28 Ecosystem Effects Modeling

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We must seek to model somehow the passing of a butterfly along with the growing of a tree.

Allen and Starr (1982)

28.1 AN ECOSYSTEM PARADIGM

The ecosystem remains a fundamental conceptual unit not only in basic ecological research, but also in environmental assessment and management. The limitations of organism-level ecological assessments raised decades ago remain (NRC 1981; O'Neill and Waide 1981; Kimball and Levin 1985). To address these limitations, ecologists, environmental toxicologists, and risk assessors have continued to develop, apply, and evaluate methods and models for characterizing ecosystem-level risks (Pastorok et al. 2002). Ecosystem modeling continues to contribute importantly to assessing ecological risk.

This chapter defines and describes ecosystem risk assessment and emphasizes the use of ecosystem models for estimating risk. In this presentation, *ecosystem models* include physical models (e.g., micro-, mesocosms), network analytical models, and compartmental simulation models. Physical models are discussed briefly. The intent is to underscore the similarities in issues (e.g., model structure, scale, initial conditions) that must be addressed in effectively using physical and mathematical models to characterize risk. Network analytic techniques (e.g., flow analysis, loop analysis) are mentioned because they offer a largely unrealized potential application in ecosystem risk assessment. Not surprisingly, the majority of the presentation addresses ecosystem simulation models as tools for assessing risk.

The chapter identifies and describes several ecosystem simulation models (AQUATOX, CASM, and IFEM) available for assessing ecological risks posed by chemical contaminants and other agents. These models have been developed with ecological risk assessment as a principal modeling objective. This chapter does not present an exhaustive list of ecosystem models that might be used to assess risk. Pastorok et al. (2002) comprehensively reviewed existing ecosystem models that might be adapted for estimating ecological risks, and the interested reader should consult this reference. Nevertheless, criteria for selecting among existing models are presented within this chapter. Following a discussion of the relative strengths and limitations of ecosystem models in assessing risk, the focus shifts to adapting available ecosystem models and developing new models for ecosystem-level risk assessment.

The development of practical capabilities in assessing ecosystem-level risks cannot proceed independently from the continuing evolution of ecosystem concepts and theory (e.g., Golley 1993; O'Neill 2001). Ecosystems are not simply places and the term "ecosystem" should not be used in risk assessment simply to denote habitat. Perhaps the most significant contribution of ecosystem theory to modern ecology includes the recognition of important biotic–abiotic feedback mechanisms that determine the dynamics of system structure and function. That is, physical–chemical factors dictate the nature and kinds of organisms that can inhabit a specific area or volume. In turn, the effects of resident organisms on those factors can result in subsequent habitat conditions that preclude the continued occupation by those organisms and open the area for new inhabitants. The essence of *ecosystem* lies not in habitat, but in the biotic–abiotic feedback mechanisms that strongly influence system dynamics and response to disturbance. Ecosystem-level risk assessments ought to rightly focus on risks to these feedback mechanisms.

Another conceptual contribution of ecosystem theory lies in the recognition of the significance of asymmetry in functional relationships among organisms and between biotic and abiotic components of ecosystems. Not all structures, processes, and interactions are of equal importance at all times or locations. Ecosystem dynamics integrate spatial–temporal shifts in interaction strengths (e.g., competition, grazing, predation) among participating organisms within a changing physical–chemical context. Seasonal changes in the relative importance of "bottom–up" and "top–down" control of production in aquatic systems provide one example of such asymmetry (e.g., Bartell et al. 1989).

Asymmetry in ecosystems is important to risk assessment. Characterization of ecosystem asymmetry can provide insights to the selection of endpoints for risk assessment (Chapter 16) and suggest relevant scales in time and space (Chapter 6) to guide the development of a conceptual model (Chapter 17). Knowledge of relevant scales of exposure can be used to identify corresponding species and ecosystem processes that appear important in relation to the hazardous agents.

Ecosystem asymmetry facilitates the simplifying assumptions that provide a basis for less comprehensive descriptions (e.g., population models) used to estimate risks. If a population model provides accurate estimates of measured population fluctuations, it is because the simplifying assumptions underlying the population model are congruent with the overarching ecosystem asymmetries relevant to the population model.

Properly structured ecosystem models afford the opportunity to incorporate biogeochemical asymmetries and examine their implications for estimating risk. For example, positive effects of nutrient enrichment on ecological production can mask the detrimental effects of simultaneous exposure to toxic chemicals (e.g., Breitburg et al. 1999; Riedel et al. 2003). Differential affinity for nutrients and susceptibility to toxic chemicals can together determine how any added productivity will be apportioned among the food web components. Such opportunity to explore asymmetry in ecosystem structure and function is absent from other ecological modeling constructs (e.g., organism models, population models, landscape models).

28.2 ECOSYSTEM RISK ASSESSMENT

Following from the proposition that asymmetric functional relationships and biotic–abiotic feedback control mechanisms are key concepts that distinguish ecosystem ecology from other levels of ecological inquiry, ecosystem risk assessment should correspondingly focus on changes in functional relationships and feedback mechanisms caused by single or multiple agents. In the proper parlance of ecosystem theory and risk assessment, ecosystem risk assessment ought to emphasize assessment and measurement endpoints specifically related to effects on the flow of energy, cycling of materials, strengths of competitive, grazing, and predator/prey interactions, and corresponding implications for system structure (e.g., species composition, community structure), function, and stability (e.g., resistance, resilience). These are the kinds of endpoints that cannot be addressed by assessments that focus on organisms or populations.

In practice, ecosystem risk assessment tends to emphasize population-level effects characterized within a dynamic physical–chemical context. Explorations into the relative contribution of direct and indirect effects on population risks do, however, provide examples of ecosystem models used to address some of the biogeochemical (minus the geochemical) asymmetries that connote ecosystem risk.

28.2.1 Ecosystem Assessment Endpoints

The specification of ecosystem-level endpoints follows logically from the preceding consideration of ecosystems. Suter and Bartell (1993) identified four kinds of ecological effects that can be observed in ecosystems, but are not possible for an organism or a population: (1) the effect of an agent on the nature of ecological interactions (e.g., predation, competition) among resident populations; (2) indirect effects that propagate through organisms sensitive to the agent and subsequently impact organisms not directly affected (e.g., reduced abundance of a predator resulting from toxic effects on prey); (3) alterations in the trophic structure or number of species; and (4) alterations in ecosystem function, including production, decomposition, and nutrient cycling. Suter and Bartell (1993) distinguished between assessment of population-level effects (i.e., effects 1 and 2) in an ecosystem context and true ecosystem-level effects (i.e., effects 3 and 4).

One of the key ecosystem concepts concerns feedback control mechanisms between biotic and abiotic system components. Abiotic factors (e.g., soil chemistry) can importantly determine the growth and establishment of species adapted for the existing conditions—abiotic factors determine ecological structure. Subsequently, the biological activities of resident organisms can modify the abiotic conditions to the point that the resident species can no longer tolerate the modified conditions and different species adapted to these conditions can replace the current inhabitants—here, biological activity determines the abiotic environment and eventual ecological structure. Thus, alterations in evolved patterns of abiotic–biotic feedback control mechanisms could pose serious threats to ecosystem integrity. Alterations in such patterns would in theory constitute important ecosystem-level endpoints. Yet, these sophisticated ecosystem endpoints have seldom been included in ecological risk assessments. Ecosystem models can be used to address these kinds of endpoints.

28.3 ECOSYSTEM SIMULATION MODELING

For this discussion, ecosystem simulation models refer to those ecological models which include both biotic state variables that describe one or more primary producers and consumers and one or more abiotic state variables or processes that are functionally linked to the biotic state variables. Their models should demonstrate functional interrelationships, e.g., grazing, predation, and competition, expressed between the producer and consumer state variables. The abiotic factors, e.g., light or nutrient limitation of primary production, should influence the expression of the biological and ecological interaction represented by the model. Importantly, the biological and ecological processes included in the model should permit the modification of the abiotic state variables (e.g., nutrient uptake or remineralization influencing dissolved or soil nutrient concentrations).

An ecosystem risk assessment model should be spatially defined. The modeled temporal dynamics should be specified over some spatial scale, e.g., a square meter or hectare for models of terrestrial ecosystems or similar volumetric scales for aquatic ecosystem models. Recent advances in ecosystem modeling have produced spatially articulated models wherein a single description of biotic and abiotic structures and interactions are defined repeatedly for multiple locations that are functionally interconnected by the flow of water, energy, or materials (e.g., Costanza et al. 1990; Bartell and Brenkert 1991; Voinov et al. 1998).

Several features of ecosystem models strongly recommend them for assessing ecological risks. The structural and functional complexity of ecosystem models provides risk assessors with tools to estimate both direct and indirect effects. The implications of differential susceptibility to chemical and other agents developed from single species tests can be explored in the context of system-level effects on structure and function. For example, ecosystem models such as CASM (Bartell et al. 1999, 2000) and AQUATOX (Park and Clough 2004) that define multiple populations within individual trophic guilds can be used to examine the indirect effects of chemicals on competitive and predator/prey interactions. Normally inferior competitors may gain the upper hand if their counterparts prove more sensitive to a chemical. Populations of prey species might increase substantially if their predators succumb more quickly to exposure to a chemical or other agent. Apart from costly and time-consuming field manipulations, ecosystem models provide the only means to address these kinds of direct and indirect effects that can propagate throughout complex ecological systems.

Ecosystem models can address ecological risks posed by simultaneous exposure to multiple agents of differing kinds. For example, CASM can be used to estimate risks posed by a combination of several toxic chemicals (organic and inorganic), nutrient enrichment (N, P, Si), sediment loading, depletion of dissolved oxygen, and fishing pressure, if necessary. Spatially explicit ecosystem models can also examine the implications of spatial patterns in habitat degradation and loss, as well as the effects of regional pollution and climatic change.

More detailed and explicit representation of ecological structure and function suggest that ecosystem models are more realistic descriptions of complex ecological systems (Pastorok et al. 2002; Bartell et al. 2003). Ecosystem models provide the capability to address subtle, but important, ecosystem-level endpoints, such as energy flow, nutrient cycling, alterations of abiotic–biotic feedback control mechanisms, and system stability (i.e., resistance and resilience). Ecosystem models emphasize the description of ecological systems as complex networks that propagate cause and effect, where the network complexity partly reflects current description and observations relevant to the system of interest. The network complexity also results from the biases introduced by the model makers and the specific nature of the assessment. The currency of flows through these complex networks can be energy (i.e., joules) or its material equivalents (e.g., carbon, dry mass, nutrients). Ecosystem models, as representative of complex and ecologically realistic networks, can be used to examine the probable ecological implications of even subtle alterations in these kinds of flows, whereas models of organisms or populations, given their structural limitations, cannot.

Ecosystem models can, in addition to addressing multiple and complex assessment endpoints, potentially provide insights for risk management and decision making that cannot be obtained using models of organisms or populations. The strictly empirical parameters of statistical models (e.g., regression coefficients) usually defy interpretation in relation to management practices; the models may prove accurate in estimating risk, yet provide little utility to managers who desire to use the models to reduce or mitigate risks. Similarly, the highly aggregated parameters of some population models (e.g., the carrying capacity, K) are difficult to use in managing risk. The process-level equations and parameters generally characteristic of ecosystem models are directly interpretable in terms of physical, chemical, biological, and ecological phenomena that underlie the model. This detailed level of description provides information that can be used to develop and evaluate the likely success of alternative management actions.

28.3.1 Physical Ecosystem Models

Physical model ecosystems (e.g., microcosms, mesocosms, whole-system manipulations) provide an alternative approach to characterizing ecological risk (Section 24.3). The appeal of these "tangible" ecosystem models is not surprising. Risk can be characterized using the results of controlled and replicated experiments: organisms can be counted; chemistry can be analyzed; and variability in responses can be quantified. These attributes engender a perception of reality associated with physical ecosystem models.

At the same time, it should be remembered that the derivation and use of physical ecosystem models are subject to many of the same assumptions, limitations, and sources of uncertainty as their mathematical counterparts. In constructing or excising physical ecosystem models, decisions must be made concerning scale (i.e., physical dimensions) and how much ecological structure should be included and measured (Gardner et al. 2001). Initial values of the physical model "state variables" must be determined. The environmental context (e.g., light, temperature, precipitation) for physical models has to be defined or simply used as an uncontrolled regime defined by local conditions. All of the sources of bias and imprecision involved in sampling frequency, sample collection, sample processing, and data management are inherent to the use of physical ecosystem models. In addition, the resources required to use physical models routinely limit the number of replicates, and associated variability among replicate models can be substantial. Finally, the results of the physical models must be interpreted within the context of the ecosystem that they are intended to represent.

28.3.2 Ecosystem Network Analysis

Ecosystems can be conveniently described using networks (e.g., Figure 28.1). The "box and arrow" schematic illustrations of ecosystem structure and function have been basic to ecological instruction for decades (e.g., Odum 1971) and practicing ecologists are familiar

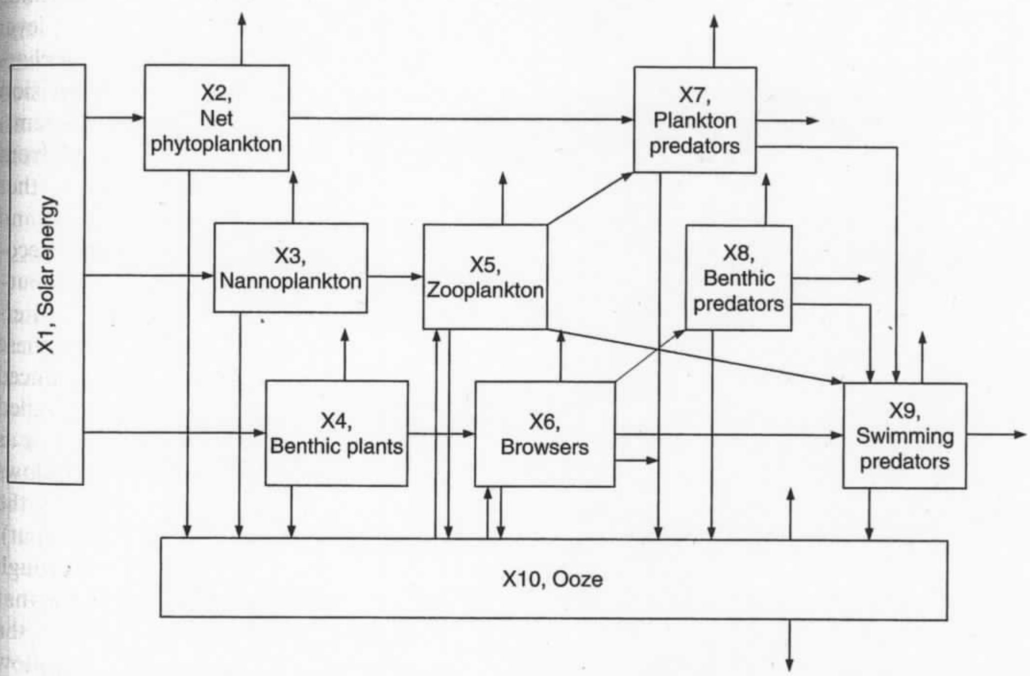

FIGURE 28.1 Example "box and arrow" flow chart for the ten-compartment Cedar Bog Lake ecosystem model. (Redrawn from Williams, R.B., in *Systems Analysis and Simulation in Ecology*, Vol. I, Patten, B.C., ed., Academic Press, New York, 1971. With permission.)

with such conceptual network models. Beyond mere illustration, more formal network models and network analyses of compartmental descriptions of ecosystems provide powerful tools for qualitative and quantitative understanding of ecosystem structure and function. These ecosystem network tools can help risk practitioners to characterize ecological risks. The following sections briefly outline several of these network ecosystem models.

Qualitative network analyses (e.g., "loop" analysis) can be used to describe the stability of ecosystems in the absence of detailed quantification of interactions among system components (Levins 1974). Simple knowledge of positive, negative, and neutral interactions among system components can be used to develop an interaction matrix, sometimes referred to as a "competition matrix" (Levins 1974; Lane and Collins 1985). Relationships among system components are designated by signs: (+,−) denotes a predator–prey relationship; (−,−) indicates competition between two components. The system is described as a directed graph, wherein each component is represented as a circle and interactions are described by connecting arrows. Mathematical analysis of the numbers and locations of these various signed interactions throughout the matrix can provide information concerning the general stability properties of the system. Relevant to risk assessment, the methods can be used to examine the stability implications of anthropogenic changes in the nature of the interactions or removal of a system component (e.g., Lane and Collins 1985). The sensitivity of these analyses to initial system specification and the overall qualitative nature of the approach have minimized the application of loop analysis since its introduction into ecology. In addition, the quantitative magnitudes of component interactions are likely more important than the overall qualitative network structure in determining the stability of ecological networks. However, Ortiz and Wolff (2002) have recently revitalized the use of this method. They apply loop analysis to evaluate the qualitative stability properties of north-central Chilean coastal marine benthic systems in relation to harvesting pressures on scallops. This recent application serves as a reminder that qualitative methods of ecosystem analysis are possible and that these kinds of analyses remain potentially useful as tools in contemporary assessment of system-level ecological risk. Given the incomplete and sparse data routinely available for ecosystem characterization, this ecosystem modeling approach might provide useful results for decision making based on more easily obtained qualitative description of structurally complex systems.

In the early 1970s, quantitative methods of network flow analysis were borrowed from economics and applied to ecological systems (Hannon 1973). Flow analysis was further developed for quantitative description of nonsteady-state ecosystems (e.g., Finn 1976) and subsequently elaborated for detailed characterization of hierarchical structure within ecological networks (Patten et al. 1976). Central to flow analysis is the construction of an input–output or production matrix (Figure 28.2), wherein the quantitative flows among all interconnected system components are estimated along with inputs to, and losses from, these components. The inputs, outputs, and intercompartment flows can be measured or produced by corresponding dynamic models (Bartell 1978). The production matrix provides a detailed description of system state and patterns of energy or material flux, either at steady-state or as a snapshot at a selected point in time for nonsteady-state conditions. Normalization of flows among components to inputs (outputs) provides quantitative information concerning the change in each component associated with a unit increase or decrease in input (output). Additional calculations can be made to estimate the total flow of energy or material through the system over a specified time scale. It is further possible to estimate a ratio of flow that is recycled to total system throughflow. This ratio quantifies the cycling efficiency of the system represented by the production matrix (Patten et al. 1976). Total system throughflow and cycling efficiency could serve as higher-order, ecosystem-level endpoints in ecological risk assessment.

To/from	x_1	x_2	..	x_n	Inflow	Outflow	Row Σ
x_1	φ_{11}	φ_{12}	..	φ_{1n}	z_{10}	0	T_1
x_2	φ_{21}	φ_{22}	..	φ_{2n}	z_{20}	0	T_2
.	.	.		.	.	.	.
.	.	.		.	.	.	.
x_n	φ_{n1}	φ_{n2}	..	φ_{nn}	z_{no}	0	T_n
Inflow	0	0	..	0	0	0	0
Outflow	y_{01}	y_{02}		y_{0n}	0	0	Σy
Column Σ	T_1	T_2	..	T_n	Σz	0	TST

FIGURE 28.2 Generalized production or flow matrix.

The main challenge in using flow analysis to describe ecosystem dynamics lies in accurately quantifying inputs, outputs, and flows among system components. This challenge increases nonlinearly as the number of components in the production matrix increases. The necessary values can be provided by detailed field studies (i.e., physical ecosystem models). Alternatively, dynamic models can be used to provide the value needed to develop a production matrix for the system of interest (e.g., Bartell 1978). In this case, the methods of flow analysis are used as another means to summarize modeled system dynamics. This integration of dynamic models with flow analysis can be used to assess potential effects on higher-order ecosystem endpoints (e.g., total system throughflow, cycling efficiency).

Flow analysis can be used to characterize ecosystem risk if exposure–response relationships are developed to quantify changes in flows, inputs, or outputs in relation to the agent of interest.

Figure 28.3 shows a production or flow matrix developed for the Cedar Bog Lake ecosystem. The values reflect the system inputs, outputs, and flows corresponding to the network compartmental diagram of this ecosystem. The balance between inflows and outflows characterizes a system that is in a state of dynamic equilibrium. The steady-state dynamics can also be inferred from the linear differential equations with constant coefficients used to describe this system (see Section 28.3.3).

To/from	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}	Inflow	Outflow	Row Σ
x_2										13.1		
x_3										21.4		
x_4										61.4		
x_5		0.68										
x_6			0.21									
x_7	1.01			0.90								
x_8				0.17	0.48							
x_9					0.28	0.19	0.07					
x_{10}	8.79	15.32	45.99	5.13	0.20	0.30	0.07	0.15				
Inflow										0	0	0
Outflow	3.30	5.40	15.20	3.90	0.52	1.42	0.34	0.56	65.35	0	0	95.99
Column Σ										95.90	0	~96

FIGURE 28.3 Flow matrix based on the Cedar Bog Lake model.

Recent methods for network analysis have been derived in part to address the inability to completely define a network for any single ecosystem or comprehensively quantify the production matrix in flow analysis. These newer methods (ECOPATH/ECOSIM, NTWRK) focus on equilibrium conditions and attempt to identify plausible network structures that are compatible with available information that quantifies flows among specified system components (Christensen and Pauly 1992; Monaco and Ulanowicz 1997). These methods have been used to assess effects of selected agents on aquatic systems (e.g., Pauly et al. 2000); however, these studies have not been performed within a formal framework for ecological risk.

The preceding network methods for describing ecosystems are offered as complementary analyses to the more common ecosystem compartment simulation models described in Section 28.3.3. Importantly, the network analyses can be used to characterize changes in the patterns and magnitudes of energy flow or material cycling in systems subjected to pollution. Even the more qualitative method of loop analysis can provide some insights concerning alterations in the stability properties of ecosystem networks.

28.3.3 Compartment Models

The term "ecosystem model" has become more routinely associated in risk assessment with complex compartment simulation models (Pastorok et al. 2002). The ecosystem compartment model includes some calculus that describes time-dependent changes in the values of the model state variables as functions of changes in the inputs of abiotic factors and the values of the biotic state variables. Traditionally, ecosystem models have been formulated as coupled differential (or difference) equations, where one governing equation is defined for each modeled state variable, biotic and abiotic (e.g., Smith 1969; Patten 1971; Park et al. 1974). The values of the state variables change through time as a function of the model equations that describe ecological and environmental processes internal to the model, e.g., nutrient-dependent primary production, temperature-dependent grazing, predator/prey relations, and decomposition. Modeled temporal dynamics can also result from the time-varying input values of external environmental factors (e.g., temperature, nutrient loading, toxic chemical concentrations).

The temporal dynamics of each state variable defined in the ten-compartment model of the Cedar Bog Lake can be described by the following system of coupled differential equations (Williams 1971):

$$
\begin{aligned}
X_1' &= 118{,}625\,\text{cals cm}^{-2}\,\text{y}^{-1}\\
X_2' &= f_{12} - X_2\,(\rho_2 + \mu_2 + \varphi_{27})\\
X_3' &= f_{13} - X_3\,(\rho_3 + \mu_3 + \varphi_{35})\\
X_4' &= f_{14} - X_4\,(\rho_4 + \mu_4 + \varphi_{46})\\
X_5' &= \varphi_{35}X_3 + \varphi_{10,5}X_{10} - X_5\,(\rho_5 + \mu_5 + \varphi_{57} + \varphi_{59})\\
X_6' &= \varphi_{46}X_4 + \varphi_{10,6}X_{10} - X_6\,(\rho_6 + \mu_6 + \varphi_{68} + \varphi_{69} + \lambda_6)\\
X_7' &= \varphi_{27}X_2 + \varphi_{57}X_5 - X_7\,(\rho_7 + \mu_7 + \varphi_{79} + \lambda_7)\\
X_8' &= \varphi_{68}X_6 - X_8\,(\rho_8 + \mu_8 + \varphi_{89} + \lambda_8)\\
X_9' &= \varphi_{59}X_5 + \varphi_{69}X_6 + \varphi_{79}X_7 + \varphi_{89}X_8 - X_9\,(\rho_9 + \mu_9 + \lambda_9)\\
X_{10}' &= \mu_2X_2 + \mu_3X_3 + \mu_4X_4 + \mu_5X_5 + \mu_6X_6 + \mu_7X_7 + \mu_8X_8 + \mu_9X_9 - X_{10}\,(\rho_{10} + \varphi_{10,5} + \varphi_{10,6} + \lambda_{10})
\end{aligned}
$$

Although simpler in form than other aquatic ecosystem models (e.g., CASM, AQUATOX), the Cedar Bog Lake model demonstrates features that are characteristic of these kinds of models. The model indicates losses to respiration (ρ_i), mortality losses to the "ooze" or sediments (μ_i), and physical losses from the system (λ_i) for each compartment i. Trophic transfers from compartment i to j are designated by the φ_{ij} terms. The same terms common to two or more equations define the functional interconnections between the model state variables as illustrated by the "arrows that connect the boxes"' in Figure 28.1. Indirect effects manifest themselves through these functional interconnections.

The critical requirement in selecting or developing an ecosystem model for assessing ecological risks is the derivation of a functional relationship between exposure to the agent and an associated response of one or more of the model process formulations or state variables. In addition, the exposed process formulations and model state variables should map onto the endpoints of interest for the assessment.

28.3.4 Existing Ecosystem Risk Models

Pastorok et al. (2002) reviewed the ecological modeling literature and identified only three ecosystem models that were developed to estimate ecological risk. These models essentially extrapolate the results of laboratory toxicity assays to anticipated effects in complex aquatic systems. Given the emphasis on aquatic toxicity testing, it is not surprising that terrestrial ecosystem models are absent from the list of available models. Each of the available models is briefly described. The interested reader is referred to the provided references for detail.

28.3.4.1 AQUATOX

AQUATOX (Park and Clough 2004) models the fate and effects of toxic chemicals, nutrients, and sediments in a variety of aquatic systems, including lakes, ponds, streams, and reservoirs. This model estimates risks posed by these agents on modeled populations of aquatic producers (e.g., phytoplankton, periphyton, submersed aquatic plants) and consumers (e.g., zooplankton, benthic invertebrates, and several functionally defined guilds of fish). AQUATOX addresses lethal and sublethal effects on important ecological processes, including photosynthesis, consumption, reproduction, and mortality. Such toxic effects are integrated to estimate the impacts of chemicals on the daily sizes of modeled aquatic populations. Toxic effects are modeled in relation to biologically available chemical, which is determined by modeled chemical transport and fate processes (e.g., sorption, hydrolysis, volatilization, photolysis). The model has been developed within a user-friendly interface to facilitate site-specific applications. Necessary input data include nutrient, sediment, and toxic chemical loadings to the system of interest; general limnological characteristics of the site; growth characteristics of each modeled population; and sensitivity of each population to the agents of concern.

28.3.4.2 CASM

The Comprehensive Aquatic Systems Model (CASM) is a bioenergetics-based compartment model that describes the daily production of biomass (carbon) by populations of aquatic plants and animals for an annual cycle. CASM permits site-specific specification of food web structure and delineation of daily values of surface light intensity, water temperature, and nutrients (N, P, Si) that determine rates of photosynthesis of modeled plant populations. The model provides for as many as 30 populations of phytoplankton, periphyton, and macrophytes. Up to 40 populations of zooplankton, benthic invertebrates, decomposers, and fish can be specified. Modeled populations can be defined taxonomically or functionally. The model was designed originally to examine theoretical relationships between food web structure, nutrient cycling, and ecosystem stability (DeAngelis et al. 1989). Since its adaptation for risk estimation, CASM has been applied to generic assessments for rivers, lakes, and reservoirs in Canada (e.g., Bartell et al. 1999), as well as smaller lakes in central Florida (Bartell et al. 2000). It has also been implemented for site-specific assessments of ecological risk posed by chemicals in Lakes Biwa and Suwa, Japan (Naito et al. 2002, 2003). CASM has been designed for probabilistic risk estimation using Monte Carlo simulation and characterizes risk as the probability of specified decreases in the annual production of each modeled population. It has also been adapted to assess more site-specific risks posed by pesticides in littoral ecosystems (i.e., the Littoral Ecosystem Risk Assessment Model (LERAM); Hanratty and Stay 1994).

28.3.4.3 IFEM

The Integrated Fates and Effects Model (IFEM) is an integration of the toxic effects model Standard Water Column Model (SWACOM) (Bartell et al. 1992) and a polycyclic aromatic hydrocarbon (PAH) fate model Forecasting Ocean Assimilation Model (FOAM) (Bartell et al. 1981). It combines environmental fate processes, bioaccumulation, bioenergetics descriptions of growth, and toxicity data to estimate the probable effects of PAHs on the production dynamics of lotic ecosystems (Bartell et al. 1988). Sublethal toxic effects of accumulated PAHs are modeled for 11 representative populations of aquatic plants and animals; toxic effects and risk are estimated as a function of a dynamic body burden. Body burden reflects the differential uptake, metabolism, and depuration of PAHs. Available PAH is determined by loading rate and environmental fate processes (dissolution, photolysis, sorption, volatilization). Fate process rates can be estimated using quantitative structure–activity relationships developed for PAHs. The data demands of the IFEM have thus far permitted only assessment of risks posed by naphthalene (Bartell et al. 1988).

28.4 MODEL SELECTION, ADAPTATION, AND DEVELOPMENT

Because few ecosystem risk assessment models are available (Pastorok et al. 2002), risk assessors interested in applying ecosystem models will likely be challenged to (1) adapt an existing model or (2) develop a new model. The following discussion addresses these challenges.

28.4.1 Model Selection

The first step in selecting an existing model is to identify candidate ecosystem models. Pastorok and Akçakaya (2002) recommended nine criteria for evaluating the potential selection and application of ecological models, including ecosystem models, for assessing risks posed by toxic chemicals. Their recommendations included six technical and three regulatory criteria:

Technical criteria

1. Model realism and complexity
2. Relevance of ecological effects addressed by the model
3. Flexibility
4. Characterization of uncertainty
5. Degree of development, consistency, and validation
6. Ease of parameter estimation

Regulatory criteria

1. Acceptance among regulators
2. Credibility
3. Resource efficiency

TABLE 28.1
Brief Description of Nine Criteria for Selecting an Ecological Model for Adaptation to Risk Assessment

Criterion	Description
Technical	
Model realism	The model includes ecological structure and processes known to be important in determining the dynamics of the ecosystem of interest in the assessment. Model assumptions are realistic in relation to ecological understanding of the system.
Relevance of ecological effects	The kinds of model calculations (e.g., change in biomass, trophic structure, energy flow, material cycling) can be easily mapped onto one or more of the ecosystem-level assessment endpoints.
Flexibility	The model can be implemented for systems similar to its original derivation without major restructuring or reformulation of governing equations, major alteration of external forcing functions, or redefining model parameters and outputs.
Characterization of uncertainty	The model has been developed to explicitly describe and include potential sources of bias and imprecision in its calculus. Model outputs reflect the uncertainties propagated through model calculations (e.g., distributions, intervals, fuzzy numbers).
Development, consistency, and validation	The physical manifestation of the model (e.g., spreadsheet, commercial software, custom program) has become essentially error-free (i.e., "debugged," verified). The user is warned of potentially erroneous input values in model applications. The model has been compared with observations from systems similar to the ecosystem of interest; model biases have been characterized.
Parameter estimation	Model input values can be estimated from commonly available data. Model parameters have clear ecological or toxicological interpretation.
Regulatory	
Acceptance	The model is frequently used by the regulatory community or the models results are routinely accepted as useful by regulators and decision makers.
Credibility	Previous model applications have been peer-reviewed and accepted by the technical community; the model has been widely published and it is generally familiar to ecological modelers.
Resource efficiency	The time and effort required to adapt the model to a particular assessment does not discourage selection of the model.

Source: Summarized from Pastorok, R.A. and Akçakaya, H.R., in *Ecological Modeling in Risk Assessment—Chemical Effects on Populations, Ecosystems, and Landscapes*, R.A. Pastorok, S.M. Bartell, S. Ferson, and L.R. Ginzburg, eds., Lewis Publishers, Boca Raton, FL, 2002. With permission.

Pastorok and Akçakaya (2002) discuss each of these reasons for selecting an existing model in useful detail. These criteria are briefly annotated in Table 28.1.

28.4.2 Model Adaptation and Development

If an ecosystem-level assessment is necessary or desired, the risk assessor might be able to adapt an existing model or might be forced to develop a new model. The following sections describe some of the key issues to be addressed in either situation. More in-depth treatments concerning the development of ecological models were provided in some of the earlier references on ecological modeling (e.g., Patten 1971, 1972; Levin 1974; Hall and Day 1977; Halfon 1979; Shugart and O'Neill 1979). The detailed instructions for model building and application provided by these pioneers remain largely relevant today. Recent treatments include Odum and Odum (2000) and Swartzman and Kaluzny (1987). Additionally, the works edited by Hall and Day (1977) and Halfon (1979) include case study applications of ecosystem models to environmental problems, although these studies predate "ecological risk assessment" per se. Decades prior to the formalization of ecological risk assessment (EPA 1992a), ecosystem scientists were examining the usefulness of ecosystem models in assessing human influences on natural systems (e.g., Loucks 1972).

In adapting an existing model or developing a new model, the risk practitioner must address model structure, model process, scaling, exposure–response relationships, necessary input data, model results, and model performance.

28.4.2.1 Model Structure

Model structure refers to the ecological entities that are represented in the model. In the modeling lexicon, structure defines the state variables in the model and there will be one governing equation for each state variable. The "boxes" in an ecosystem "box and arrow" flow diagram identify the model state variables and thus model structure. Examples of biotic state variables in an ecosystem model include the numbers, biomass, or energy equivalent of two or more kinds of organisms. Concentrations of particulate organic matter and dissolved inorganic nutrients (e.g., N, P) are examples of abiotic state variables in ecosystem models. Importantly, the model must contain state variables that correspond to the assessment endpoints identified in the problem formulation.

In adapting or developing an ecosystem model for risk assessment, the risk assessor must examine the feasibility of incorporating ecological structure germane to the assessment if it is not already present. In adapting a model, this might mean adding structure. Adding structure to an existing model requires an evaluation of compatibility with other state variables already in the model. In developing a new model, the necessary structure can be designed at the outset. The challenge will then take the form of deciding how many other state variables (i.e., additional structures) are needed to describe the dynamics of the variables corresponding to endpoints with sufficient accuracy and precision to usefully characterize risk.

28.4.2.2 Governing Equations

In addition to the ecological structure of ecosystem models, structure might also refer to the mathematical structure, i.e., the calculus of the model. For example, many traditional ecosystem models have been designed as sets of coupled differential or difference equations. Methods of calculation can range from simple algebra to analytical calculus to sophisticated schemes for numerical integration. Recent developments in ecosystem modeling have used numerical algorithms and cellular automata or combinations of automata and various forms of equations to determine how the values of the state variables change in space or time.

The equations or mathematical formulations that govern the calculations of the model should be compatible with the nature of the endpoints. For example, if an endpoint is the biomass (e.g., dry weight, carbon) of a particular population, the calculus of the governing equations should be in the same units. Otherwise, a conversion will be required (e.g., kcals to grams carbon) if the model calculations are performed in other units. These kinds of conversions can serve as a source of inaccuracy or imprecision in model performance.

28.4.2.3 Scaling

Here scale refers to the spatial and temporal dimensions explicit to the model. In space, the model describes some spatial subset (i.e., extent) of the biosphere defined by the selected ecosystem boundaries. The spatial resolution (i.e., grain) within this extent defines the smallest spatial unit represented by the model (e.g., 1 m^3). Parallel concepts apply in the temporal domain. Temporal scales include the duration (e.g., 1 y) of the model calculations and the temporal resolution (e.g., daily values of the state variables).

Four scales are important in adapting or developing an ecosystem model for ecological risk assessment. The *ecological scales* relevant to the ecological structure(s) of concern are fundamental to useful model application in support of risk characterization. The ecological scale will have been already determined for models being adapted for risk assessment. The risk practitioner will have to evaluate the scale of the model in relation to the scales appropriate to the assessment at hand. It might prove feasible to rescale an existing model, depending on the specification of the state variables and formulation of the governing equations. It is generally easier to "scale up" or aggregate structure and process than to add finer resolution to an existing model. In developing a model, the model builders can apply basic knowledge of organism life history and previous observations of their ecology to identify spatial–temporal scales that are appropriate for the assessment and compatible with the scales of the exposures. Similar understanding of important physical–chemical processes, augmented by local or regional data, can be used to characterize spatial–temporal variability in environmental forcing functions that must be integrated with biological and ecological scales in the selection of an overall scale for a new ecosystem risk assessment model.

The characteristic spatial–temporal *scales of the agents* must be factored into selecting among existing models, adapting a model, or developing a new model. For example, if the agent is a toxic chemical, the measured or anticipated frequency, magnitude, and duration of exposure can be used to define corresponding temporal scales in the ecosystem model. The spatial extent of an agent can be used to determine a relevant or necessary scale of the ecosystem model in order to effectively characterize risk. Clearly, there must be some overlap in ecological and agent scales for the model to be useful.

The *scales of measurement*, defined by the number, location, and frequency of samples in a monitoring program, determine the quality and quantity of data used to implement and subsequently evaluate the model. Simply stated, as the variability of the measured entity increases in space or time, more and more frequent samples will be required to accurately and precisely quantify it. Scales of measurement also pertain to the agents. As the scales of measurement become increasingly congruent with the inherent ecological or agent scales, the statistical variance estimated from the measured values ought to decrease to a minimum, whereupon additional sampling will not further reduce the variance.

The *scales of risk management* define the spatial–temporal characteristics of actions that risk managers have at their disposal for avoiding, minimizing, or mitigating risks. Management scales are also important in quantifying the possible significance of estimated risks.

In adapting or developing an ecosystem model for risk assessment, efforts should be made to obtain as much overlap as possible among these four scales.

28.4.2.4 Exposure–Response Functions

Given a model structured appropriately for an assessment, the next most important attribute to address is a functional relationship between the model structure representing the endpoints and the exposures central to the assessment. The model must be able to translate a quantitative description of the exposures to one or more agents to corresponding changes in the modeled values of the endpoint state variables so that it is useful in characterizing ecological risks. Ecological risk assessment can be fairly described as examining the implications of uncertain exposure–response functions.

The exposure–response function can assume different forms, depending in part on the nature of the exposure and the response. For chemicals, exposure–response functions are characteristically sigmoidal and monotonic (Figure 23.1). An additional consideration in developing these functions is the existence of a threshold value, the no observed effect concentration (NOEC), which can be incorporated into the overall formulation, shown conceptually in Figure 23.5. Probit functions (Figure 23.4) have proven useful in defining exposure–response functions used by ecosystem models for estimating risks posed by toxic chemicals (e.g., Bartell et al. 2000).

Regardless of the exact nature of an exposure–response function, the risk practitioner should attempt to quantify the uncertainties associated with the function. For example, an exposure–response function for a chemical might be more realistically described by a set of exposure–response functions that address the variability in response associated with organism size or age, depending on how such biological structure is represented in the ecosystem model.

28.4.2.5 Data

A perfect ecosystem model cannot inform the risk assessment process if the necessary supporting data are not available to perform the model calculations. While this is true for all ecological models, ecosystem models, being structurally complex by definition, commonly exhibit greater demands for data to perform the model calculations. The data needs of ecosystem models include values for initial conditions of the model state variables, values of the parameters in the governing equations, and values that quantify any necessary external forcing functions. The beginning values of all the model state variables define the initial conditions of the ecosystem model. The nature of the data required to quantify the initial conditions is largely a consequence of the units selected to describe the dynamics of the state variables. Initial conditions might include population sizes (numbers, biomass, or energy equivalents) of various biotic components. Initial values might also be required for environmental parameters (e.g., light, temperature, nutrient concentrations) that have been incorporated into the model.

The mathematical formulation of an ecosystem model will define the nature of the parameters that determine the dynamics of the state variables. Model parameters can range from simple linear constant coefficients to highly detailed values that are nonlinear functions of other biotic state variables and environmental forcing functions (e.g., temperature). Regardless of their nature, the values of model parameters (e.g., rates of growth, survival, and reproduction) are necessarily derived from site-specific or more generalized sources of data.

Site-specific monitoring programs can provide the physical–chemical data used by ecosystem models. Comprehensive databases maintained by various agencies (USEPA, USGS, USDA, etc.) can be used in the absence of monitoring or to augment sparse data.

Additional data needs include values of the state variables used to compare with the model calculations for purposes of model evaluation (validation). The nature of the calculations performed by the model delineates the data needed to assess model accuracy and precision. For example, time series of population sizes for key model components might be required to evaluate model performance. The criteria for assessing model performance (see below) will determine the level of effort necessary to acquire the needed data.

In practice, the often substantial data needs of ecosystem models are met through a collation of site-specific data, data from similar ecosystems, and data from the technical literature.

28.5 INNOVATIONS IN ECOSYSTEM MODELING

The preceding discussion emphasized more traditional approaches to ecosystem modeling for characterizing ecological risk. This modeling construct was developed by ecosystems ecologists and modelers primarily in the 1970s and has not changed dramatically since then. Nevertheless, there are opportunities for innovation in the development and application of ecosystem models used in risk assessment. Several possible opportunities are described in the following sections.

28.5.1 Structurally Dynamic Models

Traditional approaches to ecosystem modeling have relied on some initial description of system structure (e.g., Figure 28.1). Once implemented, the model structure typically does not change during the course of execution, except perhaps for some of the modeled state variables becoming zero, i.e., effectively removed from the system. Current ecosystem models seldom, if ever, permit the addition of new structure (state variables) while the model is running. Given observations that systems under stress might become increasingly susceptible to invasion by nonnative species (e.g., zebra mussel, golden mussel, round goby), risk assessors might desire a model construct that permits such dynamic addition or deletion of state variables to address this kind of assessment endpoint. It is entirely feasible to develop operating "rules" whereby modeled "novel species" can challenge the current model structure to become established and possibly persist throughout the course of simulation. In the case of invasive species, such rules would include, for example, ecological characteristics of the novel species, corresponding traits of the initial model components, and physical–chemical habitat requirements of the invaders.

28.5.2 Interactive Modeling Platforms

Risk assessors might desire the capability to interactively design and develop an ecosystem model for a particular risk application. User-friendly modeling platforms (e.g., STELLA) can provide this capability. These modeling platforms allow the user to (1) efficiently build and apply models and (2) explore the implications of alternative model formulations in relation to risk estimation. In the hands of a trained modeler, this interactive modeling capability can produce useful results with a minimum investment in time and resources. This same technology can, however, lead to fundamental mistakes in model development and application, if the user does not have the necessary training or experience in ecosystem modeling.

It is in the interest of risk assessors to advocate the continued development of such interactive modeling platforms to facilitate the development of ecosystem models for assessing risk. Commensurate with this continued innovation is the need to train risk assessors in the fundamentals of ecosystem modeling and analysis in order to make full and accurate use of this technology.

28.5.3 Network-Enabled Ecosystem Models

Ecosystem modelers or modeling centers can make ecosystem models accessible for use via the Internet. In addition to downloading existing models, network-enabled modeling capabilities would permit the assessor to actually execute the selected model on some remote server. One advantage of this service would be to make models that require substantial computational power (i.e., multiple, parallel processors; "super-computers") accessible to assessors who might lack access to these kinds of machines.

28.5.4 Ecosystem Animation

Continued advances in computational power and graphic software make it increasingly possible to present the results of ecosystem models as animated sequences of model results—either in space, time, or both. Inspection of such animated model output by the user can help identify interesting patterns in system response that are not obvious from looking at a number of tables or graphs. Mathematical techniques can be used to evaluate identified visual patterns to determine if they are numerically "real" or just perceptions.

Substantial amounts of information can be communicated efficiently through animation of ecosystem model results. Animation might more effectively enter the large volumes of results into risk management and decision making.

These opportunities for innovation in ecosystem risk assessment modeling are being realized to some extent through an integrated modeling and assessment effort involving 14 European countries (Brack et al. 2005). The MODELKEY project comprises an interdisciplinary approach to developing interactive, interlinked environmental fate and effects models (aquatic food web/ecosystem models) for characterizing risks posed by contaminants in freshwater and marine systems. The models are designed to be integrated with a user-friendly decision support system. The decision-support system will apply neural network and Geographical Information System (GIS)-based analysis of predicted effects and composite risk indices to evaluate risks, identify sources of contamination, and set priorities among contaminated sites. The developed models will be verified in case studies that focus on applications in the Mediterranean Sea, as well as selected river basins in western and central Europe.

As another example of future modeling approaches, Sydelko et al. (2001) describe plans for a dynamic information modeling architecture that permits efficient development of object-oriented (OO) simulations. This approach was used to develop an integrated dynamic landscape analysis and modeling system (OO-IDLAMS). The OO-IDLAMS was derived initially as a prototype resource conservation model to inform decision makers in natural resources planning and ecosystem management. Sydelko et al. (2001) emphasize the potential for integrating the OO-IDLAMS with ecological models of chemical uptake and effects in order to forecast the magnitude and extent of contamination and associated ecosystem risk.

28.6 ECOSYSTEM MODELS, RISK ASSESSMENT, AND DECISION MAKING

Ecosystem models have numerous possible roles in environmental decision making and management, as is briefly illustrated in this section. In the first case, an ecosystem model was used to both explore the implications of a test endpoint that is commonly used for screening benchmarks and quality criteria. In the second, the same model was used with the results of several microcosm and mesocosm tests for risks to ecosystems with different structures.

28.6.1 Model Results and NOECs

Recently, efforts have been made to understand the results of ecosystem models in the context of more traditional or familiar ecological benchmarks. Naito et al. (2002) used the CASM to estimate risks posed by seven quite different chemicals in Lake Suwa, Japan. The chemicals included insecticides, herbicides, organic contaminants, and one trace element. These investigators used the model to calculate changes in selected model populations compared to a reference simulation for various exposure scenarios. In addition, the model was used to estimate the probabilities of observing selected percentage decreases (or increases) in production for these same populations. However, a unique aspect of this risk assessment centered on "calibrating" the CASM results to chronic NOECs for zooplankton reported for these chemicals. The implicit hypothesis was that some constant degree of modeled effect on zooplankton would correspond to the zooplankton NOECs across this wide range of chemicals. Analysis of the model results for these chemicals demonstrated that the modeled endpoint of a 20% reduction in total annual zooplankton biomass (designated as the "BR20") correlated well with the NOECs (Figure 28.4).

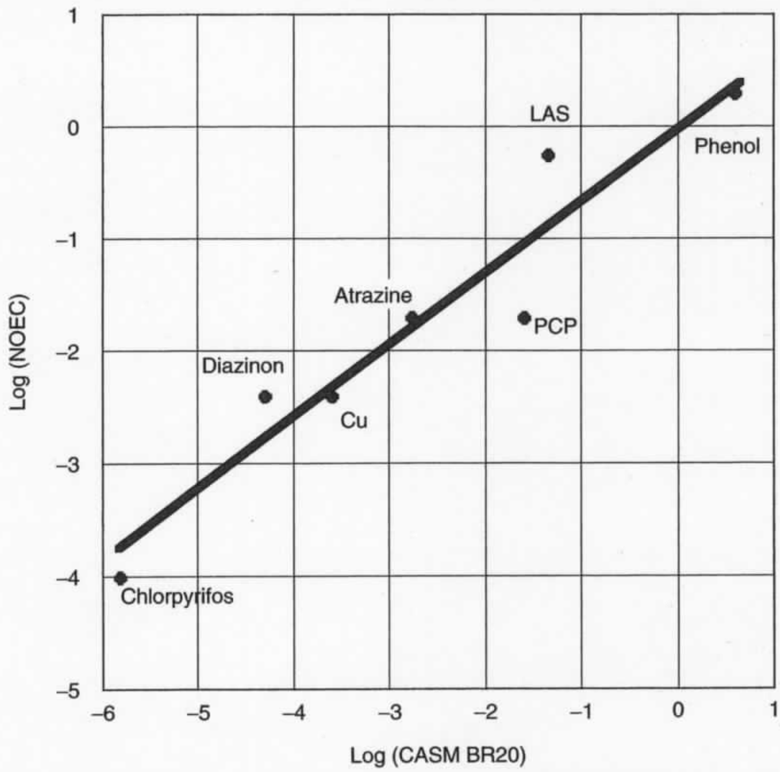

FIGURE 28.4 Correlations between Comprehensive Aquatic Systems Model (CASM)-modeled endpoint of a 20% reduction in total annual zooplankton biomass (designated as the "BR20") and estimates of no observed effect concentrations (NOECs) for several toxic chemicals. (Redrawn from Naito et al. 2003. With permission.)

This result is important for several reasons. First, calibrating the model to more familiar toxicological endpoints provides a tool for estimating the zooplankton NOEC for chemicals that can be assessed using CASM, but for which NOECs have not yet been developed. Second, the result demonstrates the relevance and reliability of the CASM in assessing risks across a considerable range of chemicals with different patterns of exposure, modes of toxicity, and species sensitivities. Finally, the correlation of the zooplankton BR20 with the NOECs further supports previous claims (i.e., Bartell et al. 1992) that the underlying stress syndrome used in CASM (and SWACOM) is biased towards conservative (i.e., pessimistic) estimates of risk. That is, an exposure concentration corresponding to no observed effect in laboratory assays produces a 20% reduction in total annual production in the model. The model has a 20% bias towards overestimating risk compared to laboratory assay results. Furthermore, this bias appears consistent across a wide range of chemicals and NOECs. The correlation of the NOECs with the CASM BR20s also provides a decision maker with a better understanding and ability to interpret the ecosystem model results in relation to more traditional species-level endpoints.

28.6.2 Atrazine Levels of Concern

The previous examples and discussion hint at the use of ecosystem models in risk management and decision making. The following discussion describes the use of CASM in determining acceptable levels of atrazine in surface waters subject to agricultural runoff. CASM was implemented to represent, in a generalized manner (i.e., generic application), the food web structure and temporal patterns of production characteristic of second- and third-order Midwestern streams. A CASM reference simulation was developed using a collation of ecological and environmental data from Midwestern streams.

The novel application of CASM in this example lies in using the results of the generic stream ecosystem model to discriminate among the severity of measured effects in micro- and mesocosm studies of atrazine. In all, 25 separate studies were evaluated in relation to 77 reported effects (endpoints) on aquatic plants. Of these, 24 results were from tests on ponds or lakes, 20 on artificial streams, and 33 were microcosm tests. Typically, 1 to 3 concentrations of atrazine were tested in these studies, each with a single application to the test system at initiation. Atrazine concentrations were often kept constant for a variable duration period. Eight effects on plants were recorded on macrophytes, 29 on periphyton, and 40 on phytoplankton. Brock et al. (2000) analyzed a majority of the study results and quantified them as follows: 1 = no effect; 2 = slight effect; 3 = significant effect followed by return to control levels within 56 d; 4 = significant effect without return to control levels during an observation period of less than 56 d; 5 = significant effect without return to control levels for more than 56 d. Several studies not analyzed by Brock, but considered in this analysis, were scored with the same methods.

The 77 effect scores representing the results from the micro- and mesocosm studies were plotted against the study-specific test concentrations and exposure durations in Figure 28.5. The effects on plants observed in micro- and mesocosm studies generally became more severe with increasing exposure magnitude and duration.

The average daily percent difference in modeled plant community similarity between the CASM reference simulation and the simulated effects of atrazine was the principle model result used in evaluating the results of the micro- and mesocosm studies. Corresponding

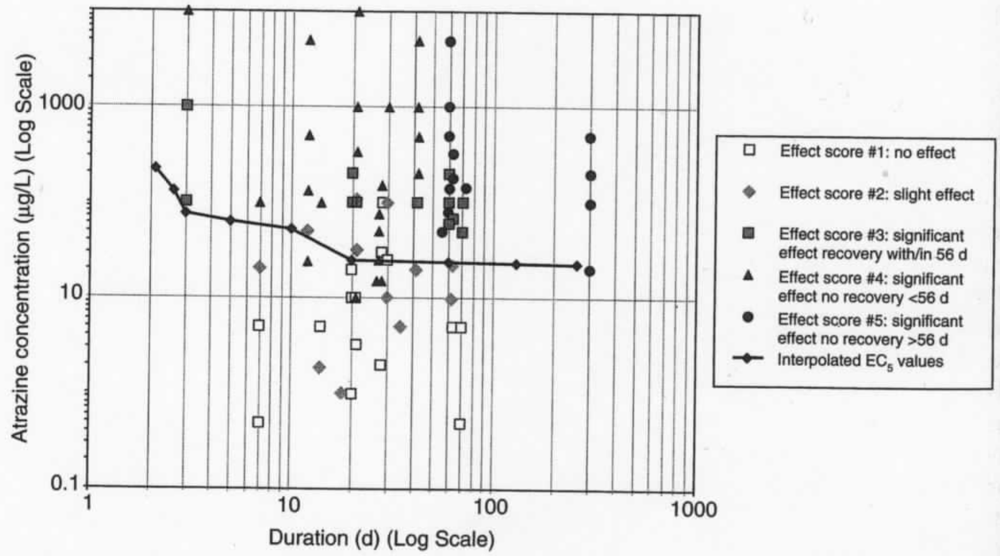

FIGURE 28.5 Concentration–duration interpolations of Comprehensive Aquatic Systems Model (CASM) simulations that produce a 5% change in average total producer community similarity.

relative changes in modeled biomass of phytoplankton, periphyton, and macrophytes were also examined. Based on the results of numerous CASM simulations that used exposure scenarios of varying atrazine concentrations and exposure durations, a decrease of 5% in average community similarity was found to discriminate the studies by Brock et al. with scores of 1 and 2 from the studies scored between 3 and 5 (Figure 28.5). The 5% average deviation in producer community similarity will be used to evaluate the results of field studies that monitor atrazine concentrations in surface waters. If the exposure profile developed from the monitoring results produces an average daily deviation in community similarity that is 5% or greater when analyzed using the generic CASM, the study site may become subject to additional monitoring or remediation. If the resulting modeled average deviation in producer community similarity is less than 5%, monitoring will simply continue.

Importantly, CASM was not used to forecast the site-specific effects anticipated for varying exposures to atrazine. Rather, the generic CASM was used as an ecosystem-modeling tool to assess the potential effects of atrazine in relation to observed responses in field and laboratory studies.

28.7 MODELS OR MODELERS

This chapter has discussed as much about the process of ecological modeling as it has about particular ecosystem models. Unarguably, the development of user-friendly, off-the-shelf, and readily applied ecosystem risk assessment models constitutes a worthwhile goal for model makers and produces desirable end products for model users. Progress in the previously outlined technical areas will generate increasingly sophisticated, readily accessible, and "user-seductive" ecosystem risk assessment models. Future assessment models will undoubtedly feature highly interactive and increasingly intelligent user interfaces. Model calculations will be completed in seconds on ever-increasingly fast computers and the rate-limiting step will become the user's ability to summarize, understand, interpret, and apply the voluminous model outputs in risk assessment, management, and decision making. Useful summarization and effective presentation of model results will be facilitated by advances in data visualization methods.

Despite a reasonable technological optimism, continuing challenges in improving quantitative ecosystem understanding (e.g., strange attractors, chaos) and the requirements of unique and novel assessments (e.g., genetically engineered organisms, invasive species, habitat degradation, landscape fragmentation) cannot overemphasize the importance of the ongoing scientific training of successive generations of ecosystem modelers. The technical skills, training, and experience of the "people behind the models" will continue to determine the success of ecosystem modeling in supporting ecological risk assessment and the intelligent management of valued natural resources.

For performing an evaluation of model realism and relevance, the categories of individual-based, population, ecosystem, and landscape provide a convenient (but somewhat arbitrary) grouping of ecological models. Models within each group reflect the ecological phenomena or topics of interest from different perspectives in quantitative ecology (Bartell et al. 2003). Associated with each perspective and resulting modeling approach are hypotheses concerning simplifying assumptions that facilitate the specification of model structure in relation to the ecological topic of interest. However, the ecologists, modelers, and observers are each exploring ecological complexity in the same natural world. Simplifying assumptions does not simplify nature. For example, the carrying capacity, K, in the logistic model simply represents all of the biotic and abiotic constraints on population size in a single aggregate parameter. In a real sense, the logistic model could be classified as a simple ecosystem model. The more structurally complex system models such as AQUATOX and CASM attempt to explicitly model many of the biotic and abiotic interactions that are believed to influence the production dynamics of aquatic populations included in these models. These structurally more complex models can justifiably be called population models. One important implication of this recognition is that a convenient categorization of ecological models does not imply that the measurable world can be similarly decomposed and categorized. Apart from evaluating the efficacy of existing models for assessing risks (e.g., Table 28.1), a major and continuing challenge lies in determining the necessary and sufficient structures (i.e., in terms of complexity and scale) of ecological models that provide risk estimates of known accuracy and precision.

The arbitrariness inherent in developing and classifying ecological models can lead to fatuous statements concerning the relative merit of different modeling approaches for assessing ecological risks. Models comparatively simpler in structure (e.g., demographic population models) might initially appear "better" for assessing risks than more structurally complex ecosystem models even though the demographic models are less realistic according to the criteria developed from a risk assessment viewpoint. Given that the model classifications derive as much from ecological shorthand and convenience as from ecological reality, assertions of this kind are analogous to positing that the "wave model" is better than the "particle model" for describing electromagnetic radiation. Such assertions are often framed in the context of model validation, i.e., simpler models might appear more easily validated than complex models. In other words, it would seem that accurately predicting the value of one or two state variables is a priori more likely than obtaining predictions of similar accuracy for 10 or 20 state variables. However, probability theory and modeling experience remind us that validating models, like proving hypotheses, cannot be done in any absolute or meaningfully relative sense. All possible future model/data comparisons cannot be made for any of the modeling approaches. No nonarbitrary baseline for comparing the relative validity of the different modeling approaches exists.

Selection and development of models for assessing ecological risks would benefit from focusing on the relative strengths and limitations of alternative modeling approaches. Evaluations of model realism, endpoint relevance, flexibility, ease of use, and other characteristics help to guide users in their choice of specific models for further development and for application to current risk assessment problems. Future efforts in ecological risk modeling should focus on identifying the necessary model complexity required to achieve sufficiently accurate and precise estimates of risk as determined by the needs of risk management and risk-based decision making. Working backwards from the perspective of risk management might provide additional insights concerning necessary and sufficient model structure for decision making. Working forwards from continuing advances in ecosystem understanding can help inform managers on scientifically defensible minimum model structures. Ecosystem models for risk assessment should be sufficiently complex, but no more so.