 1995. Linking landscape data with population viability analysis: Management options for the helmeted honeyeater. Biological Conservation **73**:169–176.

Akçakaya, H.R. and B. Baur. 1996. Effects of population subdivision and catastrophes on the persistence of a land snail metapopulation. Oecologia **105**:475–83.

Akçakaya, H.R. and J.L. Atwood. 1997. A habitat-based metapopulation model of the California gnatcatcher. Conservation Biology **11**:422–434.

Akçakaya, H.R. and M.G. Raphael. 1998. Assessing human impact despite uncertainty: Viability of the northern spotted owl metapopulation in the northwestern USA. Biodiversity and Conservation **7**:875–894.

Akçakaya, H.R. and P. Sjögren-Gulve. 2000. Population viability analysis in conservation planning: An overview. Ecological Bulletins **48**:9–21.

Armbruster, P. and R. Lande. 1993. A population viability analysis for African elephant (*Loxodonta africana*): How big should reserves be? Conservation Biology **7**:602–610.

Bulak, J.S., D.S. Wethey, and M.G. White III. 1995. Evaluation of management options for a striped bass population in the Santee-Cooper system. North American Journal of Fisheries Management **15**:84–94.

Burgman, M.A., S. Ferson, and H.R. Akçakaya. 1993. Risk Assessment in Conservation Biology. Chapman and Hall, London, UK.

Breininger, D.R., M.A. Burgman, H.R. Akçakaya, and M.A. O'Connell. 2002. Use of metapopulation models in conservation planning. *In* K. Gutzwiller, editor. Applying Landscape Ecology in Biological Conservation. Springer-Verlag, New York, New York, USA.

Brevard County Office of Natural Resources. 1995. Scrub Conservation and Development Plan. Brevard County Office of Natural Resources, Melbourne, Florida, USA.

Brook, B.W., J.J. O'Grady, A.P. Chapman, M.A. Burgman, H.R. Akçakaya, and R. Frankham. 2000. Predictive accuracy of population viability analysis in conservation biology. Nature **404**:385–387.

Burgman, M.A., S. Ferson, and H.R. Akçakaya. 1993. Risk Assessment in Conservation Biology. Chapman and Hall, London, UK.

Caswell, H. 1989. Matrix Population Models: Construction, Analysis, and Interpretation. Sinauer Associates, Sunderland, Massachusetts, USA.

Crowder, L.B., D.T. Crouse, S.S. Heppell, and T.H. Martin. 1994. Predicting the impact of turtle excluder devices on loggerhead sea turtle populations. Ecological Applications **4**:437–445.

Crutchfield, J. and S. Ferson. 2000. Predicting recovery of a fish population after heavy metal impacts. Environmental Science & Policy **3**:S183–S189.

Drechsler, M., et al. 1999. Modelling the persistence of an apparently immortal *Banksia* species after fire and land clearing. Biological Conservation **88**:249–259.

Fahrig, L. and G. Merriam. 1985. Habitat patch connectivity and population survival. Ecology **66**:1762–68.

Gilpin, M.E. and I. Hanski, editors. 1991. Metapopulation Dynamics. Academic Press, London, UK.

Goldingay, R. and H.P. Possingham. 1995. Area requirements for viable populations of the Australian gliding marsupial, *Petaurus australis*. Biological Conservation**73**: 161–167.

Goldstein, P.Z. 1999. Functional ecosystems and biodiversity buzzwords. Conservation Biology **13**:247–255.

Gross, K., J.R. Lockwood, III, C.C. Frost, and W.F. Morris. 1998. Modeling controlled burning and trampling reduction for conservation of *Hudsonia montana*. Conservation Biology **12**:1291–1301.

Hanski, I., A. Moilanen, and M. Gyllenberg. 1996. Minimum viable metapopulation size. American Naturalist **147**:527–541.

Heppell, S.S., L.B. Crowder, and D.T. Crouse. 1996. Models to evaluate headstarting as a management tool for long-lived turtles. Ecological Applications **6**:556–565.

Kaye, T.N., K. Pendergrass, and K.K. Finley. 1994. Population Biology of *Lomatum bradshawii*: I. Population Viability Analysis under Three Prairie Burning Treatments. Oregon Department of Agriculture, Salem, Oregon, USA.

Kokko, H., J. Lindström, and E. Ranta. 1997. Risk analysis of hunting of seal populations in the Baltic. Conservation Biology **11**:917–927.

LaHaye, W.S., R.J. Gutiérrez, and H.R. Akçakaya. 1994. Spotted owl metapopulation dynamics in southern California. Journal of Animal Ecology **63**:775–785.

Lamberson, R.H., B.R. Noon, C. Voss, and K.S. McKelvey. 1994. Reserve design for territorial species: The effects of patch size and spacing on the viability of the northern spotted owl. Conservation Biology **8**:185–195.

Lawton, J.H. 1999. Are there general laws in ecology? Oikos **84**:177–192.

Leslie, P.H. 1945. On the use of matrices in certain population mathematics. Biometrika **33**:183–212.

Levin, L., H. Caswell, T. Bridges, C. DiBacco, D. Cabrera, and G. Plaia. 1996. Demographic responses of estuarine polychaetes to pollutants: Life table response experiments. Ecological Applications **6**:1295–1313.

Levins, R. 1970. Extinction. Pages 77–107 *in* M. Gerstenhaber, editor. Some Mathematical Questions in Biology. American Mathematical Society, Providence, Rhode Island, USA.

Lindenmayer, D.W. and H.P. Possingham. 1996. Ranking conservation and timber management options for Leadbeater's possum in southeastern Australia using population viability analysis. Conservation Biology **10**:1–18.

Litvaitis, A.J. and R. Villafuerte. 1996. Factors affecting the persistence of New England cottontail metapopulations. Wildlife Society Bulletin **24**:686–693.

Marschall, E.A. and L.B. Crowder. 1996. Assessing population responses to multiple anthropogenic effects: A case study with brook trout. Ecological Applications **6**:152–167.

Maschinsky, J., R. Fyre, and S. Rutman. 1997. Demography and population viability of an endangered plant species before and after protection from trampling. Conservation Biology **11**:990–999.

Mladenoff, D.J., G.E. Host, J. Boeder, and T.R. Crow. 1996. LANDIS: A spatial simulation model of forest landscape disturbance, management, and succession. Pages 175–179 *in* Second International Conference on Integrating GIS and Environmental Modeling. National Center for Geographic Information and Analysis, Santa Barbara, California, USA.

Nantel, P., D. Gagnon, and A. Nault. 1996. Population viability analysis of American ginseng and wild leek harvested in stochastic environments. Conservation Biology **10**:608–621.

Oregon Department of Fish and Wildlife. 1995. Public review draft. Marbled Murrelet: Biological Status Assessment. Oregon Department of Fish and Wildlife, Wildlife Division, Portland, Oregon, USA.

Pascual, M.A. and M.D. Adkinson. 1994. The decline of the Steller sea lion in the northeast Pacific: Demography, harvest or environment? Ecological Applications **4**:393–403.

Price, M. and M. Gilpin. 1996. Modelers, mammalogists, and metapopulations: Designing Steven's kangaroo rat reserves. Pages 217–240 *in* D.R. McCullough, editor. Metapopulations and Wildlife Conservation. Island Press, Washington, D.C., USA.

Regan, T., K. Bonham, H. Regan, R. Taylor, D. Tuson, and M. Burgman. 1999. Forest Management and Conservation of *Tasmaphena lamproides* in North West Tasmania: Use of Population Viability Analysis to Evaluate Management Options. Final report to Forestry Tasmania. University of Melbourne and Forestry Tasmania, Melbourne, Australia.

Root, K.V. 1998. Evaluating the effects of habitat quality, connectivity and catastrophes on a threatened species. Ecological Applications **8**:854–865.

Root, K.V., C.S. Grogan, and H.R. Akçakaya. 1997. RAMAS Ecological Risk Model for Assessing Temperature Effects on Redhorse Sucker Species in the Muskingum River. Applied Biomathematics, Setauket, New York, USA.

Sjögren-Gulve, P. and C. Ray. 1996. Using logistic regression to model metapopulation dynamics: Large-scale forestry extirpates the pool frog. Pages 111–137 *in* D.R. McCullough, editor. Metapopulations and Wildlife Conservation. Island Press, Washington, District of Columbia, USA.

U.S. Department of the Interior (USDOI), Fish and Wildlife Service. 1996*a*. Golden-Cheeked Warbler Population and Habitat Viability Assessment Report. USDOI, Fish and Wildlife Service, Austin, Texas, USA.

U.S. Department of the Interior (USDOI), Fish and Wildlife Service. 1996*b*. Black-Capped Vireo Population and Habitat Viability Assessment Report. USDOI, Fish and Wildlife Service, Austin, Texas, USA.

Verboom, J., A. Schotman, P. Opdam, and J.A.J. Metz. 1991. European nuthatch metapopulations in a fragmented agricultural landscape. Oikos **61**:149–156.

Verner, J., M.L. Morrison, and C.J. Ralph, editors. 1986. Wildlife 2000: Modeling Habitat Relationships of Terrestrial Vertebrates. University of Wisconsin Press, Madison, Wisconsin, USA.

Walthall, W.K. and J.D. Start. 1997. Comparison of two population-level ecotoxicological endpoints: The intrinsic (r_m) and instantaneous (r_i) rates of increase. Environmental Toxicology and Chemistry **16**:1068–1073.

14 Educational Investments in Environmental Science and Management

Thomas P. Maxwell, Jim Berkson, Tania Schoennagel, Karen A. Poiani, and Robert Costanza

14.1 Introduction

Modern society is driving changes in a number of ecological, political, and economic systems that are interacting in complex and often unpredictable ways with potentially disastrous consequences. These systemic problems are impossible to address in isolation, requiring an integration and transcendence of existing boundaries of knowledge across the natural and social sciences (Costanza et al. 1997). A shift in emphasis is required from studying and managing problems in isolation to studying whole systems and the complex, dynamic interactions between the parts. Analytical models can play a crucial role in organizing and synthesizing knowledge about these complex systems.

Modeling is an essential prerequisite for the comprehension of system dynamics and for choosing among alternative management scenarios. Challenges facing natural resource managers and decision makers increasingly occur at broad spatial and temporal scales, requiring the use of mathematical models to evaluate alternative future scenarios of ecological change. Model building can also play an important role both in understanding complex system dynamics and in transcending the compartmentalization of knowledge by facilitating synthesis and consensus building. Models provide a common language and conceptual framework to organize knowledge and make sense of a complex world.

Although some management questions can easily be addressed with the aid of existing models (see Chapter 13, this volume), complex systems demand new complex models and modeling processes. Yet, despite the great need for improved model development and the substantial advances in ecological modeling that have been made in the past two decades, analytical modeling has not achieved its potential in environmental decision making. Significant investments are needed to develop the potential role of ecological modeling in the management of our natural resources.

An effective way to expand the role of ecological modeling in natural resource management involves education. A greater understanding of the goals, uses, and benefits of modeling by managers, scientists, stakeholders, and the public must be accomplished for modeling to be incorporated and applied. Also, a concerted effort must be made to increase the effectiveness of communication among modelers, scientists, stakeholders, managers, and the public. Managers must be able to explain their needs to modelers, and modelers must be able to explain their results effectively to managers. This paper focuses on four areas of education needed to facilitate the application of ecological modeling in earth-systems management: the education of (1) managers and decision makers, (2) students, (3) scientists and modelers, and (4) stakeholders.

14.2 Educating Managers and Decision Makers

Two primary areas of needed investment are communication to and education of on-the-ground managers and decision makers (i.e., those who influence resources allocated to these managers). Most managers and decision makers have only a vague understanding of the importance and capabilities of ecological models to aid in management decision making. In fact, many managers view models as complex black boxes that can only be understood and used by technicians, scientists, and mathematicians. In some cases, these perceptions are correct. However, ecological models range in complexity and purpose. Many models and their results, regardless of how complex or simple, can often be used to inform decisions with proper assistance and interpretation (Starfield 1997).

Thus, to increase the use and effectiveness of ecological models in management, managers and decision makers must be educated about model value and usability. Several issues are of particular importance, including

- Relevance and importance of modeling
- Sensitivities and uncertainties of models
- Available models and methods
- Methods for educating managers and decision makers

14.2.1 Relevance and Importance of Modeling

Managers and decision makers need to understand the relevance and importance of modeling. An ecological model is a conceptual or mathematical representation of a natural phenomenon. Ecological models are abstractions or simplifications of the real world that portray the dominant components and key processes. Typically, ecological models define relationships among the parts of an ecological system and the dynamic processes that change and influence these parts (e.g., states and transitions). These relationships are the basis on which one can predict changes in system behavior or component pieces over time in response to external forces.

Models perform a variety of functions. Ecological models are excellent tools for formulating questions about the behavior of an ecological system and potential threats to system integrity (Lauenroth et al. 1998). Increased understanding of system behavior resulting from model predictions and exploration can be very useful in guiding management decisions. For example, simulation results from a spatially explicit, cell-based model of vegetation and fire dynamics at Eglin Air Force Base in Florida helped natural resource managers understand that current and planned fire management would not maintain the desired extent of longleaf pine (*Pinus palustris*) habitat across the base (Hardesty et al. 2000). The model showed that, after a period of 50 years, many primary longleaf pine habitats would be converted to hardwoods (mainly *Quercus laevis*) and sand pine (*Pinus clausa*). Managers realized from these predictions that prescribed fire management needed to be doubled to maintain and restore the desired amount and quality of longleaf pine habitat. Moreover, the model allowed managers to select and implement an adaptive approach that promised to reduce greatly the per-acre cost of burning while maximizing desired ecological effects (J. Hardesty, The Nature Conservancy, personal communication, November 2001).

Models also document and record major assumptions and current understanding and help organize our knowledge about a particular ecological system or process (Maddox et al. 1999). Developing a simple conceptual model of the koa/'ohi'a (*Metrosideros polymorpha*) mesic forest on the island of Hawai'i, has helped The Nature Conservancy scientists and on-the-ground practitioners articulate and document dominant system dynamics and understand key processes and threats to these forests (S. Gon, The Nature Conservancy, personal communication, October 2001). The conceptual model also incorporated potential conservation and management strategies that could be used to reverse the current trend of unchecked degradation. Such conceptual models and the information contained within them provide a powerful communication tool for both managers and key stakeholders.

14.2.2 Sensitivities and Uncertainties of Models

Ecological models, however, are not a panacea for solving every management problem or answering every question, and managers and decision makers must understand the sources of variation in a model [e.g., Reed et al. (1998)]. Models are a means of integrating data to more comprehensively understand complex ecological dynamics. Managers must realize that models are not answers in and of themselves. They are useful tools for organizing and communicating ideas, synthesizing current understanding and data, developing management goals and objectives, elucidating unknowns, and generating hypotheses. In the best of circumstances, they provide a glimpse into the future to help guide present decisions [e.g., Gustafson et al. (2000)]. Users and managers must exercise caution in interpreting model results and in using resulting information to make decisions.

Model results should be used to *support and guide* decisions rather than to *dictate* decisions.

Models typically have significant uncertainties associated with their results and output. Uncertainties in the input data are sometimes explicit and obvious. Often, however, model uncertainties are not recorded or are unknown and unstated. Sidebar 14.1 gives an example of how information

Sidebar 14.1
Propagating uncertainty with RAMAS Red List

RAMAS Red List version 2.0 implements threatened-species criteria of the International Union for the Conservation of Nature (IUCN) (IUCN Species Survival Commission 2001). Those criteria constitute

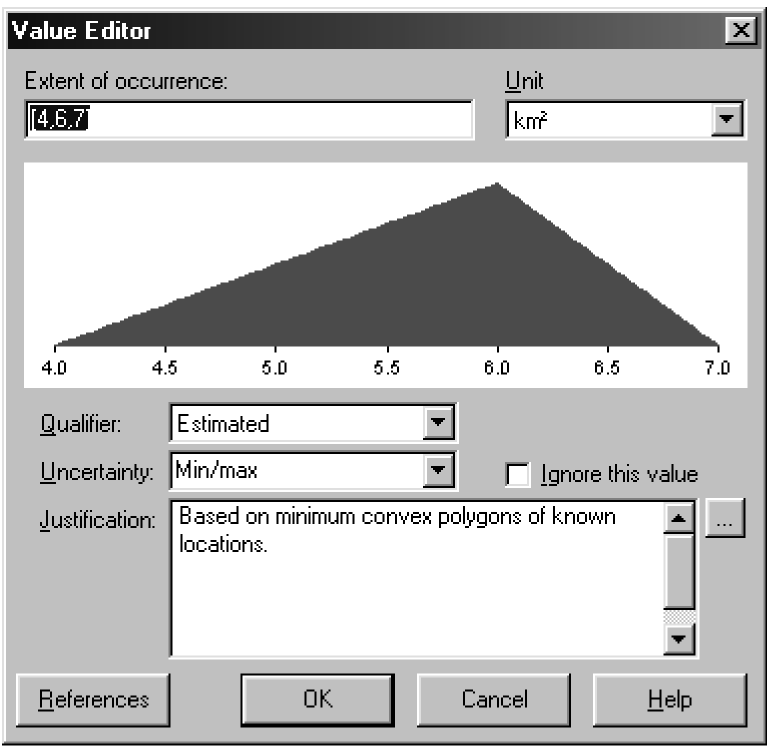

FIGURE 14.1. The RAMAS Red List dialogue for entering an uncertain value. In this example, the extent of occurrence for *Grevilla caleyi* (an Australian shrub) is entered as a best estimate of 6 km^2 and a plausible range of 4 to 7 km^2. This uncertainty is represented as a triangular fuzzy number [Data from Akçakaya et al. (2000)].

rules for assigning species into categories representing different levels of threat. The IUCN rules are based on such characteristics as number and distribution of individuals, fluctuations and decline in abundance and distribution, and risk of extinction. These characteristics are used as input data; the output is a classification into one of the categories, such as critically endangered, endangered, vulnerable, near threatened, or least concern. These threatened-species categories are used in the Red List of Threatened Species (www.redlist.org) and provide an easily and widely understood method for highlighting those species under higher extinction risk to focus attention on conservation measures designed to protect them. The categories are widely recognized internationally, and they are now used in a whole range of publications and listings produced by the IUCN as well as by numerous governmental and nongovernmental organizations (NGOs).

The software package RAMAS Red List (Akçakaya et al. 2001) implements the rules as used by the IUCN and allows the user to explicitly incorporate uncertainties in the input data. Input data, such as the number of mature individuals, can be specified either as a number or as a range of numbers, or as a range of numbers plus a best estimate (Figure 14.1). The RAMAS Red List propagates the uncertainties by using fuzzy arithmetic [see Akçakaya et al. (2000) for the details of the method of propagating uncertainty]. Depending on the

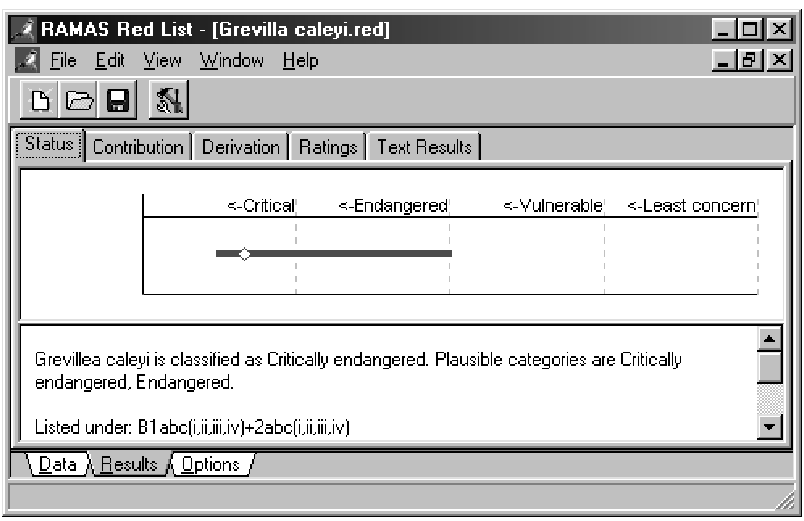

FIGURE 14.2. The RAMAS Red List result for *Grevilla caleyi*. The status is uncertain and includes both "critically endangered" and "endangered" categories, reflecting the uncertainties in the input data [see Akçakaya et al. (2000)].

uncertainties, the resulting classification can be a single category or a range of plausible categories (Figure 14.2). The range of categories relects the uncertainty in the input data. Results for a set of species can be viewed together (Figure 14.3), allowing a comparison based on the threat category as well as on the uncertainty of the results.

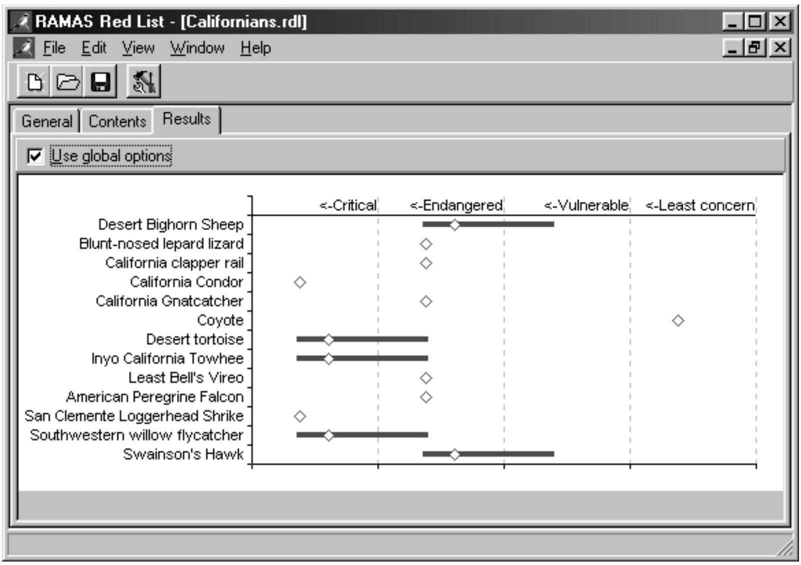

FIGURE 14.3. The RAMAS Red List result for several species. In some cases, the status is uncertain and includes more than one threat category. In other cases, there is no uncertainty in the status, and the species is assigned to only one category.

about uncertainties can be maintained in an analysis. *Uncertainty analysis* indicates the influence of a parameter, given the actual variation it represents, on the output variable. *Sensitivity*, on the other hand, is the degree to which the model outcome depends on the variability of one parameter. Thus, uncertainty analysis complements sensitivity analysis. Identifying the sources of uncertainty in a model helps a user know when the limits of the model's applicability have been reached. Such analyses are designed to shed light on the sources of variation of model output. Managers and decision makers must be aware of the importance of this type of information and be advised about how to interpret and use model results given sensitivities and uncertainties. Although ecological models have sensitivities and uncertainties, knowledge of these sources of variation can serve to enhance the use of a model and its results.

Using existing models and developing new mathematical models not only elucidate important patterns and processes in natural systems, but may also highlight the variety of challenges in addressing real-world problems facing natural resource managers. An important challenge to effective environmental decision making is the ability to evaluate levels of uncertainty in model predictions. Taylor et al. (2000) underscore the need to incorporate uncertainty in management models, and this important component in ecological modeling is often overlooked.

In environmental management applications, models that do not effectively quantify or communicate uncertainty in their outputs may lead to decisions that produce unintended results. On the other hand, these models may simply lead to management inaction because relative risks cannot be evaluated and, therefore, no single scenario can be demonstrated to be better than another (Akçakaya and Raphael 1998). Hence, models that do not adequately quantify uncertainty in their output undermine their utility as effective management tools.

The software RAMAS Red List: Threatened Species Classifications Under Uncertainty is a classroom example that highlights the importance of uncertainty propagation within an applied model (Akçakaya et al. 2001). Users can explicitly incorporate uncertainties in the input data, allowing those uncertainties to propagate through the model, affecting the final classification of particular threatened species (see Sidebar 14.1). Such models clearly demonstrate how the predictive power of models hinges on the robustness of the input parameters, how managers must evaluate model outcomes in light of such uncertainties, and how models may direct future sampling protocols and monitoring programs.

14.2.3 Available Models and Methodologies

Modeling is a powerful tool for scientific exploration with extremely diverse applications that span ecological models ranging from conceptual to mathematical to simulation. For example, ecological models are often simple conceptualizations consisting of narrative descriptions, schematic diagrams, and/or box-and-arrow flowcharts. They can also consist of simple or complex numerical equations, graphs, or computer algorithms forming the basis of a dynamic simulation model. This latter group of models varies greatly. Computer simulations include, for example, models of population viability, forest succession and disturbance, fires, animal habitats and dispersion, wetland and river dynamics, and whole-ecosystem biogeochemistry.

To increase the effective use of models in management, managers and decision makers need to be introduced to the plethora of available models and methods like those discussed in this book. Often, they also need to be assisted in choosing the type of model that would best help them understand their system and guide their management decisions. In outlining and exploring the scope of a problem with managers and stakeholders, developing a simple conceptual box-and-arrow diagram of an ecological system is generally more appropriate and helpful than developing a complex computer simulation model. Sometimes modelers are too quick to build comprehensive, complex simulation models when managers need simpler models to help organize their thinking and to communicate ideas and assumptions (Starfield 1997). In other instances, models may not be useful because they fail to adequately represent necessary details of the problem.

Managers primarily need to understand

- Data requirements to build and test different kinds of models
- Appropriate spatial and temporal scales needed to answer their management questions
- Tradeoffs between model complexity and generalization for their applications
- Tradeoffs between using resources to develop models versus collecting more field data (Reed et al. 1998)

Developing this understanding requires that managers and decision makers be knowledgeable about the time and resources needed to build and use ecological models. Time and resources will vary with the type and purpose of the model and the level of complexity and accuracy needed for the project. Providing accurate and reliable cost estimates for the development and use of models will be key in increasing the use of models in management.

14.2.4 Methods for Educating Managers and Decision Makers

Methods to educate managers and decision makers need to be flexible and appropriate for different needs and different people. For example, education of on-the-ground managers will probably occur under different circumstances and using different methods than for mid- and high-level decision makers. Decision makers may require less technical information and more information on capabilities, limitations, and costs. Decision makers will likely be educated and informed by the managers themselves. Thus, managers will need to become articulate spokesmen for allocating resources for modeling. Case studies that illustrate model capabilities and how models have helped inform management decisions can be a powerful method for educating and persuading decision makers [e.g., Tester et al. (1997); see Table 13.2 in Chapter 13, this volume).

In contrast, on-the-ground managers and practitioners may demand more detailed knowledge of models ranging from some of the technical aspects to cost and resources. Resource managers often are essential partners in determining the most useful output of models. In some circumstances, managers may become the final users of the model and may need training on running the model and interpreting results. Managers will likely need to be educated about the ecological system and the ways it can be expressed mathematically by modelers and scientists. Some managers will be self-educated, but most are focused primarily on day-to-day activities and have little time or interest to learn about models. It often takes an influential advocate to educate managers about the value and importance of modeling. Again, case studies can be particularly important.

In addition, managers must be able to articulate their needs and questions. They must be presented insights about how to formulate appropriate model questions, how to help modelers focus on the core issues, how to cope with model limitations and uncertainties, and how to appropriately interpret and use model results.

14.3 Training Modelers and Scientists

Ecological modelers need to become more effective in the process of environmental management, a task that demands both scientific and communication skills. Communication skills are often overlooked in preparing modelers for a career in environmental management, yet communication is a crucial aspect of collaborative problem solving.

In real life, modelers usually have to develop the modeling tool within the constraints of the project rather than having the luxury of determining the problem, goal, or timeline themselves. They must clearly and immediately understand:

- What is the goal of the assignment?
- Who needs the model?
- How will it be used?
- What are the applicable timelines?
- What management actions are being tested?

For many modelers, particularly those with less applied backgrounds, understanding the constraints of a problem is often deemed a lower priority than their own independence and creativity. What could have been an important applied management tool may become an irrelevant theoretical study or a creative solution to the wrong problem. As a result, models resulting from such efforts are seldom used. Misapplied models also become a disincentive for policy or decision makers to incorporate models into future management decisions. Therefore, modelers must improve their understanding of the problem to deliver an effective, well-targeted product. This task involves both effective listening and the ability to ask appropriate questions to clarify the needs and constraints of the users.

Modelers must also improve their ability to communicate their methods and results to policymakers and stakeholders who typically have little technical background. Most modelers have experience making technical presentations to technical audiences, but few have substantial experience making technical presentations to nontechnical audiences. The surest way to make an ecological modeling effort irrelevant is for the modeler to be incapable of explaining the results to policymakers. Intuitively, scientists, and in particular modelers, who can communicate technical results effectively to nontechnical audiences will be more likely to find their modeling efforts more greatly relied upon and used. One can improve one's public presentation skills by participating in Toastmasters International, joining an amateur theater group, speaking to Rotary Clubs and other organizations, taking a public-speaking class at a community college, or getting a mentor who is a good public speaker.

Environmental scientists who do not have a modeling background could benefit from additional training to improve their understanding of the uses and limitations of specific models and modeling in general. Most importantly, these scientists must understand the potential role of models in an environmental management program. Modeling is often a team process. Modelers rely on the assistance and guidance of scientists who are experts in the system being modeled. Usually, the expert scientist describes to the modeler how the system works, and the modeler creates a computational analog of the system. In some cases, managers and stakeholders may be involved in the modeling process. Together, the team decides what is feasible or infeasible given various fiscal, technological, logistical, physical, or biological constraints. For those scientists who do not understand the process, modeling is intimidating and something to be avoided. They likely assume that everyone working on a model must know how to program a computer and must know complex mathematics. It is the job of the *modeler* to work with these aspects of the project. In many modeling projects, the expert scientists do not even see the programming code or complex mathematics. When nonmodelers understand the purpose of modeling and the role they would likely play, modeling is no longer intimidating. In fact, it often becomes interesting and exciting.

There are two main benefits to this education. First, the nonmodeling scientists and stakeholders are often in a position to identify projects where modeling can play an important role. Second, their willingness to participate in the process improves the productivity of the modeling team and makes life easier for the modeler. In many cases, they are also in the best position to explain the results to the policymakers. Educating this group during the course of the development effort would greatly improve the use of ecological models in management.

How can we educate current practitioners? There are many ways that this can be accomplished. Web-based training is becoming very popular because it allows individuals to learn at their own pace, on their own time, in their own location. Workshops are an excellent way to train modelers and nonmodelers, alike. There is a growing trend toward scheduling workshops immediately before, during, or after major professional society meetings. This scheduling takes advantage of opportunities when a large group of individuals would already be together. Many agencies sponsor training workshops. For example, the National Conservation Training Center, under the U.S. Fish and Wildlife Service in Shepherdstown, West Virginia, has developed a week-long course titled "Introduction to Natural Resource Modeling." It is designed to familiarize nonmodelers with the process, benefits, and limits of resource modeling.

Participation in the modeling process is one of the most effective methods for educating both modelers and nonmodelers. Agencies and other management organizations should encourage broad participation in modeling projects, allowing modelers to improve their communication skills and allowing nonmodelers to familiarize themselves with the process. Inviting scientists to work on case-study projects with university classes can provide an enlightening experience for all participants. Students learn by working with scientists in the field, and scientists are often challenged to rethink and reorganize their knowledge base so they can present it to an audience that does not have the full, prior knowledge that they do.

14.4 Training Students

Optimally, student education should develop a balance of skills in analysis, synthesis, and communication structured around a participatory, problem-focused, collaborative learning experience. Modeling can play a key role in this learning process. Students should be well trained in applying models to link biological processes and management needs. Unfortunately, the incorporation of mathematical and conceptual modeling in undergraduate and graduate student training in this field remains limited.

14.4.1 Synthesis and Creative Problem Solving

Most university science programs emphasize analysis, the ability to break down a problem into its component parts and understand how each part functions. Students should augment a solid grounding in analytical techniques with courses, research, and workshops that develop the strategies and tactics required to achieve synthesis: the ability to put the pieces back together in a creative way to solve problems. Synthesis complements analysis and is an essential element of any transdisciplinary program, particularly one that addresses important, global environmental problems (Pickett 1999). Yet, training in synthetic skills is too often neglected in university science curricula, as is training in effective communication. Scientists must be able to share their knowledge across disciplines to strengthen their own understanding, interact with stakeholders to integrate local knowledge and concerns into their models, and communicate their results to policymakers and the broader public. To meet these objectives, university programs should emphasize integrated analysis, synthesis, and communication.

14.4.2 Systems Thinking and Model Conception

Systems thinking [e.g., Kitching (1983)] and conceptual modeling are critical starting points for introducing students to the process of model conception and development. However, they remain infrequent components of undergraduate biology training or graduate-level applied-ecology course curricula. The challenge of understanding complex-system behavior and developing simple models can be great (Hannon and Ruth 1997). The process of developing conceptual models, however, may help teach problems and important processes in ecological systems by introducing students to the process of synthesizing complexity into salient relationships, boundaries, and components. Applying conceptual models to real biological scenarios is also an important tool in hypothesis formulation and testing, in determining practical and ecological constraints to a problem, and in assessing an understanding of a system. Constructing conceptual models is a valuable step in getting students in ecology and environmental management to become systems thinkers. This process can provide a critical foundation for ecological practitioners and mathematical modelers to define common vocabularies and to master the process of problem definition. The process of deriving conceptual models can also help build consensus and common understanding among students, which not only is relevant to understanding the biological system, but also is a critical element in collaborative research across disciplinary boundaries common to many management problems (Walters 1986; Carpenter 1992; Jackson 2000).

14.4.3 Quantitative Modeling

In addition to conceptual modeling, quantitative training in undergraduate biology and ecology curricula is also generally weaker than that in the physical sciences. Quantitative concepts and exercises should be integrated into ecology curricula rather than remaining isolated in mathematical courses. Such integration would highlight the importance of quantitative solutions to ecological questions. At the same time, ecological examples should be more commonly applied in mathematical training to underscore the applicability of mathematical skills to contemporary management problems. Such integration both emphasizes the utility of using quantitative methods in ecological decision making and underscores how mathematical models can enhance biological understanding (Gross 2000).

A number of software packages are geared toward introducing students to the process of quantitative model building, from conception and construction to verification and validation [e.g., Akçakaya et al. (1999);

Hannon and Ruth (1997); Jackson et al. (2000)]. For example, Madonna, ModelMaker, SimuLink, PowerSim, and STELLA are icon-driven programs useful for introducing students to the basics of quantitative modeling, allowing the student to build a quantitative model from start to finish. Such software simplifies model building by generating equations defined by constructing graphical relationships between input parameters in an ecological system of interest (Costanza 1987). In some cases, simulations displayed as graphs, tables, or animations can be automatically generated from mathematical formulae. These programs are valuable and popular in teaching environments because simple quantitative models can be easily constructed to illustrate diverse phenomena, from simple logistic growth to percolation models of landscape pattern, to movement of phosphorus through a salt marsh, to complex predator–prey relationships. Excellent software packages, such as RAMAS and Populus, or texts, such as the *Applied Population Ecology (*Akçakaya et al. 1999) and *A Primer of Ecology* (Gotelli 1998), introduce basic quantitative approaches specific to population dynamics and conservation biology with applied, interactive examples. In addition, simple spreadsheet programs, such as Excel, can also be effectively and creatively used to construct basic quantitative ecological models, including simple spatial process models (Weldon 1999; Gergel and Reed 2001). Although many of these programs may be limited to relatively simple models, they provide tractable, creative segues into the sometimes daunting world of quantitative modeling by removing the hurdles of arcane programming languages (Jackson et al. 2000). There is a broad array of ecological models and texts that can be useful in integrating a variety of modeling exercises into the classroom, which may increase quantitative literacy and competence critical to effective environmental management [e.g., Alstad (2001); Bossel (1994); Brown and Rothery (1993); Gergel and Turner (2001); Hannon and Ruth (1997); Othmer et al. (1997); Starfield et al. (1990)].

14.4.4 The Process of Modeling and Environmental Decision Making

Abundant research suggests that transdisciplinary education is best pursued not in the abstract but by means of applied problem solving [e.g., Grigg (1995); Scott and Oulton (1999); Wheeler and Lewis (1997)]. This approach forces students and faculty to integrate and synthesize the methods and insights of the various disciplines. Rather than mastering a single set of tools to apply to all problems, students should learn to select and apply the tools required by the specific problem they address in their research. Modeling toolkits can facilitate this synthetic approach to learning (see Chapters 11 and 12, this volume). Providing real-life scenarios in classroom modeling exercises is critical.

It is also important that students have realistic expectations of how the process of environmental decision making works and, most importantly, the role of science and scientists within the process (Berkson and Harrison 2001; Berkson and Harrison 2002). Students must understand how they will fit into the process so they can enter the field as effective and productive players. Many of our university science programs teach how the decision-making process could work. Students are taught that decisions are based on best available science and the recommendations of scientists. In reality, however, decisions are typically based on incomplete information and a combination of scientific, political, economic, and social factors. Students need to be taught how the process *does* work, not how it *could* work based on best-case scenarios. This learning may be best achieved by teaching synthesis and integration and by providing examples of the multiple roles that models play in the environmental-decision-making process. The template for a course that provides exposure to the actual process of environmental decision making has been developed and is currently in use (Berkson and Harrison 2001; Berkson and Harrison 2002) (see Sidebar 14.2).

This practical education in real-world environmental modeling can be greatly enhanced by linking students with agencies in developing modeling projects for class. This interaction not only exposes students to the complexity of real-life management issues but may also provide managers with useful products at the end of the semester. In addition, application of real-life scenarios during modeling training may force modelers to produce creative solutions within the temporal and financial constraints of the real world.

14.4.5 Communication and Interpretation of Models

Another important element in student training is effective communication and interpretation of models to scientists, land managers, decision makers and the public. Collaborative, problem-focused learning environments require sharing knowledge across disciplines, interaction with multiple stakeholders, and the communication of results to policymakers and the broader public. Thus, collaborative learning environments can provide a key component in the education of students.

Modeling exercises should incorporate written and oral presentations to groups that require the description of the model development and the evaluation of the results, tailored to the ecological and technical background of particular groups. Other techniques, such as role-playing exercises, are useful exercises in learning how to effectively communicate across institutional boundaries. For example, students can give testimony based on their model results in a public hearing or can act as a decision maker describing the pertinence of model results to other modelers, environmentalists, field biologists, or a regulatory agency.

Sidebar 14.2
Teaching model development and implementation

Promoting effective communication skills is an important component of the "Systems Approaches to Natural Resource Modeling" course offered to graduate students in the Department of Fisheries and Wildlife Sciences at the Virginia Polytechnic Institute and State University. This course is an introductory modeling course that teaches students the goals, processes, applications, benefits, and limitations of natural resource modeling. Students learn by participating in the modeling process, from defining the goals of a model related to their dissertation topics, to building a prototype of the model, to presenting their results.

At the end of the class, each student gives two presentations of the model's results. One presentation is meant to be a formal technical presentation, similar to one that might be given at a professional society. Students are expected to present the methods and results to their fellow students as peers. The second presentation is meant to be a presentation to a decision maker, to someone without a strong technical background who would need to apply the results of the model.

The students have very little trouble with the technical presentation. Most have given many scientific presentations previously. It is quite different with the nontechnical presentation. They are given 10 minutes to tell the room full of "decision makers" the bottom line of their model in terms that the decision makers will understand and in a way to keep them interested. The students say that this is one of the toughest parts of the class. But it is one of the most important. When the students get to the real world, they will be giving many nontechnical presentations, and if they want to be effective, they need to give them well.

14.4.6 Atelier Courses

Another approach that has proved effective in student education is to develop graduate-level "atelier" style workshop/field-courses that integrate transdisciplinary graduate education and environmental problem solving. The atelier approach is being developed by the University of Maryland Institute for Ecological Economics. "*Atelier*" is French for "artisan's workshop," and the method employs a combination interdisciplinary workshop, case study, design studio, and guest lecture system rolled into one. Each workshop focuses on a specific environmental problem selected and researched in close consultation with the relevant stakeholders. The introductory and analytical materials for the workshops can be delivered via a Web-based educational module to economize on precious field time. The ateliers then move to the field, to study the problem first hand and to develop the tools and methods necessary to tackle it. Ateliers emphasize peer-to-peer interactions, where all participants share their disciplinary perspectives in an effort to forge an appropriate synthetic approach to the problem. The result is practical experience in the integrated application of methods and insights from diverse disciplines to the resolution of a specific problem. Along the way, they build the skills in interdisciplinary synthesis expected from student dissertations. Participants develop communication skills by sharing their perspectives with each other, by communicating research results to the group and the stakeholder community (including relevant policy makers), and by producing publication-quality articles. Other outcomes of this approach include experience in teamwork, knowledge sharing and problem solving desirable to future employers, and concrete steps toward resolving an actual environmental problem.

The student's learning experience in applied environmental problem solving can be enhanced by arranging internships with governmental, international, or nongovernmental organizations. These internships will provide the students with insights and approaches from outside academia, as well as experience, professional skills, and valuable future contacts. Universities should develop strong ties with governmental environmental management agencies and NGOs so that student cooperation can extend beyond internships toward collaboration on mutually beneficial research and mentoring.

14.5 Educating Stakeholders: Consensus Building

Involving the range of parties interested in or affected by the policy decisions in the modeling process builds confidence in the models developed. The collaborative process fosters consensus about the appropriateness of the model's assumptions and results and promotes compliance with the policies derived from the model. Interactions between managers, modelers, and scientists can help keep the program firmly grounded in relevant observable biology. Managers are much more likely to trust and understand a model that they helped develop.

Modeling can play an important role in breaking down the gap between expert knowledge and the public. Information in the modern world is compartmentalized and is often controlled by various isolated technical elites. This fractionation allows experts from various fields to hold contradictory opinions and the public to hold inconsistent and volatile opinions. Coming to consensus is the process of confronting and resolving these inconsistencies by breaking down the barriers between compartments of knowledge and information. The process of modeling can serve this consensus-building function. It can help to build mutual understanding, solicit input from a broad range of stakeholder groups, and maintain a substantive discussion among members of these groups. What is required is a new role for modeling as a tool in building a broad consensus not only across academic disciplines but also between science and policy (Costanza and Ruth 1998; Yankelovich 1991; Weisbord 1992).

14.5.1 Modeling and Consensus Building

The consensus-building function of the modeling process can be facilitated with a three-stage approach to collaborative management (Costanza and Ruth 1998). The first stage uses collaborative development of a high-generality, low-resolution scoping and consensus-building model to involve a broad representation of stakeholder groups affected by the problem. Graphic modeling tools make it feasible to involve a group of modeling novices in the construction of relatively complex models, as long as a few people competent in modeling act as facilitators. The projected graphical representation of the model can serve as a blackboard for group brainstorming, allowing students, educators, policymakers, scientists, and stakeholders to all be involved in the modeling process. Using the model as the topic of group discussion allows investigation of new scenarios and testing of new ideas. The model develops and evolves through this collaborative process of exploration. When applied in this manner, the process of creating a model may be more valuable than the finished product because most of the learning occurs during the collaborative development process.

The second stage of building consensus uses models that are more detailed and that include realistic attempts to replicate the dynamics of the complex system of interest. This stage involves collecting large amounts of historical data for calibration and testing and then performing a detailed analysis of the uncertainties in the model. It may involve traditional "experts" and is concerned with analyzing the details of historical development of a particular system with an eye toward developing specific scenarios or policy options in the next stage. It is still critical to maintain stakeholder involvement and interaction at this stage. This involvement may include the exchange of models and regular workshops and meetings to discuss model progress and results.

The third stage of building consensus with management models is focused on producing scenarios and management options in the context of adaptive feedback and monitoring. This stage is based on the earlier scoping and research models. It is also necessary to place the modeling process within the larger framework of adaptive management (Holling 1978) if management is to be effective. Adaptive management views regional policy exploration as experiments, where interventions at several scales are made to achieve understanding and to test policy options. This perspective means that models and policies based on them are not taken as the ultimate answers but rather as guiding an iterative experimental process with the regional system. Emphasis is placed on monitoring and feedback to check and improve models rather than on using models to obfuscate and defend a policy that does not correspond to reality. Continuing stakeholder involvement is essential to adaptive management (Holling 1978).

14.5.2 Computational Methods and Toolkits

The collaborative scoping and consensus-building process can be facilitated by the use of a wide range of modeling tools. In graphic-icon-based tools (see Chapter 8, Section 8.4.1.1, this volume), the structure of the module is represented diagrammatically so that new users can recognize the major interactions at a glance (Costanza 1987). One of the main strengths of such tools is their ability to enable scientists and decision makers to quickly and easily build "scoping models" that focus and clarify their mental models. Running these models enables visualization of the dynamic consequences hidden in the modelers' assumptions and understanding of a system. With relative ease of use, these graphical programming tools offer a powerful method for investigating the workings of complex systems (Hannon and Ruth 1997).

Building on the initial scoping models to develop effective research and management tools often requires the inclusion of spatial interactions in the model. This phase of the modeling process usually requires more sophisticated tools such as a geographic information system (GIS). In cases that involve effects on or management of landscapes or habitats, GISs can serve two distinct but related roles. First, a GIS can improve communication and understanding among the stakeholders by allowing a way to visualize the options or impacts in a spatial context. Also, it relates the actions and results to a known, concrete, familiar place to which the stakeholders can relate. Second, a GIS can function as an analytical tool that is an integral part of the modeling process for addressing spatially explicit questions.

A good example of a modelers' toolkit that integrates disparate applications into a unified, seamless environment is the Spatial Modeling Environment (SME) (Maxwell and Costanza 1997). The SME links the STELLA modeling tool with advanced computing resources, allowing users to easily develop their scoping models into a high-performance spatial modeling and visualization environment. It is being applied jointly with state, local, and federal management agencies as an integrated, adaptive framework for managing ecological–economic systems. Current application areas include the Patuxent River watershed (Voinov et al. 1999) and the Baltimore metropolitan area.

Developing an awareness of the potential of and limitations of available computational hardware and software and training potential users are important aspects of the education process for everyone involved in environmental management. These tools can open the simulation arena to a much wider set of participants and can allow analytical modeling to play a key role in addressing complex management problems that would otherwise be intractable.

14.6 Conclusions

To address the substantial challenges facing our society, an integrative, transdisciplinary approach to environmental management must be adopted. The ability to build abstract representations of reality (models) that are useful in understanding and solving complex problems is at the core of this new approach. Because of the complexity of linked ecological and socioeconomic systems, a sophisticated, pluralistic, and participatory approach to modeling is becoming increasingly important. Modeling is essentially a form of synthesis that allows the emergent understanding to be tested, communicated to others, and further developed to draw new conclusions and insights.

A significant investment in education and training of all involved groups is necessary to realize the potential of environmental modeling in the management process. Managers and decision makers must be educated about the value of analytical modeling, particularly the relevance and importance of modeling, limits and uncertainties of models, and available modeling approaches. Modelers and scientists will benefit from training in communicating their results to nontechnical audiences, understanding the needs and constraints of the environmental management process, and facilitating the collaborative aspects of the modeling process. Students should augment a solid grounding in analytical techniques with courses, research, and workshops that develop their capabilities in synthesis and creative problem solving, systems thinking, and quantitative modeling methodology. They should be facile in communicating with interdisciplinary and nontechnical audiences. Other stakeholders can be included in a collaborative modeling process, which can help build mutual understanding; solicit input from a broad range of participants; and maintain a substantive interaction among managers, scientists, modelers, and stakeholders.

Investment in targeted educational initiatives may be the quickest and most cost-effective way to facilitate the application of modeling to environmental management. This conclusion is particularly evident for small-scale, local problems that can be effectively isolated from the sociocultural context in which they are embedded. These initiatives can help build a common understanding of the goals, uses, and limitations of models among managers, policymakers, modelers, and stakeholders and can facilitate effective communication among these groups. Modeling toolkits that support graphic model interfaces and visualization of model output can play a crucial role in enabling communication, collaboration, and consensus building. We believe that major improvements can be made quickly in this area if desired. To elevate the role of ecological modeling in the natural-resource-management process, it is critical to teach those involved how ecological models operate and why they are useful.

Other important research and development investments are necessary if modeling is to play an integral role in addressing the large-scale, interconnected environmental problems facing humanity, such as global warming, resource depletion, and biodiversity loss. Addressing these complex problems will require new tools and infrastructure to enable collaborative modeling across a large, distributed, interdisciplinary group of experts. Many important modeling applications are intractable without toolkits that support graphical, modular, and hierarchical model development and integrated visualization of model output. Virtual reality hardware and software may play an important role in the construction of hypothetical worlds for scenario analysis. High-performance computing can make important contributions in the simulation of complex environmental systems, but it will rarely be used unless the modeling infrastructure seamlessly and transparently integrates the investigators into the high-performance domain. Model sensitivity analysis can determine the most pressing data collection needs. Further development of data standards and metadata is crucial. Improved financial support for the development and application of ecological models and additional funding for basic research leading to new modeling approaches is needed, as well.

The process of environmental modeling should be framed not as an oracle prescribing a specific solution to a problem but as a learning experience for all involved. This education process develops an understanding of the dynamics of the managed system and its most probable responses to management interventions. It may also facilitate the exploration of policy options, the synthesis of disparate knowledge sources, consensus building, conflict resolution, and scenario generation and evaluation. Enabling this educational process will require significant investments. Top priority should be given to investments in targeted educational initiatives to inform managers and stakeholders of the potential and limitations of the modeling process and to train scientists and modelers in facilitating the educational process. Opening the educational process to a wider range of participants and enabling its collaborative aspects will require additional investments in the modeling tools and toolkits, improved databases and standards, and modeling methods described in other chapters in this volume.

References

Akçakaya, H.R. and M.G. Raphael. 1998. Assessing human impact despite uncertainty: Viability of the northern spotted owl metapopulation in the northwestern USA. Biodiversity and Conservation **7**:875–894.

Akçakaya, H.R., M.A. Burgman, and L.R. Ginzburg. 1999. Applied Population Biology Using RAMAS EcoLab. 2d edition. Sinauer Associates, Sunderland, Massachusetts, USA.

Akçakaya, H.R., S. Ferson, M.A. Burgman, D.A. Keith, G.M. Mace, and C.R. Todd. 2000. Making consistent IUCN classifications under uncertainty. Conservation Biology **14**:1001–1013.

Akçakaya, H.R., W.T. Root, and S. Ferson. 2001. RAMAS Red List: Threatened Species Classifications under Uncertainty (Version 2.0). Applied Biomathematics. Setauket, New York, USA.

Alstad, D. 2001. Basic Populus Models of Ecology. Prentice-Hall, Upper Saddle River, New Jersey, USA.

Berkson, J.M. and A.L. Harrison. 2001. An integrative capstone course for the conservation biology curriculum. Conservation Biology **15**:1461–1463.

Berkson, J.M. and A.L. Harrison. 2002. Achieving scientific literacy in the natural resource management curriculum. Journal of College Science Teaching. **XXXI**: 464–469.

Bossel, H. 1994. Modeling and Simulation. A. K. Peters, Wellesley, Massachusetts, USA.

Brown, D. and P. Rothery. 1993. Models in Biology: Mathematics, Statistics, and Computing. Wiley, Chichester, UK.

Carpenter, S.R. 1992. Modeling in the Lake Mendota program: An overview. Pages 377–380 *in* J.F. Kitchell, editor. Food Web Management: A Case Study of Lake Mendota. Springer-Verlag, New York, New York, USA.

Costanza, R. 1987. Simulation modeling on the Macintosh using STELLA. BioScience **37**:129–132.

Costanza, R., J. Cumberland, H. Daly, R. Goodland, and R. Norgaard. 1997. An Introduction to Ecological Economics. St. Lucie Press, Boca Raton, Florida, USA.

Costanza, R. and M. Ruth. 1998. Using dynamic models to scope environmental problems and build consensus. Environmental Management **22**:183–195.

Gergel, S.E. and T. Reed. 2001. Modeling ecosystem processes. Chapter 18 *in* S.E. Gergel and M.G. Turner, editors. Learning Landscape Ecology: A practical Guide to Concepts and Techniques. Springer-Verlag, New York, New York, USA.

Gergel, S.E. and M.G. Turner, editors. 2001. Learning Landscape Ecology: A practical Guide to Concepts and Techniques. Springer-Verlag, New York, New York, USA.

Grigg, N. 1995. Case method for teaching water-resources management. Journal of Professional Issues in Engineering Education and Practice **121**:30–36.

Gross, L.J. 2000. Education for a biocomplex future. Science **288**:807.

Gottelli, N.J. 1998. A Primer of Ecology. Sinauer Associates, Sunderland, Massachusetts, USA.

Gustafson, E.J., S.R. Shifley, D.J. Mladenoff, K.K. Nimerfro, and H.S. He. 2000. Spatial simulation of forest succession and timber harvesting using LANDIS. Canadian Journal of Forest Research **30**:32–43.

Hannon, B.M. and M. Ruth. 1997. Modeling Dynamic Biological Systems. Springer-Verlag, New York, New York, USA.

Hardesty, J., J. Adams, D. Gordon, and L. Provencher. 2000. Simulating management with models: Lessons from ten years of ecosystem management at Eglin Air Force Base. Conservation Biology in Practice **1**:26–31.

Holling, C.S., editor. 1978. Adaptive Environmental Assessment and Management. John Wiley & Sons, London, UK.
International Union for the Conservation of Nature (IUCN) Species Survival Commission. 2001. IUCN Red List Categories, Version 3.1. International Union for the Conservation of Nature, Gland, Switzerland.
Jackson, L.J., A.S. Trebitz, and K.L. Cottingham. 2000. An introduction to the practice of ecological modeling. BioScience **50**:694–706.
Kitching, R.L. 1983. Systems Ecology: An Introduction to Ecological Modeling. University of Queensland Press, St. Lucia, Queensland, Australia.
Lauenroth, W.K., C.D. Canham, A.P. Kinzig, K.A. Poiani, W.M. Kemp, and S.W. Running. 1998. Simulation modeling in ecosystem science. Pages 404–415 *in* M.L. Pace and P.M. Groffman, editors. Successes, Limitations and Frontiers in Ecosystem Ecology. Springer-Verlag, New York, New York, USA.
Maddox, D., K.A. Poiani, and R. Unnasch. 1999. Evaluating management success: Using ecological models to ask the right monitoring questions. Pages 563–584 *in* N.C. Johnson, A.J. Malk, W.T. Sexton, and R. Szaro, editors. Ecological Stewardship: A Common Reference for Ecosystem Management. Elsevier Science, Oxford, UK.
Maxwell, T. and R. Costanza. 1997. An open geographic modelling environment. Simulation Journal, **68**:175–185.
Othmer, H.G., F.R. Adler, M.A. Lewis, and J.C. Dalton, editors. 1997. Case Studies in Mathematical Modeling: Ecology, Physiology, and Cell Biology. Prentice-Hall, Upper Saddle River, New Jersey, USA.
Pickett, S.T.A. 1999. The culture of synthesis: Habits of mind in novel ecological integration. Oikos **87**:479–487.
Reed, J.M., D.D. Murphy, and P.F. Brussard. 1998. Efficacy of population viability analysis. Wildlife Society Bulletin **26**:244–251.
Running, S.W. 1994. Testing FOREST-BGC ecosystem process simulations across a climatic gradient in Oregon. Ecological Applications **4**:238–247.
Scott, W. and C. Oulton.1999. Environmental education: Arguing the case for multiple approaches. Educational Studies **25**:89–97.
Starfield, A.M. 1997. A pragmatic approach to modeling for wildlife management. Journal of Wildlife Management **61**:261–270.
Starfield, A.M., K.A. Smith, and A.L. Bleloch. 1990. How to Model It: Problem Solving for the Computer Age. McGraw-Hill, New York, New York, USA.
Taylor, B.L., P.R. Wade, D.P.D. Master, and J. Barlow. 2000. Incorporating uncertainty into management models for marine mammals. Conservation Biology **14**: 1243–1252.
Tester, J.R., A.M. Starfield, and L.E. Frelich. 1997. Modeling for ecosystem management in Minnesota pine forests. Biological Conservation **80**:313–324.
Voinov, A.R., L. Costanza, R. Wainger, F. Boumans, T.M. Villa, and H. Voinov. 1999. The Patuxent landscape model: Integrated ecological economic modeling of a watershed. Environmental Modelling and Software **14**:473–491.
Weldon, C. 1999. Using spreadsheets to teach ecological modeling. Ecological Society of America Bulletin **80**:64–67.
Walters, C. 1986. Adaptive Management of Renewable Resources. Macmillan, New York, New York, USA.
Weisbord, M., editor. 1992. Discovering Common Ground. Berrett-Koehler, San Francisco, California, USA.

Wheeler, K. and L. Lewis. 1997. School-community links for environmental health: case studies from GREEN. Health Education Research **12**:469–472.

Yankelovich, D. 1991. Coming to Public Judgement: Making Democracy Work in a Complex World. Syracuse University Press, Syracuse, New York, USA.

Part 4

Finale

15
What in the World Is Worth Fighting for? Using Models for Environmental Security

Wendell Chris King and Virginia H. Dale

15.1 Introduction

Dramatic human-induced changes occurring in our environment adversely affect the Earth today and, if left unabated, will seriously impact the safety and security of our world in the future. A burgeoning population and its demands for natural resources, renewable and nonrenewable, are leading this assault on the environment. Some consider technology a coconspirator in the degradation of the environment. Certainly, technology has evolved to the point that it can do great harm; conversely, technology can also heal and mitigate.

Conceptually, threats to peace and security associated with environmental issues have been collected under the term *environmental security*. Environmental security is a process for effectively responding to changing environmental conditions that have the potential to reduce peace and stability in the world and thus affect a country's national security. Accomplishing national environmental security goals requires planning and the execution of programs to prevent and/or mitigate anthropogenic adverse changes in the environment and to minimize the impacts of potential environmental disaster or ecoterrorism (King 2000).

The concept of environmental security is not new, particularly for the academic community where the environmental movement began. Many of the eminent scientists who advanced our understanding of the Earth's environment were also the "doomsayers" (as they were characterized at the time) who predicted catastrophic environmental consequences as a result of uncontrolled human activity. Norman Myers (1986), an early environmental security scholar, expressed the relationship between the environment and world stability well when he wrote,

> Hence national security is not just about fighting forces and weaponry. It relates to watersheds, croplands, forests, genetic resources, climate and other factors that rarely figure in the minds of military experts and political leaders, but increasingly deserve, in their collectivity, to rank alongside military approaches as crucial in a nation's security.

An unfortunate sideline in the early work on environmental security was that, as the concept developed, it was couched in the old civics debate of whether the government should spend its money on "guns or butter." In hindsight, it certainly appears that Myers was on target, at least in identifying future environmental security issues. It is also understandable that mainstream security leaders did not embrace his concepts in national security thinking, considering Myers' view that reduced military spending was the appropriate source for funding environmental security initiatives. This rejection may be one reason that environmental security never received full consideration within security policy discussions.

Today, the environmental security debate flourishes among social and political science scholars who work to redefine security, define environmental security, and predict the political and social responses to environmental scarcities. Homer-Dixon (1991; 1994), Levy (1995), and others have helped develop and focus the early work of Myers (1993) and other scholars into a better understanding of how environmental issues will impact security in the future. Debates have centered primarily on defining environmental security and applying political science approaches to analyze how developing countries will respond to environmental stress factors. Although these debates and discussions raise many challenging social issues, it is not a goal here to enter into that fray.

This chapter is intended to focus on where and how ecological modeling must play a role in environmental security. Modeling can answer the questions posed by strategic analysts if results from ecological models are provided in a manner understandable to political scientists and policy makers.

15.2 Global Environmental Security Issues

The issues selected for this analysis are a compilation of environmental stresses identified in works published by the U.S. Environmental Protection Agency (USEPA 1999) and the Army Environmental Policy Institute (Glenn et al. 1998; Lee 1999). Note that population trend analyses are included here even though population has not generally been considered an environmental issue. Specialists in the field of human geography are making strong arguments that it should be so viewed because humans are part of the global ecosystem. It is becoming increasingly clear that one cannot consider environmental security issues without concurrently examining population trends, particularly in a regional context. For example, consider the water scarcity issues in several regions of the United States. Water scarcity is caused by pollution of existing sources, reduction of available supplies, or increases in demand from either population increases or per capita consumption. In reality, most cases of regional water scarcity result from all of these factors occurring at the same time. Clearly then, population trends must be examined in predicting water demand and anticipating scarcity issues.

Because population trends are an important variable in nearly all environmental security issues, this analysis begins by discussing population trends on a regional scale. It then proceeds to consider three major environmental areas: global climate change, land-use issues of deforestation and desertification, and water as a scarce resource. Climate change poses a significant risk because it has a high probability of occurrence and a potential for severe consequences. Results from global climate models are employed to predict the consequences of anthropogenic changes to the environment [e.g., Aber et al. (2001); Dale et al. (2001)]. Risk assessment models have been used to determine the range of impacts [e.g., Sutherst et al. (2000); Utset and Borroto (2001)]. Further, ecological models assess the synergetic effects and severity of impacts on specific biomes. Thus, modeling has been key to identifying climate change as an issue and can be used to explore effective solutions. Land-use issues are linked in both cause and effect to climate change. The linkage between water and conflict is already well established, with the concerns for the future being more fraught with danger than at any other time in history.

15.2.1 Population Growth

Modeling of human population growth is certainly of interest to national security analysts. Many estimates exist, with considerable variability in the upper bounds and predicted rates of growth. One well-accepted model predicts the world population will asymptotically approach 12 billion after 2100 (Getis 1998). The concept of "carrying capacity" can focus our understanding of the fundamental interrelationship between overpopulation and environmental security. Carrying capacity is the total population that the resources of an area can support over an indefinite period of time and is graphically represented by a leveling off of the growth curve.

From a human perspective, this principle of carrying capacity holds, even with the marvelous products of human ingenuity. Technology can change the relative value of human carrying capacity by enabling us to satisfy the demands for resources of one region at the expense of another, by changing efficiency of use, and by providing solutions to many other specific problems. However, the number of people any region can support is finite [and, by extension, the total population the world can support is limited; Brown and Kane (1994)]. Optimistic philosophies of human activity espouse the belief that technology can overcome the fundamentals of carrying capacity; to date, this belief has not proven valid. The critical resources of water and energy (food and fuel) are renewable at finite rates on which technology can have only a minor impact. Ecological models offer a means to assess ways to manage resources for environmental security [e.g., Horie et al. (1992); Giampietro et al. (1994); Sahoo et al. (2001)].

When one considers the concept of carrying capacity in the context of human population increases, one question immediately arises: What is the total carrying capacity of the Earth? Will the Earth be able to sustain a steady-state world population of more than 11 billion people after 2100, nearly double the current world population?

Answering the question requires considering the spatial distribution of both people and resources. Where will these 11 or so billion people be located, and how well aligned will the populations be with essential resources? Another issue that complicates any analysis of regional or world carrying capacity is the ability to share or transfer resources effectively. All great modern cities now operate through a worldwide supply network. Countries like Japan and the United Kingdom thrive at a very high standard of living while providing only a small portion of consumed natural resources from within their geographic boundaries. Further, no assurance exists that this transfer process can be sustained over time.

Models provide a way to explore how resource limitation can affect human population and vice versa. For example, Groot et al. (1998) examined food-supply capacity at the global scale using a spatially explicit model based on data for soils, climate, agronomy, and demography. Use of the model allows decision makers to explore scenarios of food sufficiency by region and to determine major sources of uncertainty in projections. Furthermore, models offer a means to evaluate threats to food security, such as environmental degradation, economic growth, population explosion, and climate change (Norse 1994). As one example, a model analysis has shown that deficiencies in pollinator abundance, diversity, and availability can have critical impacts on world food supply, security, and trade (Kevan and Phillips 2001). Similarly, model analysis shows how food consumption and trade can be influenced by the threat of mad cow disease in Europe (Latouche et al. 2000) and Cassava mosaic virus in East Africa (Legg and Thresh 2000).

15.2.2 Global Climate Change

Strong evidence exists that global climate change in the form of global warming caused by anthropogenic activity is occurring (IPPC 2001; Houghton 1994). Driving global climate change is a series of interwoven phenomena including, but not limited to, deforestation, burning of fossil fuels, and industrial pollution. Assessing each of these factors independently in a static model is within our scientific capability today but does not yield realistic results. Each activity occurs independently at different rates and concurrently with the natural variability in weather.

The rate of temperature change within the dynamics of greenhouse gas behavior and natural climate processes is a key area of uncertainty in the global warming debate. Several complex computer models of climate change have been developed and are being continually updated, but each has proven to have strengths and weaknesses in describing actual conditions or predicting changes. A wide range of global-temperature-change predictions exists, but they generally fall in the 0.5 to 6.0°C range. The Intergovernmental Panel on Climate Change (IPCC) predicts a 1.4 to 5.8°C temperature increase by 2100 relative to 1990 (IPCC 2001).

Complex interactions between systems, actions, and counteractions of the carbon cycle and other processes make it difficult to determine exactly how atmospheric warming will affect the Earth's ecosystem. On the basis of our current understanding of climate and weather, a rise in temperature worldwide and changes in temperature distribution, spatially and temporally, will change weather and climate over large areas of the Earth. Higher temperatures will produce more evaporation from the oceans, resulting in increased rainfall somewhere. Higher temperatures over land will increase evaporation of soil moisture, raise dry-soil temperatures, and melt ice. All of these factors will combine to change the weather patterns of a particular region in both frequency and intensity of events. These variations in weather pattern can, over time, sum to changes in regional climates in many parts of the world (Watson et al. 2000). For example, locations of grasslands, forests, and deserts may shift because of evolving climates.

Sea-level rise as a direct response to global warming has been an issue that has captured considerable public attention, although there are many other equally important possibilities that must be assessed, particularly in considering environmental security. On the basis of scientific analysis to date, the range of sea-level rise is predicted to be between –1 and +6 meters (King 2000), not a particularly informative range to use in assessing impacts. However, the factors that enter into this calculation are well defined. First, warm water occupies a larger volume than cold water, so as ocean surface temperatures warm because of contact with the warmer air, the volume of the ocean will increase, resulting in a rise in sea level. The more difficult factor to calculate is the depth change attributable to warmer air temperatures occurring in regions with snow and ice cover. Uncertainty about whether and how much ice will melt under different warming predictions accounts for the wide range in the sea-level-rise estimates. Using the IPCC (1992) warming estimate as a basis for temperature rise, Houghton (1994) predicts a 50-cm sea-level rise by the year 2100. The most detailed statistical analysis of sea rise predicts a 35-cm rise by 2100 as the most likely result, with a 10% chance of sea rise reaching 65 cm, and a 1% chance of a 1-m rise (Titus and Narayanan 1995). This rise, coupled with natural land subsidence in some lowland regions, could have large impacts in several critical areas of the world, such as Bangladesh and Egypt (Houghton 1994).

There is scientific certainty that changes in weather will affect water and forest resources, food production, human health, weather events like floods and other "natural disasters," and coastal processes, all of which have peace and security implications. The nature of these impacts is more difficult to predict than sea-level rise. To realistically predict the impacts of global climate change, models of future water, food, health, and disturbance conditions need to be driven by projected climate scenarios. Table 15.1

TABLE 15.1. Regional impacts of enhanced greenhouse effects on climate (From USEPA 2000*b*).

	North America	Tropical Asia	Temperate Asia	Arid Western Asia	Europe	Africa	Australasia
Geographic area	Canada, United States, and Arctic Circle	India, Pakistan, Bangladesh, Vietnam, Malaysia, and inclusive counties	Japan, Koreas, Mongolia, most of China, and Russian Siberia	Turkey in the west to Kazakstan in the east	West of Ural Mountains	The continent	Australia, New Zealand, and islands
Ecosystem	Shifts in location of forests and croplands; change of vegetation types; loss of waterfowl habitat	Changes in distribution of rainforest; drying of wetlands	Reduction in the boreal forests; expanded grasslands; decrease in the tundra zone	No large changes	Mostly disturbed environment now; alter wetlands through lower groundwater levels	Desertification in north, loss of forests in Subsahara; deterioration of land cover; major impacts expected throughout	Alterations of soils and vegetation could be large
Hydrology and water resources	Increased spring and winter runoff; decreased rain and soil moisture in summer	Glaciers recede in Himalayas; more seasonal impacts	Net decrease in water supply; glacier melt; North China water supplies vulnerable	Continued water shortages in the region	Increased precipitation in high latitudes and reduced in lower; loss of glaciers with water-storage processes	Reduction in supplies in Sahel and southern Africa; acute concern in many already water-scarce countries of the region	Reduced water could be critical in drought-prone areas; loss of snow and glaciers in New Zealand; flooding
Food and fiber production	Small changes, plus and minus inputs	Vulnerable to natural disasters; changes in	No agreement in predicted change	No large net change	Shift of growing seasons and patterns;	Water shortages could be acute to farming in the north; winter	Early increased production predicted, but

		production and yield very difficult to predict, but crops are sensitive to temperature and moisture			possible increased production	wheat growing in north hurt; could have moderate increases in the south	uncertain long-term impacts
Human settlements	Changes in energy use; increased natural hazards	Inundation of lowland cities; salt water intrusion into water supplies in lowlands	Land subsidence in lowlands, salt water intrusion in water supplies	No large impacts	Flooding of more inhabited areas; cooling demands higher, heating demands lower	Increased exposure to natural disasters; urban water supplies threatened; sanitation and waste disposal problems expand	No large impacts expected
Coastal systems	Up to 19,000 km^2 inundated; 23,000 km^2 added to floodplain	Large and productive lowlands flooded; more natural hazards impacts; millions displaced by 1-m sea rise	Japanese industry in coastal zones; large areas inundated	No large issues	Risk of storm surges in lowland coasts of Holland, Germany, Russia, and Ukraine	Coastal erosion in central coastal areas, particularly in storm-impacted west Africa; flooding of Nile Delta of concern	Highly vulnerable to flooding and inundation
Human health	None predicted	Increase in vector- and water-borne diseases, malaria, dengue, and schistosomiasis	Increased transmission of vector-borne disease	Small increases in disease and heat induced health problems	No major changes	All diseases exacerbated by malnutrition would damage the health of Africans	Small increases in disease and heat-induced health problems

Table 15.1 (Continued)

presents a synthesis of predicted worldwide impacts from regional climate change based upon IPCC global-climate-change studies, as summarized by the USEPA (2000*a*,*b*). As indicated in the table, regions relying on single-crop agriculture and subsistence farming, such as tropical Asia and Africa, are particularly vulnerable to changes in weather patterns. Vector- and water-borne diseases are expected to rise in the developing regions of the world and in areas where extremes in weather will increase the frequency of weather-driven disasters. Models of pasture and rangeland production have reduced uncertainties associated with effects of global change on pasture growth in cool, wet climates, but more focus on the linkages between biophysical, social, and economic factors is still needed (Campbell and Smith 2000). Furthermore, models offer opportunities to improve understanding of attempts to mitigate climate-change impacts. For example, a review of two international agricultural models examined the potential effects on crop production of measures to prevent climate change (Chen and Kates 1994).

Many of the environmental issues discussed later in this chapter are inexorably linked to global climate change: water as a scarce resource, desertification, and deforestation being prime examples. While the data are not specific in terms of exactly where impacts will be seen, they do suggest that the basic carrying capacities of many regions will change, which implies that populations will need to shift in response. Overall, the impacts of global warming, as predicted by this review, will be a major destabilizing influence on the security of the world and will constitute a major causative factor in population migration.

15.2.3 Land-Use Change

The various ways that people use and manage land are a prime cause of land-cover change on the Earth. Thus, land use and land management increasingly represent a fundamental source of change in the global environment. *Land use* refers to the purpose to which land is put by humans [e.g., protected areas, forestry for timber products, plantations, row-crop agriculture, pastures, or human settlements; Turner and Meyer (1994)]. The major environmentally significant land-use changes today are deforestation and desertification.

15.2.3.1 Deforestation

The impacts of deforestation range from the very subtle changes in climate that loss of forest areas may induce to the dire life-threatening issues that the absence of fuel wood can cause. In the context of environmental security, consider the examples of Ethiopia and Haiti. In 1900, Ethiopia was 45% forested (Food and Agriculture Organization 1990), while today only 2.5% of the country remains forest and woodland (World Resources Institute 1997). Likewise, Haiti has gone from a mostly tree-covered to a nearly barren landscape. It is reasonable to surmise that there is a correlation between the unrest in these countries and these drastic changes in their environments. This situation alone would be sufficient reason to consider the security implications of deforestation, but there are more direct issues that result from the widespread loss of forest areas in a region. In relation to environmental security, the most critical concerns are

- Reduced carrying capacity of the land
- Fewer forests as a component of the carbon cycle, resulting in loss of carbon dioxide (CO_2) removal capacity
- Loss of biodiversity with all of its known and unknown implications
- Increased flooding and loss of soils, with resultant mudslides and waterway siltation
- Reduced economic benefits resulting from loss of forests as a renewable resource

What is clearly evident in the available data and predictive modeling is that impacts from deforestation will be most severe in tropical regions, not unexpectedly because these are the regions of the highest deforestation rates. It appears that tropical regions are trading short-term economic benefits for an unknown future. Most deforestation is being caused by land-use changes, changing from forests into some agricultural or grazing use. When considering security issues in the developing temperate-forest countries, impacts on carrying capacity have the most direct and dire effects. In the developing world, the land must provide water, food, and energy for heating and cooking. Loss of fuel wood reduces the ability to properly process food, and this could lead to both malnutrition and disease.

Ecological models are key to assessing both impacts and causes of deforestation. Hansen et al. (2001) emphasize the value of models in exploring feedbacks between climate, land use, and biodiversity. Aber et al. (2001) discuss the role that different models play in assessing impacts of multiple stressors on effects of global change on forests. Dale and Rauscher (1994) point out that different models should be used to address unique levels of biological organization (global, regional, community, and tree) and impacts. No one model can consider them all. Furthermore, economics is a primary factor in deforestation; Kaimowitz and Angelsen (1998) document that modeling is a primary tool in addressing social and economic aspects of forest loss.

15.2.3.2 Desertification

Today, some 40%, or 60 million km^2, of the world's land area is classified as having a dry climate, with some 10 million km^2 of this land being considered desert (Houghton 1994). Desertification occurs when a vegetated area, such as a steppe, through natural or human-induced processes loses vegetative cover, allowing increased soil erosion, primarily by wind. This process typically further reduces the carrying capacity of an already fragile environment. Natural fluctuations in rainfall can change the shape of a desert, usually working around the margins of an existing desert. Overgrazing, mining of groundwater, and overuse in farming are primary human activities that can produce desertification of an area.

The African Sahel is the most striking example of desertification or land degradation seen in modern times. The Sahel is the belt that extends across Africa at about 15° N and forms the southern extent of the Sahara desert. An increase in the nomadic herding population of the region in combination with a drought lasting from 1968 to 1991 has produced desertification in the area (Strahler and Strahler 2000). Desertification has resulted in a drastic reduction of regional grazing capacity until conditions and time allow regeneration of the vegetative cover, if erosion and the other impacts of desertification have not been so severe as to irreversibly damage the land.

Global warming can produce desertification in the same way that natural climate change does; therefore, accurate climate modeling is a requisite component of understanding desertification. Simulation models project that the net effects of global warming and desertification will be an intensification and extension of drought conditions during dry seasons (Feddema 1999).

15.3 Water as a Scarce Resource

Water is a critical resource for life and essential for economic success in a modern, developed society. Water is required for domestic consumption, sanitary use, industrial use, cooling water in the generation of electric power, hydroelectric power generation, and agricultural irrigation. Water quantity can be measured in terms of total demand but is better represented in terms of the quantity per person over some period of time (daily or yearly). During the past century, there was an 800% increase in total water demand, driven primarily by population increases, but demand per person also doubled (Gleick 1998).

Models can be used to identify and alleviate water distribution problems. For example, Jowitt and Xu (1992) found that relatively simple time-series models can be used to predict consumer water demand and that these results can be used to design water distribution systems. As another example, Luijten et al. (2001) used a model to assess water availability and use under different development pathways of development and growth in Latin American countries with steep-slope farming. The model helped reduce the complexities of dealing with the land–water interface and spatial linkages within the watershed. These model results can help teach local stakeholders about responses of the landscape to water management practices. A third example focuses on balancing difference uses of water. Droogers et al. (2000) developed a simulation model to evaluate irrigation performance for the two dominant crops in western Turkey: cotton and grapes. Although both crops are normally irrigated, their model showed water productivity of grapes to be maximal without irrigation. Thus, to minimize risk of water shortages, cropping of grapes should be expanded. With high water availability, a mixture of grapes and cotton is preferable for the economic benefits provided.

An example of the effect that development has on water use can be seen by comparing water use in the United States with world water use. In 1900, world demand was approximately 300 m^3 per person per year; in the United States, that value was 700. In 1980, world consumption had grown to 700, while the U.S. demand had reached 2700. In terms of these units, which factor population growth out of the equation, water demand in the United States had grown by a factor of 4 while world demand had increased by a factor of only 2 (Gleick 1998). The important point here is that transforming from a developing to a developed society has greatly increased the requirement for water. Projections of water consumption in developing countries suggest that demand for household and industrial use could double in the next 25 years (Swaminathan 2001).

Many authors continue to suggest that water scarcity is the resource side of the problem that must be addressed. Former Senator Paul Simon's (1998) book on water, *Tapped Out—The Coming World Crisis in Water and What We Can Do about It*, takes this general approach (i.e., fix the water problems and avoid the crisis). While his concern with water and his solutions are valid, the underlying principle of carrying capacity remains inviolable. In the water context, climate provides a watershed with a fixed amount of water. A minimum amount of water is required per person each day for survival. The equation then becomes straightforward:

$$\text{Human carrying capacity} = \text{Gallons of water available per year}/(\text{Gallons per person per year demand})$$

Conservation and other management tools can, to some degree, change the values in both the numerator and denominator but cannot change the reality that a given environmental setting can support only a certain number of people.

The water problem is one of trying to reconcile supply with demand in a spatial context with the population. Supplies are fixed, while demand continues to grow rapidly and not always in the best locations. There has been progress in improving management practices, but those new practices have reduced the rate of growth in demand per person, not total consumption. In this context, the United States can be considered a recent good news story. By 1995, water demand in the United States had dropped from 2,700 to 2,200 m^3 per person per year, resulting in a flattening of total demand during the past 20 years. This reduction in the rate of growth of water demand was achievable only in concert with a small population growth rate during the same period.

The bottom line for water as a resource is:

- Demand will continue to increase steadily and in direct proportion to population growth.
- Modernization (development) will increase demand, not reduce it.
- In areas experiencing water shortages now, conditions will worsen, while many more areas of the world will reach their limits of available water resources.

In terms of environmental security, an important question is: What is the basic water requirement for a person to sustain life? This value must include water for drinking, cooking, and basic sanitation requirements, such as personal hygiene and cleaning. One widely accepted estimate is 50 L per day per person (Gleick 1998). Figure 15.1 shows the countries of the world that fail to meet this standard.

Water quality is an often overlooked issue that must be addressed in any discussion relating water supplies to security. The World Health Organization (1995) estimated that 1 billion people a year contract a water-borne diarrheal disease and that 3.3 million of these people die from it. This estimate does not account for many other water-borne diseases that inflict pain and suffering throughout the world. A primary quality concern in the developing world is human waste being disposed of in surface waters, which contaminates drinking water supplies, and this water being consumed without adequate treatment. Clean water is a critical

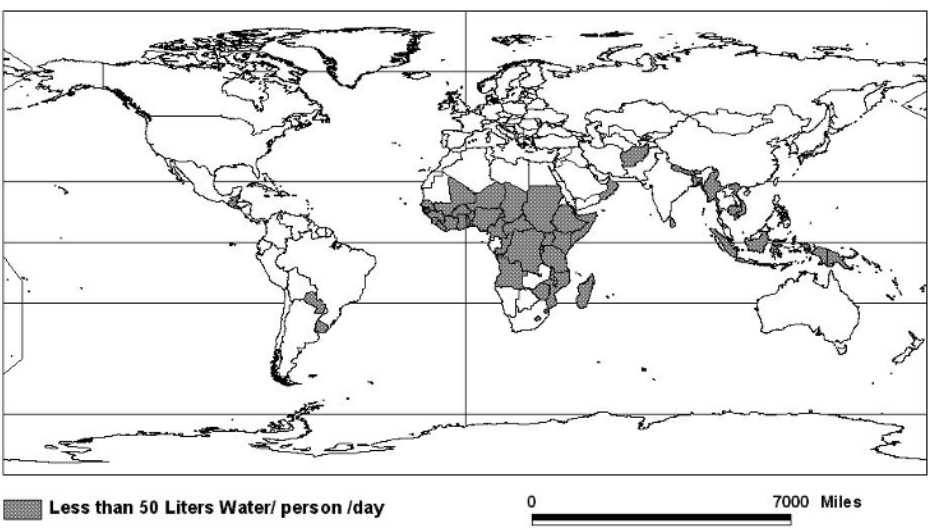

FIGURE 15.1. Countries with extreme water scarcity [Data derived from Gleick (1998)].

issue for parts of South and Central America, most of Africa, and much of Asia.

Salinity in water is another major quality issue of concern in agriculture and industry. Salts present in irrigation water are retained and concentrated in the soil as water naturally evaporates from the upper layers. Over time, without adequate rain to dissolve these salts back into the water for transport away, salt levels in irrigated soil build up to concentrations toxic to many plants. These lands are then lost to production or must be used for crops more tolerant of salt. Such crop choices are quite limited. Salination is reducing food production rates in many parts of the world today, mostly in arid regions, where lack of rainfall makes soil recovery times very long. The United States is experiencing this problem in isolated parts of the arid West and Southwest.

Overall, water is a problem affecting basic survival in at least one-third of the world and a limiting factor in development for most of the world. As an anonymous American sage once said, "People argue over politics; they fight over water."

15.4 Strategic View of the Role of Models in Environmental Security

Obviously, achieving environmental security is not going to be straightforward. This problem is compounded by the fact that environmental security is very much a contextual issue. For example, assume that two disputes over water rights exist between the United States and Mexico on one border and the United States and Canada on the other. If the technical details of these two problems are similar, will the nature of the discussions be the same? Experience supported by numerous examples suggests that scarcity of water in the south would make that dispute much more contentious. Further, the prevailing political environment could make the technical details of the issue secondary to the policy considerations.

Models can help in sorting out the complex issues of environmental security. For example, Tillman et al. (2001) developed a model that can explore ramifications on water capacity, price, and financial debt of shifting water-utility-management goals from water security to cost. Models can also illustrate the interactions between critical resources for security. For example, the role of water in the food security of China was explored by Heilig et al. (2000). They used a detailed agroclimate model to estimate China's maximum grain production under rain-fed and irrigation systems and found that about 70% of the production depends on irrigation. Given China's projected grain demand, water conservation and the development of water resources for agriculture is critical for China's food security.

Table 15.2 presents a summary of possible impacts of environmental security issues on significant environmental hazards (King 2000).

TABLE 15.2. Impacts of environmental change (From King 2000).

Environmental issue	Global Environmental Concerns				Regional Environmental Concerns			
	Farmland	Forest	Water/fish	Human	Farmland	Forest	Water/fish	Human
Climate								
Warming	Inundation of arable lands; drier soils in summer	Change in shape of temperate and tropical forests	Weather changes impact the hydrologic cycle	Natural hazards; property loss; heating and cooling costs	Wetter wet seasons; drier soils in dry season	Shifts in size and location of temperate and tropical forests	Changes in rain patterns; change in temporal and spatial distribution	Increased disease in developing countries
El Niño					Increased erosion	Change in water distribution	Increased winter rains; loss of fish in Pacific	Flooding and other natural hazards
Ozone depletion	UV damage to many species of plants and animals	UV damage to many species of plants and animals		Cancer	UV damage to many species of plants and animals	UV damage to many species of plants and animals		Cancer in Southern Hemisphere
Land								
Deforestation		Greenhouse gases produced; less CO_2 recycled; loss of biodiversity	Reduction of groundwater recharge; siltation of streams	Indigenous tribes endangered; biodiversity lost	Temporary increase in cropland	Net loss, particularly in tropical forests; biodiversity loss	Decreased groundwater recharge; increased runoff rates	Loss of Indian habitat in rainforest; loss of beneficial species

Desertification		Displacement herding populace	Loss of productive lands	Enroachment on fragile forests	Reduced soil moisture can increase runoff and reduce recharge	Migration of African nomads
Waste disposal	Contamination of surface and groundwater and fish	Toxic exposure			Poisoning of water supplies and fish	Toxic exposures; contamination of water resources and food chain
Water Quantity	Freshwater fish lost; reduced productivity in estuaries	Increased migration	Reduced irrigation and grazing	Highly variable impacts by regions	Freshwater fish lost; reduced productivity in estuaries	Increased migration
Quality	Toxicity and bioaccumulation of toxics	Increased rates of disease	Salinity reduces productivity	Acid-rain damage	Toxicity and bioaccumulation of toxins	Disease increases in developing countries
Oceans	Overfishing endangers stocks	Loss of fish; disease exposure			Overfishing is endangering stocks	Loss of fish protein; disease

Table 15.2 (Continued)

Considered together, these data offer several conclusions about the impacts of environmental degradation and change, including, in order of importance:

- Humans are threatened by loss of water and food and by increased incidence of disease.
- The greatest overall impacts from cumulative environmental change will occur in the tropical countries, which are all economically developing countries.
- Global warming with its linkages to deforestation is the issue with the potential to produce the most damage.
- Weather change is likely to produce an increase in the incidence of natural hazards as increased evaporation is counterbalanced by new, more intense weather cycles. Because of environmental degradation, many more people will be at risk.
- Issues related to water are major stress factors on human subsistence and economic development (Armitage 2000).

With these summary data, this discussion can move from "what" to conducting a geographic analysis to determine generally "where" environmental security problems and conflicts may occur. Spatially explicit models allow for quantitative deliberations of such questions. For example, a geographic information system (GIS) analysis might take the water-scarcity data from Figure 15.1 and overlay it with population-growth-rate data to create Figure 15.2. The result shows the correlation between countries with high population growth rates and the countries with drinking-water-shortage issues. Forty-one of the fifty water-scarce countries also have population growth rates above 2% per year.

Figure 15.3 shows how several issues can be correlated; in this case: population, deforestation, and water scarcity. Figure 15.3 is based on historical data and is therefore not predictive, but such hind casts can be used to improve understanding of underlying causal factors.

One example will bring the connection between the environment and security into focus; consider Afghanistan. Following the line of analysis just presented, we begin by examining the country's population trends. Despite 20 years of war, Afghanistan continues to have a very high annual population growth rate (2.9%) and one of the world's highest fertility rates (Palka 2001). Data on infant mortality and life expectancy clearly demonstrate a country that is losing the battle to feed and care for its people. Next, Afghanistan has less than 9% of its land classified as forests, so forest resources are not available for subsistence uses, such as shelter and fuel. Only 12% of the population has access to clean water, and this availability is not adequate to meet minimum supply needs. Finally, 92% live without adequate sanitation systems. Overall, these data reveal a country with a population living on the edge of survival. Based on this form of analysis, Afghanistan is somewhere in the 10 worst environmental settings in the

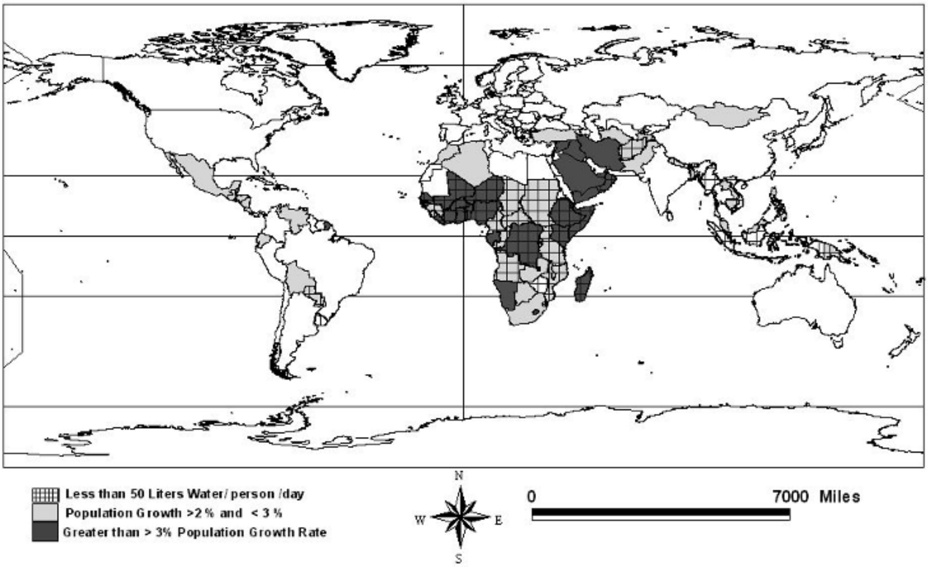

FIGURE 15.2. Correlation of population growth rates with water scarcity.

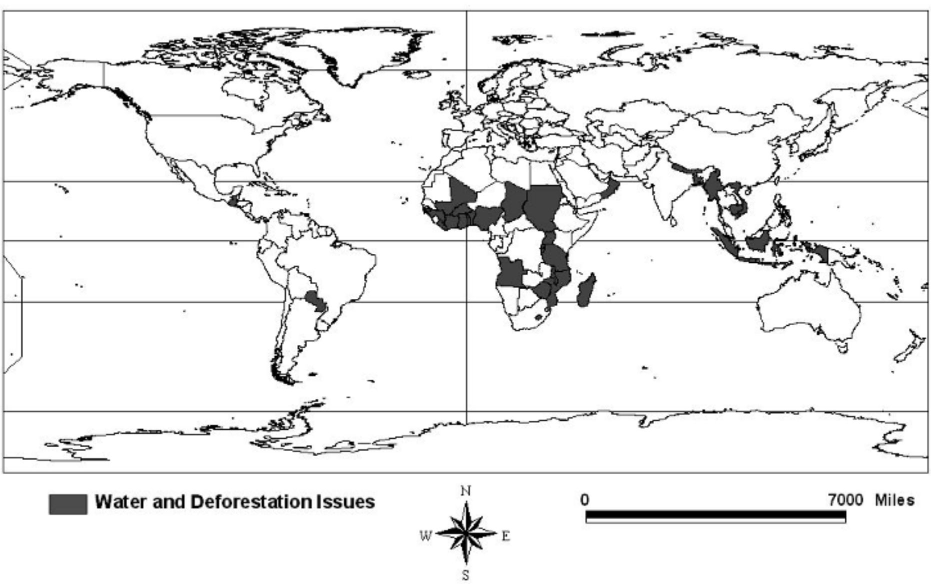

FIGURE 15.3. Countries with high population growth rate, water scarcity, and deforestation [From: King (2000)].

world, and therefore is highly likely to pose a threat to security and stability in the region. Environmental conditions are certainly not the only reasons war rages in Afghanistan, but it is very fair to summarize that environmental security considerations are definitely contributory issues. The key to anticipating issues and preventing problems will be in attaining both understanding of processes and reasonable estimates of such factors as deforestation rates, water scarcities, and population growth. Ecological modeling will be a key element in being able to predict the future and to respond to changes in the environment. To develop useful approaches, modelers will have to consider the needs of strategic planners and to develop ways to reduce uncertainty and risk in projections. Only then will policy planners be equipped to address the issues in a coherent way.

Throughout this chapter, issues that require or can be improved through the effective use of ecological modeling have been highlighted. In a final analysis, it appears that two general categories of problems need to be addressed: one is a process, and the other is communication. Many reading this chapter may find it remiss in not purporting the need for more and better science as a major concern. Certainly, there are unknowns in modeling such issues as climate, critical species and habitats, and many of the other environmental security issues, but fuller use of the science available now would go a long way toward solving current problems. Therefore, this chapter focuses on opportunities that optimize the use of the existing models and their products.

A major deficiency in environmental security analysis is that results of ecological modeling are not being well utilized in environmental security decision making. The scientific community may not be answering the really critical questions or may not be presenting results in ways that are understandable by decision makers, people who typically lack highly scientific backgrounds. Consider one important example. A *USA Today* (Watson 2000) front-page headline reported that new climate models were predicting even more global warming than some previously thought. Each of the two presidential candidates, Gore and Bush, had brief quotes on the meaning of these results. Then–Vice President Gore found the reported results disturbing and of great concern, while then-Governor Bush thought the information was insufficient to make any conclusions from at the time. Based on the risk of dire consequences associated with increased global warming, some sort of call for action or review would seem appropriate. However, these model results did not produce this kind of response.

More effort is required to put the modeling community and the decision makers who will use the results together early in the process of conducting scientific discovery. This alliance is essential when ecological modeling is intended to support planning and decision making, such as in environmental security analysis. Early discussions on goals for research and results reporting can improve the applicability of modeling results. At a minimum, up-front customer and user input should produce better acceptance and understanding of model results.

Early in the development of environmental regulation, and particularly in dealing with toxic and hazardous wastes, the environmental community learned the hard lesson that they were not communicating with the lay public. This fact was particularly evident with communicating the concept of health risk, which is the basis for all regulatory standards. The modeling community is now in a similar position in explaining the error bounds and uncertainty inherent in predictive modeling. Not all results from modeling projects can or should be published in a manner found most impressive to a scientific audience. Nor should all scientific modeling be designed to produce the most elegant results when simpler, but more useable results can be achieved.

In conclusion, ecological modeling is essential to achieve environmental security goals. It is simply the only method capable of projecting future conditions that are needed to understand the environmental impacts of human activity. There is much good work available already that should be better utilized. Policy analysts and planners are remiss in their poor use of the data and model projections, but the scientific community can do better in developing and communicating results. If the model projections of environmental change are even close to accurate, we cannot afford to fail in this mission.

References

Aber, J., R.P. Neilson, S. McNulty, J.M. Lenihan, D. Bachelet, and R.J. Drapek. 2001. Forest processes and global environmental change: Predicting the effects of individual and multiple stressors. BioScience **51**:735–751.

Armitage, Ambassador Richard. Lecture at the Naval War College, May 2000.

Brown, L. and H. Kane. 1994. Full House: Reassessing the Earth's Carrying Capacity. Norton, New York, New York, USA.

Campbell, B.D. and D.M.S. Smith. 2000. A synthesis of recent global change research on pasture and rangeland production: Reduced uncertainties and their management implications. Agriculture Ecosystems and Environment **82**:39–55.

Chen, R.S. and R.W. Kates. 1994. Climate change and world food security. Global Environmental Change—Human and Policy Dimensions **4**:3–6.

Dale, V. and M. Rauscher. 1994. Assessing impacts of climate change on forests: the state of biological modeling. Climatic Change **28**:65–90.

Dale, V.H., L.A. Joyce, S. McNulty, R.P. Neilson, M.P. Ayres, M.D. Flannigan, P.J. Hanson, L.C. Irland, A.E. Lugo, C.J. Peterson, D. Simberloff, F.J. Swanson, B.J. Stocks, and B.M. Wotton. 2001. Forest disturbances and climate change. BioScience **51**:723–734.

Droogers, P., G. Kite, and H. Murray-Rust. 2000. Use of simulation models to evaluate irrigation performance including water productivity, risk and system analyses. Irrigation Science **19**:139–145.

Feddema, J.J. 1999. Future African water resources: Interactions between soil degradation and global warming. Climatic Change **42**:561–596.

Food and Agriculture Organization of the United Nations (FAO). 2000. Forest resources assessment 1990: global synthesis. URL: www.igc.apc.org/wri/wr-96-97/lc_ttxt2.html.

Getis, A., J. Getis, and J.D. Fellmann. 1998. Page 192 *in* Introduction to Geography. McGraw-Hill, Boston, Massachusetts, USA.
Giampietro, M., S.G.F. Bukkens, and D. Pimentel. 1994. Models of energy analysis to assess the performance of food systems. Agricultural Systems **45**:19–41.
Gleick, P. 1998. The World's Water. Island Press, Washington, District of Columbia, USA.
Glenn, J., et al. 1998. Defining Environmental Security: Implications for the U.S. Army. U.S. Army Environmental Policy Institute, Atlanta, Georgia, USA.
Groot, J.J.R., F.W.T.P. de Vries, and P.W.J. Uithol. 1998. Food supply capacity study at global scale. Nutrient Cycling in Agroecosystems **50**:181–189.
Hansen, A.J., R.P. Neilson, V.H. Dale, C. Flather, L. Iverson, D.J. Currie, and P. Bartlein. 2001. Global change in forests: Responses of species, communities, and biomes. BioScience **51**:765–779.
Heilig, G.K., G. Fischer, and H. van Velthuizen. 2000. Can China feed itself? An analysis of China's food prospects with special reference to water resources. International Journal of Sustainable Development and World Ecology **7**:153–172.
Homer-Dixon, T. 1991. On the threshold: Environmental changes as causes of acute conflicts. International Security **16**:76–116.
Homer-Dixon, T. 1994. Environmental scarcities and violent conflict: Evidence from cases. International Security **19**:5–40.
Horie, T., M. Yajima, and H. Nakagawa. 1992. Yield forecasting. Agricultural Systems **40**:211–223.
Houghton, J. 1994. Global Warming: The Complete Briefing. Lion Publishing, Oxford, UK.
Intergovernmental Panel on Climate Change (IPCC). 2001. Climate Change 2001: Impacts, Adaptation, and Vulnerability. Cambridge University Press, Cambridge, U.K.
Jowitt, P.W. and C.C. Xu. 1992. Demand forecasting for water distribution systems. Civil Engineering Systems **9**:105–121.
Kaimowitz, D. and A. Angelsen. 1998. Economic Models of Tropical Deforestation: A Review. Center for International Forestry Research, Jakarta, Indonesia.
Kevan, P.G. and T.P. Phillips. 2001. The economic impacts of pollinator declines: An approach to assessing the consequences. Conservation Ecology **5**:U211–U230.
King, W. 2000. Understanding International Environmental Security: A Strategic Military Perspective. AEPI 19–92. U.S. Army Environmental Policy Institute, Atlanta, Georgia, USA.
Latouche, K., P. Rainelli, D. Vermersch. 2000. The price of food security—contingent evaluation following the European crisis of mad cow disease. Canadian Journal of Agricultural Economics **48**:325–340.
Lee, J. 1999. Inventory of conflict and environment. AEPI 28–101. U.S. Army Environmental Policy Institute, Atlanta, Georgia, USA.
Legg, J.P. and J.M. Thresh. 2000. Cassava mosaic virus disease in East Africa: A dynamic disease in a changing environment. Virus Research **71**:135–149.
Levy, M.A. 1995. Is the environment a national security issue? International Security **20**:35–63.
Luijten, J.C., E.B. Knapp, and J.W. Jones. 2001. A tool for community-based assessment of the implications of development on water security in hillside watersheds. Agricultural Systems **70**:603–622.

Myers, N. 1986. The environmental dimension to security issues. The Environmentalist **6**:251–257.

Myers, N. 1993. Ultimate Security: The Environmental Basis of Political Stability. Norton, New York, New York, USA.

Norse, D. 1994. Multiple threats to regional food production—environment, economy, population. Food Policy **19**:133–148.

Palka, E. 2001. Pages 82–94 *in* Afghanistan: A Regional Geography. U.S. Military Academy Publication, West Point, New York, USA.

Sahoo, G.B., R. Loof, S.L. Abernethy, and S. Kazama. 2001. Reservoir release policy for large irrigation system. Journal of Irrigation and Drainage Engineering-ASCE **127**:302–310.

Simon, P. 1998. Tapped Out—The Coming World Crisis in Water and What We Can Do about It. Welcome Rain Publishing, Champaign, Illinois, USA.

Strahler, A. and A. Strahler. 2000. Introducing Physical Geography. John Wiley & Sons, New York, New York, USA.

Sutherst, R.W., G.F. Maywald, and B.L. Russell. 2000. Estimating vulnerability under global change: Modular modelling of pests. Agricultural Ecosystems & Environment **82**:303–319.

Swaminathan, M.S. 2001. Ecology and equity: Key determinants of sustainable water security. Water Science and Technology **43**:35–44.

Tillman, T., T.A. Larsen, C. Pahl-Wostl, and W. Gujer. 2001. Interaction analysis of stakeholders in water supply systems. Water Science and Technology **43**:319–326.

Titus, J. and V. Narayanan. 1995. The probability of sea level rise. EPA-230-R95-008, U.S. Environmental Protection Agency, Washington, District of Columbia, USA.

Turner, B.L., II and W.B. Meyer. 1994. Global land-use and land-cover change: An overview. Pages 3–10 *in* W.B. Meyer and B.L. Turner, II, editors. Changes in Land Use and Land Cover: A Global Perspective. Cambridge University Press, Cambridge, UK.

U.S. Environmental Protection Agency (USEPA). 1999. Environmental Security. EPA-160-F99-001. U.S. Environmental Protection Agency, Washington, District of Columbia, USA.

U.S. Environmental Protection Agency (USEPA). 2000*a*. Inventories. URL: www.epa.gov/globalwarming/emissions/international/inventories.html.

U.S. Environmental Protection Agency (USEPA). 2000*b*. Summary: 4. Overview of Regional Vulnerabilities to Global Climate Change. URL: www.epa.gov/globalwarming/publications/reference/ipcc/summary/page4.html.

Utset, A. and M. Borroto. 2001. A modeling-GIS approach for assessing irrigation effects on soil salinisation under global warming conditions. Agricultural Water Management **50**:53–63.

Watson, R.T., I.R. Noble, B. Bolin, N.H. Ravindranath, D.J. Verardo, and D.J. Dokken, 2000. Land Use, Land-Use Change, and Forestry: A Special Report of the IPPC. Cambridge University Press, Cambridge, UK.

Watson, T. October 26, 2000. Global warming is accelerating, scientists report. USA Today.

World Health Organization (WHO). 1995. Community Water Supply and Sanitation: Needs, Challenges and Health Objectives. A48/EOS/96.15. World Health Organization, Geneva, Switzerland.

World Resources Institute. 1997. World Resources 1996–1997. Website: www.igc.apc.org/wri/wr-96-97.

16 New Directions in Ecological Modeling for Resource Management

Virginia H. Dale

16.1 New Directions

New directions for the use of ecological models in resource management depend on current trends in the use of computers, environmental pressures, communication, understanding of ecological and environmental processes, globalization, and stakeholder involvement in environmental concerns. At the same time as these trends are becoming apparent, some agreement is being reached on the most pressing needs for resource management. These resource management needs point out the advantages of using models in addressing resource management concerns because models arise from a philosophy of a parsimonious approach, clear assumptions, and, when possible, generic modeling paradigms. However, models would likely be used more often if there were closer communication between modelers and decision makers, clearer definition of the environmental problems, recognition of the value in using models to enhance understanding, and more use of models for exploring alternative future conditions. These are the issues that will define the new directions in the use of models for resource management.

16.1.1 Trends

An examination of future directions in the use of ecological models for resource management requires a look at current trends. First, the use of computers is increasing in public, private, and business sectors. In developed countries, computers are available in most businesses and agency offices as well as a large number of homes. Around the world, computers are generally accessible or can be brought into remote locations. They are used to communicate; collect, access, and store information; and conduct analyses. This trend means that computers are generally available on which models can be operated.

Furthermore, global communication modes are becoming faster and more reliable. The general availability of computers is one reason why communication is improving. E-mail and the Internet provide rapid means of communication. Telephone service is quite reliable throughout the developed world. Internet access provides a way to access recent publications and newly acquired data. As a result, managers expect access to the up-to-date information and knowledge.

The world is becoming networked, not only electronically but also in reality. Many people travel to distant destinations for both business and pleasure. Air travel has become common as costs have diminished. Improved communication and transportation networks not only facilitate the flow of information, they also enhance the spread of environmental problems. For example, global transmission of disease organisms and other undesirable biota is recognized as a major concern.

Globalization of the economy is growing with increased travel, communication, and networking. Produce and goods are shipped around the world. The result is that global coffee or banana prices can rapidly affect the livelihood of small farmers in developing countries. By the same token, an untimely frost in Brazil can affect the prices, sales, and employment at coffeehouses across the United States. The availability of oil, gas, or other sources of energy is a critical resource, and the need for energy connects the world's economy. Thus, some resource management models are being designed to consider global interrelations, including economics and human population expansion.

At the same time, environmental pressures are increasing. Providing access to energy and natural resources often calls for the development of new infrastructure. Roads built into new regions to acquire resources typically provide a route for development and instigate pressures on the environment. Increases in human population density and per capita use of resources also add pressure to manipulate the environment. For instance, housing developments are being built in areas that were once thought to be environmentally undesirable.

Awareness of environmental pressures increases with these demands and enhanced networking. For example, global climate change is now a recognized phenomenon, although ways to deal with the problem are not agreed upon (IPPC 2001). Cognizance of current environmental conditions is enhanced by worldwide access to television and print media. Environmental security has become a big concern since the spread of mad cow disease, the invasion of Kuwait by Iraq, and the attacks on the World Trade Center.

Simultaneously, stakeholders are becoming more educated and more actively involved in resource management issues (Wondolleck and Yaffee 2000). The worldwide recognition of the plight of Chico Mendes in his fight for rubber tappers against large-scale development has become a call to arms for individuals to organize in their efforts to protect access to natural products. But such stakeholder groups typically lack access to information on how management or preventive measures can affect natural resources. Models offer a means to make such information available.

A final trend is an increase in the use of models for decision making. Application of models to management issues has increased but is still not meeting the full range of possibilities.

All in all, a more complex view of the world is developing. Communication and feedbacks on a global scale are part of this new perspective. Unfortunately, the use of models for resource management has not kept up with these other advances. However, the time is ripe to enhance the application and spread of models to resource management.

16.1.2 Resource Management Needs

The trends noted above have facilitated the recognition of needs for resource management. Several national and international groups have assembled principles or guidelines for managing natural resources (Tables 16.1 to 16.5). These guides all agree on the importance of natural resources, their risk under increasing development, and the need to develop integrated ways to understand how human activities can affect the integrity of resources. All of these guidelines call for a focus on changes to the environment including disturbances, changes in land use and management, and socioeconomic developments. The Santiago Agreement identified attributes of sustainability that need to be conserved (Anonymous 1995) (see Table 16.1). The Forest Sector of the United States National Assessment of Climate Variability and Change specified research needed to protect natural resources (Joyce et al. 2001) (see Table 16.2). These needs include the ability to integrate, predict, relate, and quantify—all attributes of

Table 16.1. Criteria for sustainability from the Santiago Agreement (From Anonymous 1995).

Conservation of biological diversity
Maintenance of productive capacity of ecosystems
Maintenance of ecosystem health and vitality
Conservation and maintenance of soil and water resources
Maintenance of forest contribution to global carbon cycles

Table 16.2. Research needs identified by the Forest Sector of the United States National Assessment of Climate Change (From Joyce et al. 2001).

Integrated approaches to environmental factors, climate change, and forest processes
Basic information on current forest disturbances
Predicting climate and change in climate
Quantifying the disturbance impact on forests
Understanding relationships between climate/weather patterns, trace gases, and biological species at multiple scales
Identifying interactions among forest disturbances and management
Integrating climate and land-use change into ecological models

Table 16.3. Key points for managing national forests and grasslands from the Committee of Scientists report (From Johnson et al. 1999).

Ecological sustainability as a necessary foundation for sustainability
Considering the larger landscape in which national forests and grasslands are located to understand their role in achieving sustainability
Making decisions at the spatial scale of the issue
Making "desired future conditions" and the outcomes associated with them central reference points for planning

Table 16.4. Guidelines for land use and management from the report of the Land-Use Committee of the Ecological Society of America (From Dale et al. 2000).

Examining the impacts of local decisions in a regional context
Planning for long-term change and unexpected events
Preserving rare landscape elements, critical habitats, and associated species
Avoiding land uses that deplete natural resources over a broad area
Retaining large contiguous or connected areas that contain critical habitats
Minimizing the introduction and spread of nonnative species
Avoiding or compensating for effects of development on ecological processes
Implementing land-use and -management practices that are compatible with the natural potential of the area

Table 16.5. Guiding principles of the 1994 memorandum from the Office of the Deputy Secretary of Defense for Environmental Security (From Goodman 1995).

Maintaining and approving sustainability and native biodiversity of ecosystems
Administering in accordance with ecological units and time frames
Supporting sustainable human activities
Developing a vision of ecosystem health
Developing priorities and reconciling conflicts
Developing coordinated approaches to working toward ecosystem health
Relying on the best science available
Using benchmarks to monitor and evaluate
Using adaptive management
Implementing through site-specific plans and programs

ecological models. The goals recognized for the national forests and grasslands by the Committee of Scientists (1999) added spatial concerns to the previously mentioned temporal scales (Johnson et al. 1999) (see Table 16.3). Placing environmental issues within the context of the full spatial ramifications of the problem can take advantage of the flexibility of spatially explicit modeling. The action-oriented guidelines for land use and management from the Land-Use Committee of the Ecological Society of America require some understanding how activities can impact future conditions (Dale et al. 2000) (see Table 16.4). Ecological models are specifically designed to project such conditions. Finally, the guiding principles for defense of environmental security call for developing a vision, priorities, and coordinated approaches (Goodman 1996) (see Table 16.5). Again, models are one of the most useful tools for this type of analysis.

Clearly, resource management models need to be based on hierarchical and spatially explicit approaches that incorporate key features of concern and allow for disturbances, land-use changes, socioeconomic pressures, and other anthropogenic changes. Examples of using models for such research exist (as described in previous chapters), but access to these models by resource managers is limited, and few managers are aware of the current research directions. Thus, improved availability of modeling tools for resource management is needed.

16.2 Philosophy of Modeling

One of reasons models are so appropriate to today's resource management needs is that the philosophy of modeling requires focusing on key issues. The use of models is based upon the concept that models can synthesize the best understanding of the situation given current information. This perspective builds upon a parsimonious approach to modeling. That is, modelers should strive to include the least amount of information that adequately explains the phenomena of interest. The term "adequate" is case specific, for what may be appropriate in one case will not necessarily work in another situation. A model can thus be considered a set of hypotheses about the way a system works, given certain assumptions and context. Models never contain all of the details of a system. In a discourse on science, Lagrange is reputed to have said "Seek simplicity, but distrust it." Models are an expression of this philosophy.

Assumptions are a key part of the modeling process. To clearly communicate the modeling approach to a user, the set of assumptions for a particular modeling exercise should be specified. The assumptions determine the level of detail needed in a model and situations to which it can be applied. They typically are concerned with the temporal and spatial scales of focus, abiotic and biotic processes, organisms and their relevant life stages (e.g., adults vs juveniles), and environmental factors (e.g., disturbances) that are held constant or allowed to vary in controlled ways. In general, the more the assumptions are specific to a particular case of interest, the more meaningful the model results are for that situation. However, this specificity may make the model unusable outside of that situation, which leads to the need to understand and to specify how, why, and where a model will be used.

Another aspect of the minimalist approach to modeling is that a new model does not need to be developed for every situation. Instead, some categories of models are appropriate to a particular type of ecological or resource management problem. When a model is applied to a new location or related issue, the set of driving variables and parameters usually remains the same but the parameter values can be altered to fit the situation. As an example, there have been numerous applications of the JABOWA model of forest gap dynamics first developed by Botkin et al. (1972) (see Table 16.1) [see review by Bugmann (2001)]. Although the JABOWA model has been modified over the years to include a variety of disturbances and now spatial attributes, the basic driving variables and parameters are the same in all versions. Such a generic modeling approach has allowed the users to focus on issues rather than the construction of the mathematical tool.

In summary, a model is typically designed to produce projections of change over time on the basis of a basic understanding of the system and with varying amounts of data. Assumptions and interactions need to be clearly set forth. Often, this kind of information is exactly what a resource manager needs to make decisions. Yet models are not always used, even though models would provide helpful assistance to resource management in many situations.

16.3 Areas for Improvements in the Use Ecological Models for Resource Management

Improvements to the use of ecological models for resource management can be made by giving attention to several areas:

- Establishing closer communication between field ecological/environmental scientists and modelers and, in turn, between modelers and decision makers
- Clearly defining the problem
- Using models to enhance understanding
- Exploring alternative future conditions

16.3.1 Establishing Good Communication

The need for improved communication between modelers and decision makers is a theme that runs through many of the chapters in this book. The elements of modeling need to be understood not only by those developing and applying models, but also by those who use the model results. Too often model projections are not used in decision making because they are misunderstood. Much of the frustration related to ecological models results from unrealistic expectations by all parties involved (Van Winkle and Dale 1998). Discrepancies often exist (1) between reality and the expectations of those funding or reviewing a model application concerning how the results should contribute to decision making or advancing ecological understanding and (2) between the claims made by modelers at the beginning of a project and the realities of the modeling applicability and integrity at the end. These discrepancies arise, in part, from a lack of understanding of the modeling process on the part of decision makers, marketing of the sometimes poorly understood attributes by modelers, uncertainty in the model projections, variability in the natural system, immaturity of ecological theory, and factors that were not included in the model yet influence the outcome of decisions.

One solution to addressing these frustrating discrepancies is to increase interchanges between modelers and decision makers. Such interactions can serve to improve communication and create more realistic expectations of the contributions of models. Understanding the outcome of a model is not achieved just by examining the graphical, mapped, or tabular output but also by being aware of the strengths and limitations of the particular modeling approach, the assumptions, and the uncertainties in the projections (Dale and Van Winkle 1998).

16.3.2 Defining the Problem

Careful attention to problem definition will enhance the use of models because models designed to meet the needs of explicitly defined issues will include the requisite elements. Such definition is not always straightforward; yet implementation of models for a particular problem often demonstrates the value of the models. That is true because implementing a model requires explicit definition of the spatial and temporal scales of concern, the disturbance or management actions to be considered, and explicit hypotheses about potential interactions and effects.

Ideally, the problem definition phase involves discussions between managers and modelers. Managers have intimate familiarity with the problems and factors that may influence them. Modelers have skills at examining system interactions, defining key elements of an interaction, and identifying potential sources of uncertainty. The conceptual model that derives from problem definition both guides the way that a detailed model is developed and provides insight into the key interactions of the systems. Sometimes this conceptual model is one of the most important products of the modeling process.

16.3.3 Using Models to Enhance Understanding

Modeling is a process that enhances the understanding of a system (Van Winkle and Dale 1998). The process of modeling requires formulating hypotheses about how components of a system are related and allows exploration of the implications of those hypotheses. It identifies sensitivities and uncertainties in a system and forces ecologists to specify which components can be considered as deterministic or stochastic.

The modeling process plays a valuable role in the overall iterative scientific process of hypothesis formulation (Overton 1977). It contributes to the design of experimental and monitoring studies, the development and application of mechanistic or simulation models, and the interpretation of results (Van Winkle and Dale 1998). Using models can be a part of the scientific process even when initial information about a system is sparse. Models can be used to organize existing information, indicate the sensitivities of the system, and identify gaps in knowledge. For example, Aber and Driscoll (1997) point out that "models are often more interesting when they fail than when they succeed." These failures often point to problems with original hypotheses, data collection and/or storage, development and interlinking of algorithms, or the data interpretation. Interim conclusions from modeling often cause modifications in the original hypothesis and, possibly, the model itself, thus setting the stage for the next iteration of asking questions via the scientific process.

The model-building process itself is an iterative process. Many models begin with simple assumptions or are based on general assumptions. Refinement of the model comes with more experience (e.g., data) and improved means to express the experience (e.g., more powerful formulae with statistical analysis to better define the boundaries).

Pressing needs for decisions to be made or policy actions to be taken in the face of uncertainty often force the use of incomplete or untested models. Yet it is in those instances in which information is deficient that the modeling process may be most useful. Many cases arise in which qualitative information is valuable. In fact, models typically use both qualitative and quantitative information and do not always result in quantitative projections. Modeling the effects of climate change is an example. No one knows how much a change in temperature or precipitation will alter biota in a given region, but it is still valuable to use models to explore the possible implications of various scenarios of climate change. Such scenario exploration informs policymakers about which aspects of the ecological systems they should be most concerned.

Furthermore, a clear distinction between qualitative and quantitative information used in models is neither realistic nor appropriate because information forms a continuum (Van Winkle and Dale 1998). Frequently, the lack of confidence about information is expressed by using inequalities or upper and lower bounds. At other times, a rough mean tendency is used to represent a general understanding about some unmeasured quantity [such as the assumption that past windstorms removed 20% of the biomass of impacted forests in New England (Aber and Driscoll 1997)]. This type of semiquantitative or categorical knowledge is frequently the basis of equations and parameter values that are used in models and can be important to increasing the understanding of the ecological system.

16.3.4 Exploring Alternative Futures

The purpose of many model analyses is to help predict future conditions built on a basis of "what if." Some models have short-term outlooks, while others are used to forecast possible conditions or scenarios months, years, or decades in the future. One of the newer avenues of modeling is that of "alternative future conditions" forecasting, where, on the basis of existing environmental and economic conditions and in light of present or hypothesized practices, various future scenarios can be produced and their associated probabilities can be calculated. Such modeling efforts are being used to look at changes such as human population growth and interaction with respect to developmental encroachment on military installations and other land and water preserves. The advantage of using a simulation exercise to explore alternative future conditions in environmental decision making is that options available to decision makers can be set forth without the expense or time involved in actual implementation. Of course, ramifications and feedbacks are only as realistic as how the pertinent factors and variables are incorporated into the model structure. Such simulation tools are typically designed to be readily accessible to users of all levels of computer expertise. Often, the engaging nature of these models causes users to become more involved in thinking about processes and interactions than they would have done without the simulation model.

Considering the diverse temporal and spatial scales required to model some resource management issues, the implementation and integration of these processes are difficult. For example, to model trophic dynamics, the different spatial and temporal scales of different trophic levels may need to be a part of the model. Dale et al. (1991) did just that with a nested-model approach to model the dynamics of a short-lived insect in relation to the decadal changes of its host tree. Component models can be developed at the temporal and spatial scales necessary to model each part of management concern, and model output can be designed at the scale relevant to the questions. However, it is necessary to recognize that management questions occur at different scales, as well. For example, noise maxima are experienced on the scale of minutes with remedial or mitigating actions required in a short time frame; air-quality decisions are often made on a daily basis, such as the effect of wind direction and speed on controlled burns of forests; and land-use decisions for runoff control and restoration management are made on an annual or longer basis. In some models, the users are able to narrow or expand their perspectives to different spatial or temporal scales as the question changes. In the future, as computer technologies become more advanced and available, such simulations are expected to be developed and used more frequently.

16.4 Conclusion

A clear goal of future models for resource management is to meet the challenge set forth in the National Academy of Sciences (2000) report on global environmental change, which stated that, "Recent progress has been so rapid, and the need for integration is so great, that the identity of key questions and the boundaries between disciplines needs to be flexible at a level that has never been required in the past. The world is changing too rapidly for science to address the challenges of global change with traditional, incremental approaches." Models offer the opportunity to deal with complexities and interactions without getting bogged down in details. In particular, future modeling efforts need to deal with

• *Scales*—Models can integrate processes that operate on very different temporal and spatial scales.

• *Feedbacks*—Incorporating feedbacks between different aspects of the environment that operate at different scales is one of the biggest challenges of interdisciplinary research.

• *Multiple criteria*—Environmental research has been constrained by efforts to meet a single criterion (e.g., protection of one species or keeping particulates below a certain level). Developing approaches allow the consideration of several criteria and their interactions at the same time (e.g., simultaneously satisfying requirements dealing with air, water, noise, and biotic species). Acceptable resource management practices will be those that maintain standards within all these categories. Exploration of alternative future conditions can define conditions under which multiple goals can be met under a suite of resource constraints.

Today, ecological models are becoming more an integral part of resource management. A host of tools is available for developing, testing, and implementing these models. Yet models are still not used as often as they could be. This limited use suggests a need for

- Understanding that models can be a part of the resource management process that includes exploration and refinement of management options
- Greater use of models to help improve ecological understanding
- Enhancing communication between the modeler and resource manager at all stages of model development and application

The challenge continues to be to develop and use credible models that range the gamut from improving ecological understanding to being useful for decision making.

Acknowledgments. Reviews of an earlier draft of this chapter by Tom Ashwood and Robert Holst were quite helpful. Development of the chapter was funded by contracts to Oak Ridge National Laboratory (ORNL) from the Strategic Environmental Research and Development Program (SERDP), Army Research Office, and Engineering Research and Development Center of the Corps of Engineers as well as by the U.S. Department of Agriculture (USDA) Forest Service. ORNL is managed by UT-Battelle, LLC, for the U.S. Department of Energy under contract DE-AC05-00OR22725.

References

Aber, J.D. and C.T. Driscoll. 1997. Effects of land use, climate variation, and N deposition on N cycling and C storage in northern hardwood forests. Global Biogeochemical Cycles **11**:639–648.

Anonymous. 1995. Sustaining the world's forests: The Santiago agreement. Journal of Forestry **93**:18–21.

Botkin, D.B., J.F. Janak, and J.R. Wallis. 1972. Some ecological consequences of a computer model of forest growth. Journal of Ecology **60**:849–872.

Bugmann, H. 2001. A review of forest gap models. Climatic Change **51**:259–305.

Committee of Scientists. 1999. Sustaining the People's Lands: Recommendations for Stewardship of the National Forests and Grasslands into the Next Century. U.S. Department of Agriculture, Washington, District of Columbia, USA.

Dale, V.H. and W. Van Winkle. 1998. Models provide understanding, not belief. Bulletin of the Ecological Society of America **79**:169–170.

Dale, V.H., R.H. Gardner, D.L. DeAngelis, C. Eagar, and J.W. Webb. 1991. Elevation-mediated effects of balsam woolly adelgid on southern Appalachian spruce-fir forests. Canadian Journal of Forest Research **21**:1639–1648.

Dale, V.H., S. Brown, R.A. Haeuber, N.T. Hobbs, N. Huntly, R.J. Naiman, W.E. Riebsame, M.G. Turner, and T.J. Valone. 2000. Ecological principles and guidelines for managing the use of land. Ecological Applications **10**:639–670.

Goodman, S.W. 1996. Ecosystem management at the Department of Defense. Ecological Applications **6**:706–707.

Intergovernmental Panel on Climate Change (IPCC). 2001. Climate Change 2001: Impacts, Adaptation, and Vulnerability. Cambridge University Press, Cambridge, UK.

Johnson, K.N., J. Agee, R. Beschta, V. Dale, L. Hardesty, J. Long, L. Nielsen, B. Noon, R. Sedjo, M. Shannon, R. Trosper, C. Wilkinson, and J. Wondolleck. 1999. Sustaining the people's lands: recommendations for stewardship of the national forests and grasslands into the next century. Journal of Forestry **97**:6–12.

Joyce, L.A., J. Aber, S. McNulty, V. Dale, A.J. Hansen, L. Irland, R.P. Neilson, and K. Skog. 2001. Forests. Pages 489–524 *in* Climate Change Impacts: The Potential Consequences of Climate Variability and Change, a Report of the National Assessment Synthesis Team of the U.S. Global Change Research Program. Cambridge University Press, Cambridge, UK.

National Academy of the Sciences. 2000. Global change ecosystems research. National Academy Press, Washington, District of Columbia, USA.

Overton, W.S. 1977. A strategy of model construction. Pages 49–73 *in* C.A.S. Hall and J.W. Day, Jr., editors. Ecosystem Modeling in Theory and Practice: An Introduction with Case Histories. University Press of Colorado, Boulder, Colorado, USA.

Van Winkle, W. and V.H. Dale. 1998. Model interactions. Bulletin of the Ecological Society of America **79**:257–259.

Wondolleck, J.M. and S.L. Yaffee. 2000. Making Collaboration Work: Lessons from Innovation in Natural Resource Management. Island Press, Washington, District of Columbia, USA.

Index

A
Access policy recommendations, 204
Accuracy, 97
Adverse environmental impact (AEI), 46–47, 61–62
Afghanistan, 304, 306
African Sahel, 298
Agent-based models, 140–141
Aggregation, 96
Air pollution, 72
Alternative futures, exploring, 317–318
Aquatic-impact-assessment measures, tree of, 49, 58
Artificial intelligence (AI), 150–151
Assessment endpoints, 49
Assumptions, 154, 314
Atelier courses, 277–278
ATLSS (Across Trophic Level System Simulation) project, 158
Autocorrelation, 197–198

B
Barriers
  addressing, 89
  communication, 110–111
  institutional, 111–112
  overcoming, in resource management, 89–105
  solutions for overcoming, 117–119
  to specific players in decision-making process, 115–116
  types of, 110–115
  to use of ecological modeling for resource management, 109–120
Bayesian belief networks, 137
Benchmarks, 50, 92–93
Best technology available (BTA), 46–47
Biodiversity, 125
Bioregional assessments, 83

C
Calibration, 175–176, 177
Case-specific models, developing new, 256
Case studies
  endangered-species recovery, 27–39
  library of, 103
  using new ecological modeling for resource management, 154–158
Chestnut blight, 72
Clean Water Act of 1972, 46
Climate, regional impacts of enhanced greenhouse effects on, 294–295
Climate change, global, 292–296
Collaboration tools, 228
Collaborative decision making, 117
Communicating model assumptions, 154
Communicating model structure and output, 150–154
Communication
  establishing good, 315–316
  interpretation of models and, 276
  model, 98–99
Communication barriers, 110–111
Communication modes, global, 310–311

Communications theory, 172
Community of interest, 79–80
Competing models, 102
Computational fluid dynamics model for fish movement, 154–157
Computational methods, toolkits and, 280–281
Computational technologies, new, 148–150
Computational toolkits, *see* Toolkits
Computers, 11
Conceptual models, 94, 181–182
  success criteria for, 104
  translating, into logic-based model specifications, 138–139
  utility of, 94–95
Conceptual toolkit, 223–224, 231–233
Conceptualization, 175, 228
Confidence, issues related to, 95–102
Consensus building, modeling and, 279–280
Consensus-building process, 118
Control theory models, 146–147
Coupled Eulerian-Lagrangian hybrid models, 142–144, 155

D
Data
  extrapolation and, 99–100
  flow of, 168
  information and, 172
  missing, 196–197
  misuse of, 171, 173–174
  modeling issues and, 169–170
  presentation of, 203
  remotely sensed, 190–191
  sources of error in, 194–196
  spatial, 190
  used in models, 180–183
  warehousing, 201
  visualization of, 137, 153–154, 235
Data access, 202, 204
Data access concerns, 202–204
Data appropriateness concerns, 184–187
Data attribute definitions, 186
Data availability, 114
Data backup, 201
Data collection, field, 191–193
Data collection/acquisition concerns, 187–194
Data collection efforts, previous, 188–190
Data input, 200
Data issues, 16, 180–205
Data limitations, 186–187
Data management, 218
Data mining, 234–235
Data quality concerns, 194–199
Data sharing
  limiting, 203
  voluntary, 203–204
Data simulation, 193–194
Data standards, 200
Data stewardship, 201
Data storage and management, 199–202
Data visualization, 137
Data warehousing, 201
Database design, 199–200
Decision context, 103
Decision criteria, 50
Decision makers, educating, 264–271
  methods for, 270–271
Decision maker's toolkit, 224, 235–237
Decision making
  collaborative, 117
  ecological models in, *see* Ecological modeling for resource management
  environmental, 49, 167–178
  integration of improved science into, 228–229
  models in, enhancing use of, 249–256
  value-laden, 47–49
Decision model, elements of, 236–237
Decision support, linked multihierarchical models for, 157–158
Declarative modules, 145–146
Deforestation, 296–297, 305
Demographic models, 23–24
Desertification, 297–298
Development costs, model, 100–101
Difference models, 10
Dispersal function, 130
Distributed computing, 148–149
Disturbance, 111

E
Ecological effects characterization, 90
Ecological endpoints, 91–92
Ecological modeling for resource management
  areas for improvements in use of, 315–318
  barriers to use of, 109–120
  beginnings of, 9–11
  development of computers for, 11
  effective, 180–205
  effective use of, 211–219
  for endangered-species recovery, 23–43
  enhancing role of, 135–160
  examples of using, 21–85
  exploration of, 6
  fish entrainment and impingement impacts, 46–65
  future use of, 16
  issues related to confidence in, 95–102
  key issues in, 87–285
  new, case studies using, 154–158
  new directions in, 310–319
  opportunities for using, 3–17
  overcoming barriers to use of, 89–105
  roles for, in 316(b) assessments, 50–53
  roots of, 9–12
  science and management investments needed to enhance use of, 249–259
  using projections from, 12–14
  general characteristics of, 8–9
  temporal scales of, 9
  types of, 7–8
Ecological point of view, 3
Ecological-risk-assessment process, EPA, 60–62
Ecological risk assessments, framework for, 89–94
Ecological sustainability, 4
Economic perspective, 3
Ecosystem and receptor characteristics, measures of, 49–50
Ecosystem management, 81
Ecosystem sustainability, forest, 138–139
Educating managers and decision makers, 264–271
  methods for, 270–271
Educating stakeholders, 278–281
Education, training and, 250
Educational investments in environmental science and management, 263–282
Effective Use of Ecological Modeling in Management workshop, vii
Empirical modeling, 48
Endangered-species recovery
  case studies, 27–39
  ecological modeling for resource management for, 23–43
  lessons learned, 39–42
  wolf biology and recovery status, 24–26
Endpoints,assessment, 49
  ecological, 91–92
Entrainment, fish, 46
Environment Protection Agency, *see* EPA *entries*
Environmental impact, adverse (AEI), 46–47, 61–62
Environmental managers, 6
Environmental perspective, 3–7
Environmental pressures, 311
Environmental science and management, educational investments in, 263–282
Environmental security, 289
  concept of, 289
  global issues of, 290–298
  strategic view of role of models in, 301–307
  using models for, 289–307
EPA (U.S. Environment Protection Agency), regulations, 47
EPA ecological-risk-assessment process, 60–62
Errors
  model, 102–103
    nonsampling, 195
    sampling, 194, 195
    sources of, in data, 194–196

Eulerian-reference framework, 142–144, 155
Exotic diseases, emerging, 72
Exploratory models, 152
Exposure, measures of, 49
Exposure characterization, 90
Extrapolation, 96–97, 198–199
  data and, 99–100

F
Factorial analysis, 33
Federal Endangered Species Act, 23
Federal land, 5
Feedback loops, 10
Field data collection, 191–193
Fish entrainment and impingement Impacts in, 46–65
Fish movement, computational fluid dynamics model for, 154–157
Fish population modeling, 55
Forest ecosystem sustainability, 138–139
Forest fragmentation, 127
Forest Service planning system, 73
FORPLAN linear-programming (LP) model, 158–159
Fractal approaches, 144–145
Fragmentation of habitat, 126
Futures, exploring alternative, 317–318
Fuzzy network models, 136–137

G
Game theory, 151
Global climate change, 292–296
Global communication modes, 310–311
Global environmental security issues, 290–298
Global warming, 292, 306
Goals, 97–98
Graphical user interface (GUI), 148
Gray wolves, 23–43, *see also* Wolf
Greenhouse effects, enhanced, regional impacts of, 294–295
Grid computing, 149
Groundwater Modeling System (GMS), 238–240

H
Habitat connectivity, 126–128
Habitat loss and fragmentation, 125
Habitat occupancy approaches, 126
Habitat Suitability Index (HSI) modeling, 159–160
Hardware concerns, 200
Heuristic models, 7

I
Impingement, fish, 46
Information, data and, 172
Information content, 172
Institutional barriers, 111–112
Interoperability protocols and standards, 227–228

J
Jargon, 111
Jurisdictions, overlapping, 81–82

K
Knowledge repositories and management, 229–230

L
Lagrangian-reference framework, 142–144, 155
Land management, public, 71–72
Land-use change, 296–298
Landscape conservation, evolving approach to, 125–133
Landscape networks, 129–131
Large-scale regional assessments, 70–84
Library of case studies, 103
Linked multihierarchical models for decision support, 157–158
Logic-based model specifications, 136–137
  translating conceptual models into, 138–139
Logistic equation, 10

M
Management
  ecological modeling in, *see* Ecological modeling for resource management
  ecosystem, 81
  public land, 71–72
Management decisions, resource, 52
Management goals, 49, 62

Management investments needed to enhance use of ecological modeling for resource management, 249–259
Management objectives, 49, 62–63
Management planning, heuristics of pragmatic modeling to support, 40
Management questions, wolf, 27
Managers and decision makers, educating, 264–271
  methods for, 270–271
Markov-decision approach, 147
Markov models, 140
Mathematical models, 7–8
Matrix algebra, 10
Matrix models, 254
Measurements, 49
Measurement error, 189–190
Measures, classes of, 49
Metadata, 173, 184
Metadata requirements, 231
Metapopulation model, 253, 254
Mexican spotted owl habitat, 131–132
Minimum spanning tree, 130
Models
  application of, 251–254
    examples of, 251
    examples of applications of, 252
    integration of, 254–256
Model assumptions, communicating, 154
Model communication, 98–99
Model conception, systems thinking and, 274
Model conceptualization, 170, 171
  and design, 135–139
Model development and implementation, teaching, 277
Model development costs, 100–101
Model errors, 102–103
Model formulation and construction, 182
Model implementation, 140–150
Model limitations, 183
Model makers, 213
Model standards, 152–153
Model structure and output, communicating, 150–154
Model testing, 183
Model use, investment for enhancing, 256–258
Model users, 217
Model verification and calibration, 182–183
Modelers, training, 271–273
Modeler's toolkit, 224, 237–242
  example use of, 238–240
Modeling, 263
  consensus building and, 279–280
  empirical, 48
  philosophy of, 314–315
  pragmatic, heuristics of, to support management planning, 40
  process of, 275–276
  quantitative, 274–275
  relevance and importance of, 264–265
  understanding and, 316–317
Modeling issues, data and, 169–170
Models
  abuse of, 114
  available, 269–270
  case-specific, developing new, 256
  competing, 102
  computational fluid dynamics, 154–157
  conceptual, 94–95, 104, 138–139, 181–182
  control-theory, 146–147
  data used in, 180–183
  in decision making, enhancing use of, 249–256
  demographic, 23–24
  development costs of, 100–101
  difference, 10
  fuzzy network, 136–137
  groundwater 239–240
  heuretic, 7
  ecological, *see* Ecological models
  Eulerian-Lagrangian, 142–144, 155
  interpretation of, communication and, 276
  linked multihierarchical, for decision support, 157–158
    matrix, 254
    multiregional, 254
    physical population, 27–31
  problems with, 114–115

quantitative, 274–275
statistical, 147–148
sensitivities and uncertainties of, 265–269
spatial optimization, 146–147
strategic view of role of, in environmental security, 301–307
Structures of, 150–154
Monte Carlo simulation, 152
Multihierarchical models, linked, for decision support, 157–158
Multiple criteria, 319
Multiregional models, 254
Multiscale analysis, 145
Multiuser interactions, tools for, 235
Multivariate adaptive-regression splines (MARS), 147–148

N
NetWeaver, 136
Network access, 202
Network theory, 125–133
Nonsampling errors, 195
Not in my back yard (NIMBY) attitude, 112

O
Occupancy approaches, 126
Outliers, 196

P
Parallelization methods, 149–150
Percolation theory, 126, 127, 129
Physical models, 7
Population growth, 9–10, 291–292
water scarcity and, 305
Population model, wolf, 27–31
Population trends, 291
Population viability analysis (PVA), 23, 125
Pragmatic modeling to support management planning, heuristics of, 40
Precision, 97
Predictions, 176, 177
projections versus, 13
Predictive methods, 58–59
Predictive models, success criteria for, 104
Private property, 5
Problem definition, 316
Problem formulation stage, 91
Problem solving, creative, synthesis and, 273–274
Projections, 186
predictions versus, 13
using, from ecological modeling for resource management, 12–14
Protection, mitigation, and enhancement (PM&E) measures, 50
Public land management, 71–72

Q
Quantitative modeling, 274–275

R
RAMAS GIS, 255
RAMAS Red List, 269
propagating uncertainty with, 266–268
Recreational resources, 3
Reference conditions, 92–93
Regional assessments, large-scale, 70–84
Regional impacts of enhanced greenhouse effects on climate, 294–295
Regression tree analysis, 147
Results, absolute versus relative, 101–102
Religious values, 4
Remotely sensed data, 190–191
Representation approaches, 126
Resolution, 185
Resource concerns, 113–114
ecological modeling for, *see* Ecological modeling for resource management
Resource management decisions, 52
Resource management needs, 312–314
Resources, available, 55
Retrospective methods, 58–59
Risk assessments, ecological, framework for, 89–94
Risk aversion, 112–113

Risk characterization, 93
Risk criteria, 50

S
Sahel, African, 298
Salinity in water, 301
Sample sites, 192–193
Sample size, 192–193
Sampling, consistency in, 185
Sampling errors, 194–195
Scale, 185
  variability and, 174
Scale considerations, 141–145
Scenarios, 101
Science investments, 16
  needed to enhance use of ecological modeling for resource management, 249–259
Scientists, training of, 271–273
Sea-level rise, 293
Security, environmental, *see* Environmental security
Sensitivity, 268
Sensitivity analyses, 101
Shannon-Weaver (SW) index, 172
Site specificity, 59
Software concerns, 200
Southern Appalachia, 71–72
Southern Appalachian Assessment (SAA), 70–84
Southern Appalachian Man and the Biosphere Cooperative (SAMAB), 74
Spatial data, 190
Spatial optimization models, 146–147
Spotted owl habitat, Mexican, 131–132
Stakeholders, 311
  educating, 278–281
Stakeholder's toolkit, 224–225, 233–235
Standards, role of, 242
Statistical models, developing, 147–148
Stopping-time problem, 57
STORET database, 173
Stress regime characterization, 90
Students, training of, 273–278
Success criteria for conceptual and predictive models, 104
Sustainability, 4
  criteria for, 312
  forest ecosystem, 138–139
Synthesis, creative problem solving and, 273–274
Systems ecology, 12
Systems thinking, model conception and, 274

T
Teaching model development and implementation, 277
Temporal scales of ecological models, 9
Time constraints, 113
Toolkit concept, 16, 211–212, 221–222
Toolkit design, general issues of, 225–231
Toolkit functionality, 222–225
  general issues of, 225–231
  requirements for, 230–231
Toolkit implementations, 212–216
Toolkit requirements, issues associated with, 236
Toolkit types, 222–225
Toolkits, 209–245
  computational methods and, 280–281
  conceptual, 223–224, 231–233
  decision maker's 224, 235–237
  environmental management and, 216–218
  examples of, 226, 227
  interoperability protocols and standards with, 227–228
  role of, in environmental management, 221–243
  uses of, 222
Total Maximum Daily Loads (TMDLs), 174
Training, 250, 271–273, 273–278
Training students, 273–278

U
Uncertainty, 99, 111
  dealing with, 151–152
  propagating, with RAMAS Red List, 266–268
Uncertainty analysis, 111, 268
Understanding, modeling and, 316–317

U.S. Environment Protection Agency,
see EPA *entries*
Universal modeling language (UML),
136

V
Validation, 176, 177
Value-laden decision making, 47–49
Variability, scale and, 174
Vasectomy for wolf control, 36–37
Verification, 176, 177
Visualization, 153–154
data, 137
web-based, 235
Voluntary data sharing, 203–204
Voyageurs National Park, 32–36

W
Warehousing data, 201
Water
salinity in, 301
as scarce resource, 298–301
Water quality, 300–301
Water scarcity, 290, 299
population growth and, 305
Weather forecasts, 117–118
Web-based visualization, 235
Web empowerment and
implementation, 225, 227
Weight-of-evidence approach,
54
Wildlife background, 3
Wolf biology and recovery status,
24–26
Wolf control, vasectomy for, 36–
37
Wolf decline, 25
Wolf life history, 28
Wolf management questions,
27
Wolf population model, 27–31
Wolf removal strategies, 37–39