Chapter 5

THE USE OF MATHEMATICAL MODELLING IN LAKE AND RESERVOIR MANAGEMENT

Models are being used increasingly in environmental management, primarily because they are a good tool for quantitatively relating the impacts on an ecosystem with the consequences for the state of the ecosystem. Aquatic ecosystem models have particularly been developed during the last few decades, and it is not surprising they have found wide application in lake and reservoir management efforts.

The extensive use of mathematical models in water quality management can be seen from the survey by Alasaarela et al. (1993). They assembled questionnaires from 100 institutions. The results document the use of 105 models applied in 800 situations and requiring approximately 500 person work years. The average modelling team consisted of four persons.

This chapter describes what the models represent and how they are structured (Section 5.1), and how they can be used as management tools (Section 5.2). Section 5.3 presents modelling methodology, followed by guidance on how to select appropriate management models (Section 5.4). The bulk of the chapter presents to the reader models applicable to various management problems (Section 5.5), with a focus on eutrophication models (Section 5.5.1), toxic substance models (Section 5.5.2), and then successively on models of acidification (Section 5.5.3), wetlands (Section 5.5.4) and lake fisheries (Section 5.5.5). Special attention is given to one management option, biomanipulation (Section 5.5.6). The complex water quality models most commonly used are discussed in Section 5.5.7. Finally, recent models dealing with environmental risk assessment are discussed (Section 5.5.8).

5.1 MODELLING AND ITS ELEMENTS

The rationale for the use of ecological management models is demonstrated in Figure 5.1. Urbanization and industrial development have had increasing impacts on the environment. Energy and pollutants are released into ecosystems, where they may cause rapid growth of algae or bacteria, eliminate species, or alter the entire ecological structure. An ecosystem is extremely complex, and it is an overwhelming task to predict the environmental effects that emissions, for example, will have on it. It is under these conditions that models become useful. With sound ecological knowledge, it is possible to extract the features of an ecosystem involved in a pollution problem, in order to form the basis of the ecological model. As indicated in Figure 5.1, the resulting model can be used to select the environmental technology best suited for the solution of specific environmental problems, or for legislation that reduces or eliminates the emission problems.

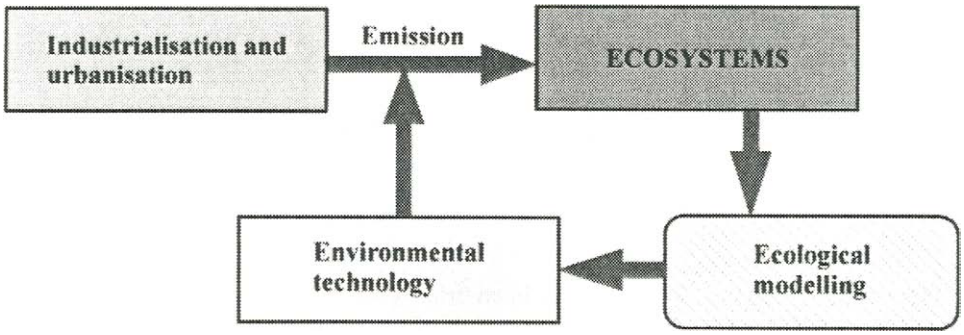

Fig. 5.1. The use of environmental models in management around 1970.

Figure 5.1 represents an introduction to ecological modelling as a management tool around 1970. The environmental management of today is more complex, and must consider such elements as environmental technology, cleaner technology and ecological engineering or ecotechnology (Mitsch and Jørgensen, 1988; Straškraba, 1993) as alternatives to present technology, in combination with environmental legislation. Ecotechnology is applied especially to solve problems of nonpoint or diffuse pollution originating from agricultural runoff and acidification. The importance of nonpoint pollution was only seriously appreciated beginning around 1975. Furthermore, global environmental problems play a more important role today than twenty years ago. The green house effect and ozone depletion, for example, are widely discussed today, and several international conferences on the governmental level have taken first steps toward the use of international standards to solve these and other crucial problems of a global nature. Figure 5.2 attempts to illustrate the more complex picture of environmental management today.

Ecological models may be compared to geographical maps (which are also models). Different types of maps serve different purposes. There are maps for airplanes, for ships, for cars, for railways, for geologists and archeologists, etc. They are all different, because they want to focus on different objects. They are also available at different scales, based on the application of the map and on the underlying knowledge. Furthermore, a map never contains all the details for a considered geographical area, because it would be irrelevant and disrupt the main purpose of the map. If a map contained all details, for example, including the positions of all cars at a given moment, the map would be invalidated very rapidly, since they would have moved to new positions in the meantime. Thus, a good map should contain only the knowledge relevant for the map user.

In the same manner, an ecological model focuses only on the objects and processes of interest for the problem considered. It would detract from the main objectives of a model to include too many irrelevant details. There are many different ecological models of the same ecosystem, as the model edition is selected on the basis of the modelling goals.

The field of ecological and environmental modelling has developed rapidly during the last two decades due essentially to the following factors:

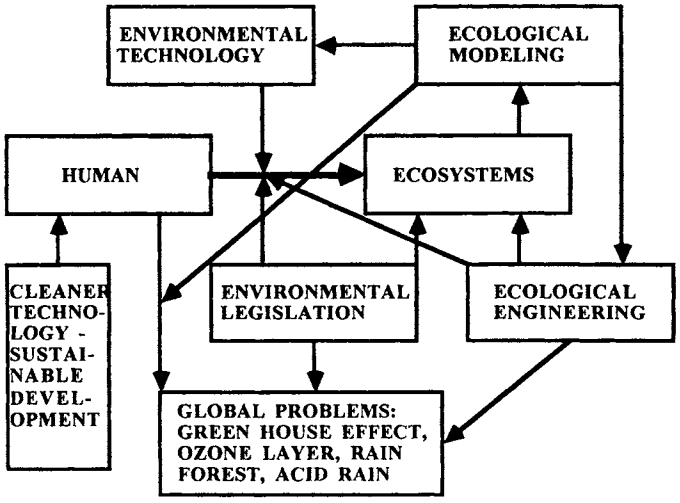

Fig. 5.2. The concept behind the use of environmental models in environmental management. Environmental management today is very complex and must apply environmental technology, alternative technology and ecological engineering or ecotechnology. In addition, global environmental problems have an increasing role. Environmental models can be used to select environmental technology, environmental legislation and ecological engineering.

- The development of computer technology, enabling us to handle very complex mathematical systems.
- A general understanding of pollution problems, including the knowledge that a complete elimination of all pollution ("zero discharge") is not feasible, but rather that a proper pollution control with often-limited economic resources requires serious considerations of the influence of various pollution impacts on ecosystems.
- Our knowledge of environmental and ecological problems has increased significantly. We have particularly gained more knowledge about quantitative relations in ecosystems, and between ecological properties and the environmental factors.

The goal of this chapter is to demonstrate to lake and reservoir managers, limnologists, chemists, sanitary engineers and other interested parties the possibilities that mathematical modelling offers as a tool to support management decisions. More technical modelling issues are discussed by other researchers, including Jørgensen (1983), Orlob (1983), Straškraba and Gnauck (1985), Jørgensen and Gromiec (1989), Jørgensen (1994) and Chapra (1997).

The main focus is a description and survey of various water quality models, and how they can be used to solve different management problems (also see Section 5.5, which presents an overview of models focusing on different problems of management interest). Models are classified in terms of their usefulness in water quality management efforts in Section 5.5, rather than to classical model categories (e.g., see Jørgensen, 1994). Methodological approaches used in different models will be mentioned only when an approach

restricts their use, or to illustrate the spectrum of models applied. Existing models that have been proved useful in decision-making processes are emphasized. Many other research-oriented lake and reservoir models exist, and are discussed elsewhere, including Straškraba (1994), Jørgensen (1994), Straškraba (1995) and Jørgensen et al. (1995).

5.1.1 Elements of Environmental Models

In its mathematical formulation, an environmental science model consists of five primary components:

1. *Forcing functions, or external variables*, which are functions or variables of an external nature that influence the state of an ecosystem. In a management context, the problem to be solved often can be reformulated as follows: If certain forcing functions are varied, how will this influence the state of an ecosystem? The model can be used to predict what properties of the ecosystem will change when the forcing functions are varied with time. The forcing functions under human control are often called *control functions.* The control functions in ecotoxicological models, for example, include the inputs of toxic substances to the ecosystem while, for eutrophication models, the nutrient inputs to a waterbody are control functions. Other forcing functions of interest could include climatic variables, which influence the biotic and abiotic components, and the ecosystem process rates. The latter are forcing functions that usually cannot be controlled by humans.

2. *State variables* describe, as the name indicates, the state of an ecosystem. The selection of state variables is crucial to the model structure, although the choice is sometimes obvious. For example, if we want to model the bioaccumulation of a toxic substance, the state variables should be the primary organisms in the most important food chains and the concentrations of toxic substance in the organisms. For eutrophication models, the state variables would at least include the concentrations of nutrients and phytoplankton. When the model is used in a management context, the values of state variables predicted by changing the forcing functions can be considered as the model results, because the model will contain and utilize the relations between the forcing functions and the state variables.

3. *Mathematical equations* are used to represent the biological, chemical and physical processes that occur in an ecosystem. They describe the relationship between the forcing functions and state variables, and between the state variables. The same types of processes may be found in many different environmental contexts, which implies the same equations can be used in different models. It does not imply, however, that the same process is always formulated by use of the same equation. In fact, a considered process may be better described by another equation because of the influence of other factors. Further, the number of details needed or wanted to be included in the model may differ from case-to-case, due to a difference in complexity of the ecosystem and/or the problem being considered. Some modellers refer to description and mathematical formulation of processes as submodels. A comprehensive overview of submodels is provided by Jørgensen (1994) and Jørgensen et al. (1991).

4. *Parameters* are coefficients in the mathematical representation of processes occurring in an ecosystem. They may be considered constant for a specific ecosystem or part

of an ecosystem. In causal models, the parameter will have a scientific definition (e.g., the excretion rate of cadmium from a fish). Many parameters are not indicated in the literature as constants, however, but rather as ranges. Even these values are of great value in parameter estimation, however, as discussed further in the following sections. Jørgensen et al. (1979) and Jørgensen (1991) provide a comprehensive collection of parameters often considered in environmental science and ecology. Our limited knowledge of parameters is one of the weakest points in modelling, however, as will be discussed further below. Further, the application of parameters as constants in ecosystem models is unrealistic, due to the many feedback processes in real ecosystems. The flexibility of ecosystems is inconsistent, and often not well represented, with the application of constant parameters in a model. A new generation of models that attempts to use parameters that vary on the basis of some ecological principles is a possible solution to this problem, but further work in this area is absolutely needed before an improved modelling procedure reflecting the processes in various ecosystems in realistic manner can be developed.

5. *Universal constants*, such as the gas constant and atomic weights, are also used in most ecosystem models.

Models can be defined as formal expressions, in mathematical terms, of the relations between essential elements of a problem. The first recognition of a problem is often verbal, and may be recognized as an essential preliminary step in the modelling procedure. A verbal model, however, is often difficult to visualize. Thus, it is more conveniently translated into *a conceptual diagram* containing the state variables, the forcing functions, and how they are interrelated by the mathematical formulation of processes.

Figure 5.3 illustrates a conceptual diagram of the nitrogen cycle in a lake. The state variables are nitrate, ammonium (which is toxic to fish in the un-ionized form of ammonia), and nitrogen in phytoplankton, zooplankton, fish, sediment and detritus.

The forcing functions in Figure 5.3 are the inflows and outflows, the nitrogen concentrations in the inflows, solar radiation and temperature (which is not shown on the diagram, but influences all the process rates). The arrows in the diagram illustrate the processes, as formulated with mathematical expressions.

5.1.2 *Modelling Procedure*

Three significant steps in the modelling procedure, calibration, verification and validation, are defined in this section.

- *Verification* is a test of the *internal logic* of a model. Typical questions in the verification phase include: Does the model react as expected? Is the model stable over the long term? Does the model follow the law of mass conservation? Verification is largely a subjective assessment of the behavior of a model. To a large extent, the verification will go on during the use of the model before the calibration phase.
- *Calibration* is meant to find the best agreement between computed and observed data by variation of some selected parameters. It may be carried out by trial-and-error, or by use of software developed to find the parameters that give the best fit between observed

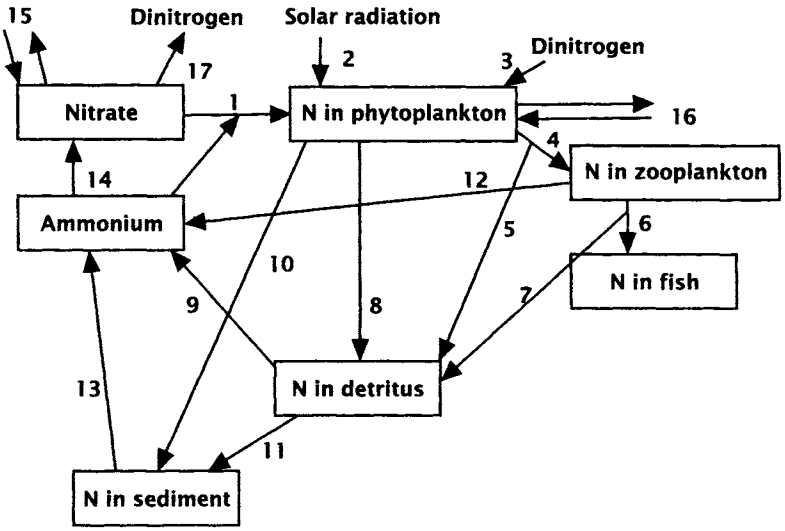

Fig. 5.3. The conceptual diagram of the nitrogen cycle in an aquatic ecosystem. The processes are: 1—uptake of nitrate and ammonium by algae; 2—photosynthesis; 3—nitrogen fixation; 4—grazing with loss of undigested matter; 5, 6 and 7—predation and loss of undigested matter; 8—mortality; 9—mineralization; 10—settling of algae; 11—settling of detritus; 12—excretion of ammonium from zooplankton; 13—release of nitrogen from the sediment; 14—nitrification; 15 and 16—inputs/outputs; and 17—denitrification.

and computed values. In some static models, and in some simple time-varying models which contain only a few well-defined or directly measured parameters, calibration may not be required.

- *Validation.* Validation consists of an objective test on how well the model output fits the data. The selection of possible objective tests is dependent on the scope of the model, although the standard deviations between model predictions and observations, and a comparison of observed and predicted minimum or maximum values of a particularly-important state variable, are frequently used. If several state variables are included in the validation, they may be given different weights.

A validation procedure, if properly carried out, can be used to determine the standard deviation of the predictions or prognosis. Model results used in environmental decisions should always be accompanied by an indication of the standard deviation of the prognosis. It also is important to clarify the meaning of this standard deviation to the decision-maker, for example, by comparison of the expected average results and the worst case situation. The modeller should give recommendations as to how to use the model results and standard deviations in their proper context. Decision-makers often use standard deviations incorrectly when they were presented to them; namely, as numbers which indicate how much the costs can be reduced without any harmful effects on environmental quality.

5.2 MODELS AS MANAGEMENT TOOLS

A management problem to be solved can often be formulated as follows: If certain forcing functions (management actions) are varied, what will be their influence on the state of an ecosystem? The model is used to answer this question or, in other words, to predict what will change in a system when the control functions that are managed by humans are varied over time and space.

Typical *control functions* are the consumption of fossil fuel, regulation of water level in a river by a dam, discharge of pollutants, or fisheries policy.

A certain class of environmental management models are called control models. They differ from other such models by the content of the following elements:

- A quantitative description of control processes,
- A formalization of objectives and evaluation of achievements.

The difference between control models and other environmental management models can best be illustrated with an example. The eutrophication model presented in Figure 5.3 can be used as a management model. If the model response to various inputs of nitrogen is obtained, the model outputs for the corresponding scenarios also are obtained. Among these scenarios, the manager can select the one scenario, from among all the possibilities, that he or she prefers from an ecological–economic perspective.The model is used as an environmental management tool. However, this is not a control model. Details of this type of model are presented in Section 5.5.

In the case of eutrophication, the management problem often is: Which control method or combination of methods should be selected from among the existing possibilities? This question can be answered by comparison of the corresponding scenarios obtained by the model runs.

It is important that, to a certain extent, the manager take part in the entire development of a management model, since he will ultimately define the modelling objectives and select the modelling scenarios. The success of the application of a management model, to a large degree, is dependent on an open dialog between the modeller and the manager.

A further complexity is the construction of ecological–economic models. As we gain more experience in constructing ecological and economic models, more and more of them will be developed. It is often feasible to find a relation between a control function and economic parameters. If a lake is a major water resource, an improvement in its water quality will inevitably result in a reduction in the treatment costs of drinking water if the same water quality is to be provided. It is also possible to sometimes relate the value of a recreational area to the number of visitors, and to how much money they spend on average in the area. In many cases, however, it is difficult to assess a relationship between the economy and the state of an ecosystem. For example, how can we assess the economic advantages of an increased transparency in a waterbody? Ecological–economic models are useful in some cases, but should be used with caution, and the relations between the economy and environmental conditions critically evaluated, before the model results are applied.

Data collection is the most expensive component of model construction. For many lake models, it has been found that the data collection needed comprises 80–90% of the total

model costs. Because complex models require much more data than simple ones, the selection of the complexity of environmental management models should be closely related to the costs involved in the environmental problem to be solved.

It is not surprising, therefore, that development of the most complex environmental management models have generally been limited to large ecosystems, where the economic involvement is substantial.

The predictive capability of environmental models can always be improved in a specific case by expansion of the data collection program, and by a correspondingly increased model complexity, provided that the modellers are sufficiently skilled to know in which direction further expansion of the entire program must develop to order to improve the model's predictive capabilities.

The relation between the economy of the project and the accuracy of the model is presented in Figure 5.4. The reduction in the discrepancy between model predictions and reality is lower for the next dollar invested in the project. But it is also clear from the shape of the curve that the associated errors cannot be completely eliminated. All model predictions have a standard deviation associated with them. This fact is not surprising to scientists, but it often is not understood or appreciated by decision-makers, to whom the modeller typically presents his or her results.

Engineers use safety factors to assure that a building or a bridge will last for a certain period of time, with a very low probability of breakdown, even under extreme conditions. No reputable engineer would propose using a smaller, or no, safety factor to save some concrete and reduce the costs. The reason is obvious: Nobody would want to be responsible for even the smallest probability of a building or bridge collapse.

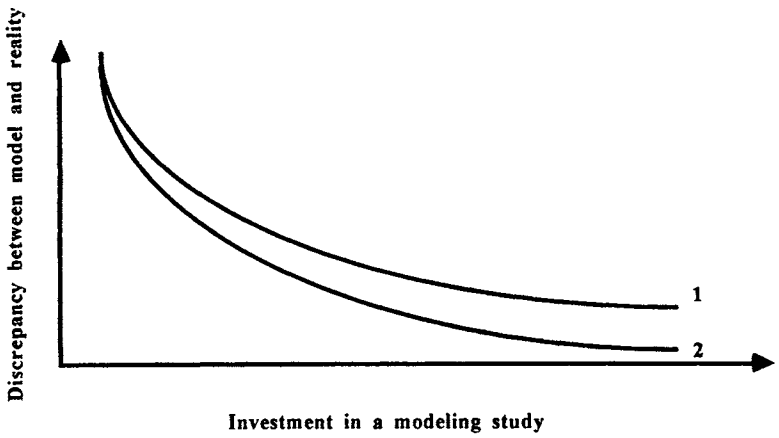

Fig. 5.4. The more a modeller invests in a model and in data collection, the closer he/she will come to realistic predictions. However, the modeller will always gain less for the next dollar invested, and will never be able to give completely accurate predictions. The curve (1) represents a less experienced modeller, while curve (2) gives the same relationship for a more experienced modeller.

When decision-makers are going to make decisions on environmental issues, the situation is strangely different. Decision-makers in this situation want to use the standard deviation to save money, rather than assuring a high environmental quality under all circumstances. It is the modeller's duty, therefore, to carefully explain to the decision-maker all the consequences of the various decision possibilities. A standard deviation of a prognosis for an environmental management model can, however, not always be translated into a probability, because we do not know the probability distribution. It might be none of the common distribution functions, but it is possible to use the standard deviation qualitatively or semi-quantitatively, translating the meaning of the model results with the use of words. Civil engineers are more or less in the same situation, and have been successful in the past in convincing decision-makers of appropriate steps to be taken in various situations. There is no reason that environmental modellers cannot do the same.

It is often advantageous to first attack an environmental problem with the use of simple models. They require much fewer data, and can give the modeller and decision-maker some preliminary results. If the modelling project is stopped at this stage for one or another reason, a simple model is still usually better than no model at all, because it will at least give a survey of the problem.

Simple models, therefore, are good starting points for the construction of more complex models. In many cases, the construction of a model is carried out as an iterative process, and a step-wise development of a complex model is illustrated in Figure 5.5. As previously mentioned, the first step is development of a conceptual model. It is used to get a survey of the processes and state variables for the ecosystem of concern. The next step is development of a simple calibrated and validated model. It is used to establish a data collection program for a more comprehensive effort closer to the final selected version. As shown in Figure 5.5, however, the third model version will often reveal specific model weaknesses, the elimination of which is the goal of the fourth version of the model. At first glance, this may seem to be a very cumbersome procedure. However, because data collection is the most expensive part of modelling, constructing a preliminary model for optimization of the data collection program will ultimately require fewer financial resources. In fact, Figure 5.5 can be considered a formalization of the iterative procedure that many modellers are forced to use under most conditions, and planning these steps at an initial phase of the project always is advantageous.

A first, simple mass-balance scheme is recommended for biogeochemical models. The mass balance will indicate what possibilities exist for reducing or increasing the concentration of a chemical or pollutant, which is a crucial issue for environmental management.

Point sources of pollution are usually easier to control anthropogenic nonpoint sources which, in turn, are more easily controlled than natural pollutant sources, as shown in Table 5.1. Distinction can be made between local, regional and global pollutant sources. Because the mass balance indicates the relative quantities from each source, it is possible to identify which sources should receive the initial attention (e.g., if a nonpoint regional source of pollutants is dominant, it would be pointless to concentration first on eliminating small, local point sources, unless the latter also might have some political influence on regional decisions).

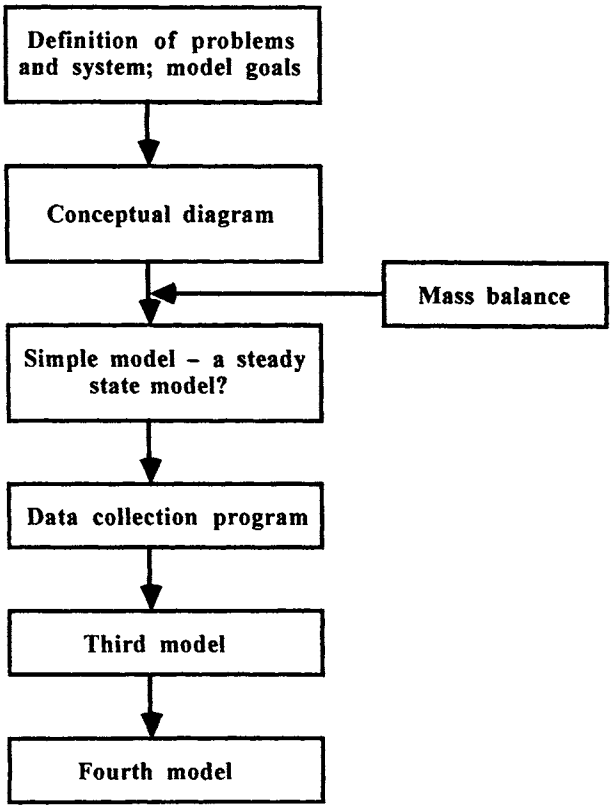

Fig. 5.5. Schematic of the development of a complex management model.

Table 5.1. Examples of water pollutant sources

Source	Examples
Point sources	Wastewater (nitrogen, phosphorus, biochemical oxygen demand); sulphur dioxide from fossil fuels; discharges of toxic substances from industries
Nonpoint man-made sources	Agricultural use of fertilizers; deposition of lead from vehicles; contaminants in rain water
Nonpoint natural sources	Runoff from natural forests

It has already been recognized that the modeller and the decision-maker should communicate with each other. It is recommended, in fact, that the decision-maker be invited to follow the model construction process from its very first phases, in order to become acquainted with the model strength and limitations. It is also important that the modeller and the decision-maker formulate together the model objectives and interpret the model results.

Holling (1978) has demonstrated how such teamwork can be developed and used phase-by-phase. Although his recommendations are not reiterated here, it is recommended that a modelling team should acquaint themselves well with the procedures outlined by him. The conclusions are clear: The modeller and decision-maker should work together in all phases of the modelling exercise. Having the modeller first build a model, and then transfer it to a decision-maker accompanied by a small report on the model, is not recommended.

Communication between the decision-maker and the modeller can be facilitated in many ways, and it often is the primary responsibility of the modeller to do so. If a model is built as a menu system, as presented by Mejer (1983), it might be possible to teach the decision-maker how to use the model in only a few hours, thereby also increasing his or her understanding of the model and its results. If an interactive approach is applied, it also is possible for the decision-maker to visualize a wide range of possible decisions. The effect of this approach is increased by the use of various graphic methods to illustrate the best possible decision in regard to what happens with the use of various management strategies. It is recommended under all circumstances that time be invested in developing a good graphic presentation of the model results for the decision-maker. Even if he or she has not been clearly informed about a model project through all its phases, the decision-maker will not necessarily understand the background and assumptions of all the model components. Thus, it is important that the model results, including the main assumptions, shortcomings and standard deviations underlying them, are carefully presented with the use of an illustrative method.

The use of expert systems and decision-support systems to facilitate communication between modellers and managers is discussed in Section 5.4. It is clear that we are not yet sufficiently advanced in environmental modelling efforts to solely use model results to define management programs, even utilizing expert systems and decision-support systems. A model should never be used in this way by a decision-maker, but rather should be considered only one useful tool in the management decision-making process. This implies that modelling results should be clearly and illustratively presented, and be considered a significant component in discussions about selecting specific courses of action. Other elements to be considered in such discussions would include potential side effects, interpretation of model predictions, and the implications of the accuracy of the prognosis.

A good environmental model can be a powerful tool in the decision-making process for management actions. A wide range of environmental problems has been modelled to varying degrees over the last 10–15 years. They have generally been of major assistance to decision-makers. With the continuing rapid growth in the use of environmental models, the situation will only improve in the future. However, we have not achieved the same level of experience for all environmental problems.

The use of models in environmental management is definitely growing. They have been widely used in several European Countries, in North America and in Japan. Further, environmental agencies in more and more countries are making use of model applications. Through such journals as *Ecological Modelling* and the *International Society for Ecological Modelling* (ISEM), it is possible to follow the progress in the field. This "infrastructure" of the modelling field facilitates communication and accelerates the exchange

of experiences, thereby enhancing the growth of the entire field of ecological modelling. It appears there will soon be a need for a model "bank" or data base, where users can obtain information about existing models, their uses, characteristics, etc. At the same time, it is not possible to blindly transfer a model from one case study to another, as is reiterated in this book. It also is difficult to transfer a model from one computer to another unless it is exactly the same type of computer. However, it is often very helpful to learn from experiences of others involved in similar modelling situations in other parts of the world. Journals such as those mentioned above facilitate such exchanges.

The issue of the generality of models also deserves discussion. Few models have been used on multiple case studies, in order to gain wide experience on this important matter. The eutrophication model presented by Jørgensen (1994) has been used on a wide range of lakes in the temperate and the tropical zone, as well as for shallow and deep lakes, and even fjords. The experience gained in these case studies is illustrative, but does not necessarily represent general properties of models. A further discussion on the generality of models is presented in Section 5.4.

Management models are used in water quality management of lakes and reservoirs for the purposes outlined below, with reference to the type of management models:

General—

- To estimate pollution sources and loads in the watershed, using simple calculation models.

For lakes and existing reservoirs—

- To predict possible future water quality conditions when control functions in the watershed are altered by human activities,
- To provide estimates for decisions between different water quality options for use in long-term planning,
- To support short-term operational management decisions regarding water quantity and quality,
- To optimize sampling schedule investigations and control of water quality,
- To assess the environmental risks associated with discharge of micro pollutants.

Prior to reservoir construction—

- To estimate budgets of major water quality components of rivers that will enter the reservoir, as well as in the reservoir and the reservoir outflows,
- To provide reasonable estimates between alternative construction sites, dam heights, and outflow and outlet structures so that management decisions are supported,
- To predict conditions in future reservoirs, and the consequences of different management options on water quality within the watershed.

5.3 METHODOLOGY

It is clear from the previous discussions in this chapter that selection of model complexity is a matter of balance. On the one hand, it is necessary to include the state variables and the processes essential for the problem being addressed. On the other hand, it is important

not to make the model more complex than the data set can accommodate. Our knowledge of ecosystem processes and state variables, together with the relevant data sets, will determine the selection of model complexity. If the knowledge is poor, the model will be unable to give many details, and will have a relatively high level of uncertainty. If we have much knowledge of the system and the problem we want to model, a more detailed model can be developed, with a relatively lower degree of uncertainty. A modeller always should identify and present the shortcomings and uncertainties of a model, and not pretend that the model is a complete picture of reality in *all* its details. In the hands of a competent researcher, a model can be a fruitful instrument to test hypotheses, but only if the limitations of the model are fully acknowledged.

It should not be forgotten that models have always been applied in science. The difference between previous and present models is that today, with modern computer technology, we are able to work with very complex models. At the same time, however, it is a continuing temptation to construct models that are too complex. It is easy to add more and more equations and state variables to a computer program, but much harder to get the data needed for calibration and validation of the model. Even if very detailed knowledge about a problem is available, it is not possible to develop a model capable of accounting for the complete input–output behavior of a real ecosystem and that is valid for all frames (Ziegler, 1976). This type of model is called "the base model" by Ziegler, and would be very complex and require such a large number of computational resources that it would be almost impossible to simulate. The base model of an ecological problem will never be fully known because of the complexity of natural ecosystems, and our inability to observe all its states. Thus, a model may be made more realistic up to a point, by adding more connections. However, addition of new parameters after that point is reached does not contribute further to an improved simulation capacity. Indeed, more parameters imply more uncertainty because of possible lack of information about the flows the parameters quantify.

For a given quantity of data, the addition of new state variables or parameters beyond a certain model complexity does not further our ability to model an ecosystem, but only adds to the unaccountable uncertainty, as visualized in Figure 5.6. The relationship between knowledge gained through a model and its complexity is shown for two levels of data quality and quantity. The question that can be formulated with relation to this figure is: *How can we select the complexity and the structure of the model to assure the optimum for knowledge gained or the best answer to the question posed by the model*?

Costanza and Sklar (1985) have examined 88 different models, and were able to show that the theoretical discussion behind Figure 5.6 is actually valid in practice. Selection of the right degree of complexity is of great importance for environmental and ecological models. This is possible on the basis of presented models and literature discussions (e.g., see Jørgensen, 1994). However, the selection will always require that the application of these methods is combined with a good knowledge of the system being modelled. The methods must work hand-in-hand with an intelligent answer to the question: Which components and processes are most important for the problem of concern? Such an answer is important even in the right use of the aforementioned methods. Thus, the conclusion

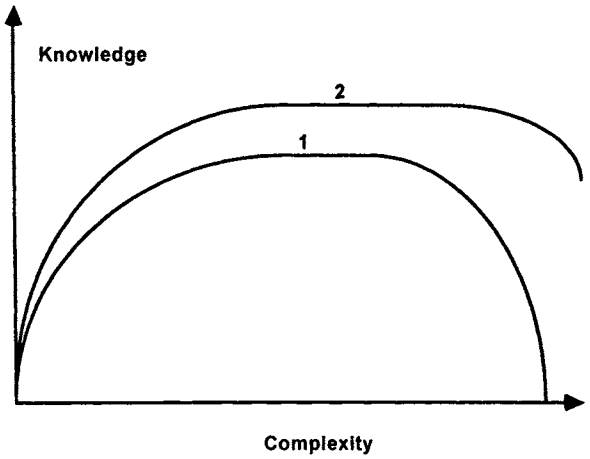

Fig. 5.6. Knowledge plotted versus model complexity measured, based on the number of state variables. The knowledge increases up to a certain level. Increased complexity beyond this level will not add to the knowledge gained about the modelled system. At a certain level, the knowledge might even be decreased, due to uncertainty caused by a too-high number of unknown parameters. (2) corresponds to an available data set, which is more comprehensive or has better quality than (1). Thus, the knowledge gained and the optimum complexity is higher for data set (2) than for (1). Reproduced from Jørgensen.

is: Know the ecosystem and the problem being addressed before a model is selected, including the model complexity. We do not need all details to get a proper overview and a holistic picture of a given ecosystem. Some details are needed, as is an understanding of how the ecosystem works on the systems level. Thus, the conclusion is that, although we can never know everything about an ecosystem needed to make a complete model (i.e., inclusion of all details), good, workable models that expand our knowledge of ecosystems can be produced, particularly of their properties as systems. Ulanowicz (1979) points out that a correct, very precise predictive model cannot be constructed. Thus, it would be most fruitful to build a model that illustrates general trends, taking into account the probabilistic nature of the environment.

Further, models are, and can be applied as, management tools (e.g., see Straškraba and Gnauck, 1985; Jørgensen, 1986b; Chapra and Canale, 1991; Straškraba et al., 1995). All in all, models should be considered only as tools—tools to provide an overview of complex ecosystems. For a complex system, a few interactive state variables already make it impossible to get an intuitive or logical overview on how a system may react to perturbations or other changes. In such cases, models are good tools to help obtain an overview or picture of the properties of an ecosystem on the systems level.

There are only two possibilities for getting around the dilemma rooted in the model complexity issue: Either limit the number of state variables in the model or describe the system by the use of holistic methods and models, preferably by using higher-level sci-

entific laws. *The trade off for the modeller is between knowing much about little, or little about much*!

More complex models require more data and more knowledge about a lake or reservoir. They imply higher costs, but they should be justified by the importance of the ecosystem being studied. Thus, it is recommended to proceed in a step-wise manner toward a more complex model, learning from simpler models before the complex model is constructed. A procedure for this step-wise development could proceed along the following lines:

- *Mass balances and lake morphology* is the first component to be considered in this procedure. Assessment of the sources of nutrient inputs, and the area, depth and water retention time of a lake will help focus attention on the main problems a lake or reservoir.
- *Set up a simple model*, an example being a phosphorus loading model of the type presented by Vollenweider (1976; OECD, 1982; Ryding and Rast, 1989) for eutrophication. This type of model gives guidance on the possible directions to solutions to the problem. For example, what nutrient limits or controls the maximum algal biomass? Which are the primary nutrient sources in the drainage basin? Will treating or conveying wastewaters produce the expected results? It may be feasible to first develop hypotheses, even at this early stage, on how to solve the problems, and even make the first coarse predictions. They will probably help identify the important factors in lake and reservoir management, and indicate which processes further modelling work should consider. The results, for example, will help define whether the point or nonpoint nutrient sources are of most importance for achievement of the desired results and, therefore, which of the two sources it is necessary to model with the greatest accuracy. The results also may indicate the relative importance of the nutrients or toxic substances stored in the lake bottom sediments, or whether or not the water retention time is an important factor that should be determined very accurately. Of course, it is important to compare these initial hypotheses and predictions with the results obtained with the use of more elaborate models at a later stage. If the first predictions are not confirmed, it should be possible to properly explain the discrepancies.
- *Set up a conceptual diagram.* The procedures for developing models are presented in Section 5.2. It includes defining the modelling goal, and its confinement in time and space. The next step is to develop a conceptual diagram, which should ideally contain all the important state variables and processes. The selection of the important components can be made on the basis of mass balances (i.e., the important processes are selected on the basis of their contribution to the mass balance of the primary components). For a eutrophication model, this means the balance of the nutrients, or at least the limiting nutrient, is of concern. It also is necessary to consider the characteristic features of a lake or reservoir (i.e., Which species are dominant? What is the dominant hydrological pattern?).
- It is usually important to discuss and *consider the model complexity* at this stage, although it should be reconsidered when the model has been calibrated and validated.
- *Assess the data requirements.* This step is in accordance with the procedure previously presented above in Section 5.2. However, the economic considerations should be added in this context. Which scale should be used for a given problem, knowing the economic

implications? It is possible to assess the optimum funding level that should be invested in a modelling project, including the data collection, if all the economic parameters of the project are known, such as wastewater treatment costs, the economic value of a lake or reservoir as a recreational area, etc. It would be to speculative to guess the economic value of recreational areas in this context. Further, how the recreational value can be calculated is also often an open question. *Experience has shown that 2–10% of the investment in wastewater treatment, for example, could be used for developing a model* that could be used to select the right management strategy. Based on this rough rule-of-thumb, it is now possible to assess whether the model selected (according to points 3 and 4 below) could be justified from an economic perspective, or whether it is possible to expand the project or if it is necessary to reduce it. When the model has been developed, calibrated and validated, the standard deviation of the model will be determined, and the model can then be tested to determine whether or not it has sufficient accuracy to be used to help choose between two or more management strategies. Modelling is an iterative process and, therefore, the possibility that a developed model cannot be used in a given management context, and that a more complex model may be needed, cannot be excluded. It is important to confront managers with this fact in the initial phase of model development. The manager, therefore, also should be prepared to accept that a project may have to be enlarged, or the model cannot be used, if its accuracy is not sufficient for the purposes. On the other hand, while an experienced modeller will be able in most cases to estimate the appropriate model complexity at an early stage, unforeseen difficulties during the model development also may lead to a model of insufficient accuracy, even for an experienced modeller. Generally, it is strongly recommended to have an ongoing dialog between the modeller and the manager during the entire development of the model. It is absolutely necessary that the manager is aware of the strengths and limitations of the modelling process, including the expected accuracy of any model being considered. Further, the modeller should attempt to apply the model interactively, in order to develop demonstrations for the manager of the simulation results obtained from different management strategies. This also will open the necessary discussion between the manager and modeller on all the possibilities that a model can offer, including alternative changes in the management strategy.

- *Strictly follow the recommended modelling procedure.* The procedure outlined in Section 5.2 should be carefully followed. All the steps, including verification, calibration and validation, should be followed without exception. Model verification is particularly important. The modeller should take sufficient time to "play" with the model, and test the feasibility of the parameters. Are the parameters in accordance with the literature? Introducing "ecological constraints" into the model also should be considered, as discussed further in Section 5.4. The ability of an ecosystem to introduce other species better suited to the model (i.e., other properties of the biological model components) may provoke the use of a structural dynamic model (see Section 5.6.7). Using the model to optimize the data collection efforts is often recommended, particularly when data collection has a high cost. Kettunen (1988) presented a method to assess this optimum situation, which means that the first complex model is only used to find the optimal data

collection scheme (i.e., to assess which data most beneficial to collect at a given cost) to offer the best support to the model development. When additional data resulting from the first provisional model are available, the final model can be developed, using all the available data.

Another crucial problem is associated with model generality. Can a model used in one lake, for example, be used without change for other case studies? The answer is not a simple yes or no. However, experience shows that simpler models can be used more generally than more complex models. They contain a description of the basic processes characterizing all lakes and reservoirs (e.g., nutrient uptake by phytoplankton, which is dependent on the nutrient concentration and the concentration of phytoplankton; mineralization of detritus). The more complex models inevitably will contain more site-specific process descriptions, which may not be important for all lake and reservoir case studies. Thus, more complex models will generally have to be modified from case to case. This is illustrated in Table 5.2, in which the experience gained with the general use of a eutrophication model containing 17–20 state variables is presented.

Table 5.2. Survey of eutrophication studies, based upon the application of a modified Glumsø model

Ecosystem	Modification	Level*
Glumsø, version A	Basis version	6
Glumsø, version B	Nonexchangeable nitrogen	6
Ringkøbing Firth	Boxes, nitrogen fixation	5
Lake Victoria	Boxes, thermocline, other food chain, herbivorous fish	4
Lake Kyoga	Other food chain	4
Lake Albert	Boxes, thermocline, other food chain	4
Lake Fure	Boxes, nitrogen fixation, thermocline	3
Lake Esrom	Boxes, silicon cycle, thermocline	4
Lake Gyrstinge	Level fluctuations, sediment exposed to air	4–5
Lake Lyngby	Basis version	6
Lake Bergunda	Nitrogen fixation	2
Broia Reservoir	Macrophytes, 2 boxes	
Lake Great Kattinge	Resuspension	5
Lake Svogerslev	Resuspension	5
Lake Bue	Resuspension	5
Lake Kornerup	Resuspension	5
Lake Balaton	Adsorption to suspended matter	2
Roskilde Fjord	Complex hydrodynamics	4
Stadsgraven, Cph†	4–6 interconnected basins	5 (Level 6: 93)
Internal lakes of Cph†	5–6 interconnected basins	5

*Level 1: Conceptual diagram selected; Level 2: Verification carried out; Level 3: Calibration; Level 4: Calibration using additional intensive measurements; Level 5: Validation by use of an independent data set; Level 6: Validation of a prognosis.

†Cph—Copenhagen.

Table 5.3. Lake models for different environmental problems

Problem	Modelling effort
Hydrodynamical problems	5
Eutrophication	5
Oxygen balance	4–5
Bacteriological water quality	3–4
Heavy metal pollution	4
Pesticide pollution	4
Acid rain	4–5
Fishery	3
Wetlands	4

Problems of interest for lake and reservoir management include: (1) eutrophication, (2) ecotoxicological effects, (3) acidification, (4) fishery management, (5) the oxygen concentration of lake water, (6) management of wetlands surrounding, (7) the bacteriological quality of the lake water, and (8) hydrodynamical problems related to water discharge, or to the use of lake water for cooling or for production of drinking water.

All eight of these problems have been modelled. Table 5.3 provides an overview of the modelling activity for each of these eight problems on a scale from 0 to 5, where 5 means very intense modelling efforts, 4—intense modelling effort, 3—some modelling effort, 2—a few models have been studied, 1—one or a few studies with not well-calibrated or validated models, and 0—no modelling efforts have been done. The table indicates that all 8 problems have been modelled to some extent, with most of the problems being intensely or very intensely modelled.

Thus, a spectrum of models is available for all eight major lake problems. Selection of the appropriate complexity dictated by the problem, the characteristics of the ecosystems, and the quality and quantity of the available data, as discussed in Section 5.4, is crucial for the modelling results. Thus, it is beneficial that lake ecosystems have been modelled intensely, and that a wide experience with models of differing complexity is available.

5.4 SELECTION OF AN APPROPRIATE MANAGEMENT MODEL

The first step in selecting a model is specification of the goals for which the model will be used. The selected model must be one intended to answer the questions of interest, as defined by the lake manager. Another consideration in selecting a model is the specific data available for use with the model. Using the most advanced models is impossible, for example, if the quantity and quality of the water inflows have not been measured. In some cases, it may be possible to obtain data required for the model, but this inevitably involves expenditures of money and time, since most lake inflows vary considerably over time. The availability of personnel skilled in the use of models also can be a significant limitation. Learning the modelling procedure, and understanding the applied basis for model development, can be both difficult and time consuming. Thus, appropriate model selection requires

balancing the importance of the problem, money and time invested in the model development, the available personnel, and the existence of appropriate models.

As emphasized in previous sections, models only provide a gross simplification of reality. Thus, caution is always necessary when considering model results. Moreover, three levels of uncertainties influence even the best models (Hilborn, 1987), including:

- Noise—the natural variability that occurs sufficiently frequently to be routine (various sampling schemes and statistical analyses are required to accommodate this uncertainty),
- The state of nature that is not well known,
- Surprises—unanticipated events (flexible management strategies cope with unanticipated events more effectively than rigid, dogmatic strategies).

These uncertainties are inherent in any complex system, and may occur in any specific case. By proper use of validation techniques, it is possible in most cases to quantify the uncertainty, which is very valuable for interpretation of the model predictions.

Models useful for water quality management may be classified as follows:

- *Simple static calculation models* consisting of algebraic equations or graphs. These models are based predominantly on the statistical elaboration of data sets, sometimes large ones. Thus, they are limited by the extent of the materials covered in the analysis. For example, many models based on empirical relationships between phosphorus and chlorophyll presented in the literature. Examples are presented in Section 5.5, which focuses on applicable models. Thornton et al. (1999) provides details on models for estimating nonpoint source pollution loads.
- *Complex dynamic models* providing analysis of the timing of water quality conditions. Several of the models presented in Section 5.5 belong to this class, and represent a wide spectrum of complexity.
- *Geographical information systems* (GIS) used for problems requiring spatial resolution. This is typical for estimating pollutant loads, particularly for nonpoint source pollution. The basis of GIS is computerized maps and procedures for entry and treatment of spatial data. For example, a specific watershed can be included in the database and corresponding pollution sources indicated. Through the use of models (usually more complex dynamic models), the expected pollution input can be calculated. Several attempts to apply GIS in watershed management (DePinto and Rodgers, 1994), or combine watershed models with reservoir models, have emerged in recent years.
- *Prescriptive models* can be used to calculate water quality conditions without indicating appropriate management options for a given situation. By means of scenario analysis, it is possible to test management alternatives and to predict the potential consequences of water quality. This can be useful in selecting the most appropriate management possibilities. These models are based either on simple static calculations or dynamic simulations, depending on whether a time-independent or time-dependent solution is required.
- *Optimization models* incorporate selection procedures to choose the most suitable option, based on a set of criteria. Such models, which are often based on complex dynamic models, can allow simultaneous analysis of several management alternatives or goals. The major component of an optimization model is called a goal function, which is a function the user seeks to minimize or maximize, including critical water quality

variables (e.g., oxygen concentration in a lake), or the money spent on attaining a specified level of water quality improvement. Optimization with constraints means that some, or all, of the management parameters are limited (i.e., they are forced to remain within specified limits due to natural conditions, management limitations, etc.). The following examples illustrate these kinds of constraints:

1. Inflow phosphorus levels cannot be reduced more than the capabilities of treatment plants or other available reduction methods,
2. It is impossible to mix a waterbody beyond its greatest depth; thus, there is a natural depth of mixing,
3. There are no feasible reasons to reduce the chlorophyll concentrations, or increase the oxygen concentrations, above a certain limit.

The *standard optimization* procedure is used when a management decision involves only one variable (e.g., reservoir outflow), and is determined by one characteristic of this variable (e.g., outflow rate by turbines). The goal in this case, for example, can be to keep the reservoir water level within certain limits. *Multiparameter* optimization also concerns one variable, although the optimal performance is searched for in a multidimensional parameter space. It can be asked, for example, to what extent should the bottom outflow gate of the reservoir be opened, and a turbine run, to keep the water level in the reservoir within certain limits. The constraints are given by the maximum capacity of the bottom outlets and the turbines, and by the minimum and maximum flow rates prescribed for the river downstream of the reservoir. The model formulation with respect to water quality, for example, may be retaining some water quality variable below a certain limit, while also modifying several parameters characterizing the use of various management options. As an example, the model GIRL OLGA is intended for making dynamic, time-dependent estimates of the best combination of the time sequence of using five different management options, each characterized by one parameter that can be manipulated within certain limits. *Multivariable* optimization simultaneously takes into account several variables. Examples would include keeping the oxygen concentration, quantity of algae and the content of organic matter in a lake within certain limits. *Multigoal* optimization is the most complex, with several goals having to be simultaneously achieved. In this latter case, a compromise set is sought, rather than a unique optimal solution, with the model user driven to make a proper selection. A combination of multiparameter, multivariable and/or multigoal formulation also is possible, although such a solution has not yet been attempted for water quality modelling. Up to the present time, more complex formulations have generally been used to address water quantity problems (e.g., optimal operation of a reservoir cascade). Nevertheless, progress in developing optimization techniques is moving forward rapidly, and useful water quality formulations will doubtless be available in the future. Table 5.4 provides a listing of optimization water quality management models.

It is emphasized that optimization procedures only allow selection among the possibilities included in the model, and is limited by the validity of the model, including its assumptions and formulations and its imposed constraints.

Thus, the model conclusions should be used with caution, with the user considering the model limitations, possible inadequacies, and possible insufficiency of input data. The

Table 5.4. Optimization water quality management models

- Dynamic optimization of eutrophication by *phosphorus removal*—used for a Japanese lake (Matsumura and Yoshiuki, 1981).
- Optimal control by *selective withdrawal* (Fontane et al., 1981).
- Optimizing reservoir operation for *downstream aquatic resources*—applied to Lake Shelbyville, IL, USA (Sale et al., 1982).
- GIRL OLGA for cost minimization of eutrophication abatement, using time-dependent selection from five management options (Kalčeva et al., 1982; Schindler and Straškraba, 1982)—applied for several reservoirs in the Czech Republic.
- Stochastic optimization of *water quality* (Ellis, 1987).
- COMMAS for prediction of environmental multiagent system (Bouron, 1991).
- DELWAG-BLOOM-SWITCH for management of eutrophication control of shallow lakes (van der Molen et al., 1994).
- GFMOLP, a fuzzy multiobjective program for the optimal planning of reservoir watersheds (Chang et al., 1996).

model can be run before any decision is taken, and several alternatives investigated. Alternatively, the model can be connected to automatic devices that activate water quality management options. As examples, chlorophyll concentrations and meteorological variables can be automatically recorded and put into a computer model. Short-term predictions by the model can be used to switch water mixing devices on or off, or to specify the intensity of phosphorus purification (see Fig. 5.7).

Expert systems use qualitative and quantitative expressions to guide the model user toward relevant answers to complex water quality questions. The major advantage of expert systems is their ability to consider qualitative characteristics, in addition to quantitative characteristics, and to handle complex decision rules. The name of this model group originated from the basis in which these answers are obtained; namely, the judgment of experts in a given field. An interactive mode is available, in which the user interacts with the computer software, selecting questions offered by the computer, obtaining answers and answering the questions. Each expert system is devoted to a particular problem. They are called *empty expert systems* or *expert shells* directed to handling the *knowledge base*, which is the specific decision tree on what to do, how to decide in the given instance, etc. A general review of expert systems applicable to different environmental problems is provided by Hushon (1990), Davis (1993) and Davis and Guariso (1994).

Decision support systems (DSS) represent a further extension of expert systems. They incorporate other computer software products relevant for a specific water quality decision problem for which the system was constructed (e.g., simple models, simulation models, optimization models, GIS systems). A graphics package that generates explanatory drawings and texts can be an integral part of DSS, and all the model types mentioned above can be incorporated in the system. The entire decision support system is driven by questions offered by the computer and answers provided by the model user.

DSS were named for their ability to *support* decisions. They are not intended to *make* decisions. Wise, experienced people must always make the final decisions. In order to make

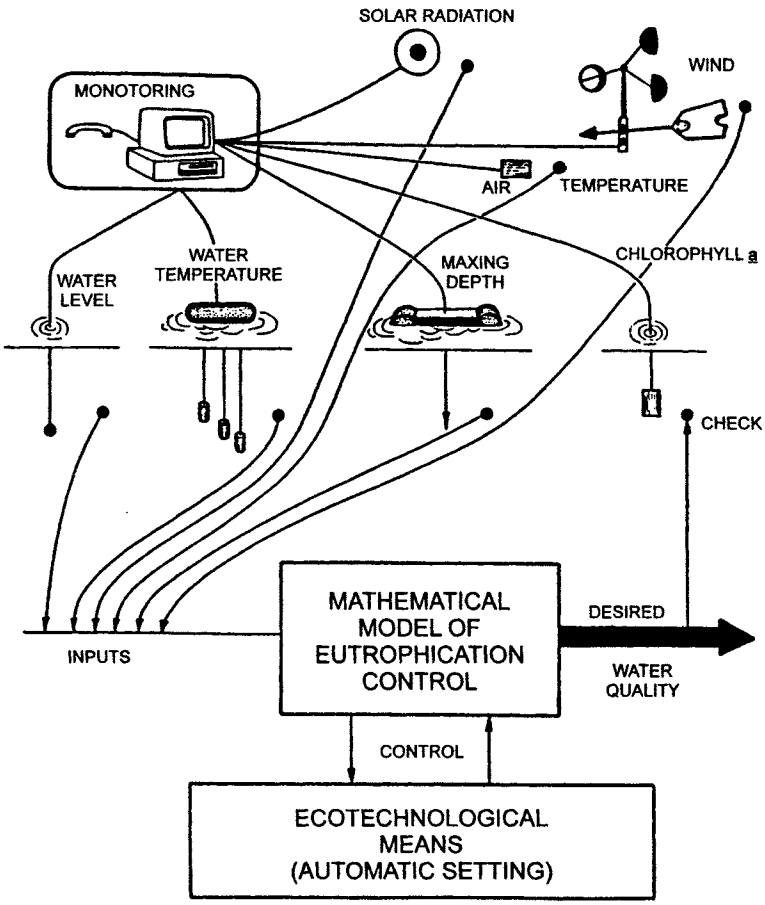

Fig. 5.7. The use of automatic monitoring, in connection with an online mathematical model to control eutrophication.

acceptable decisions, however, people need varying amounts of information that is often not easily obtainable. For complex systems such as water quality systems, it is difficult to preview the consequences of different options because there are many nonlinear relationships and complicated interactions among their components (Loucks and da Costa, 1991; Simonovic, 1996).

DSS are tools that provide managers with necessary information regarding the potential consequences of various management decisions. DSS use both the experiences of numerous experts, and the capabilities of the computer to rapidly calculate many complex relationships. The interactive function allows the user to assess the various versions of decisions under different possible situations.

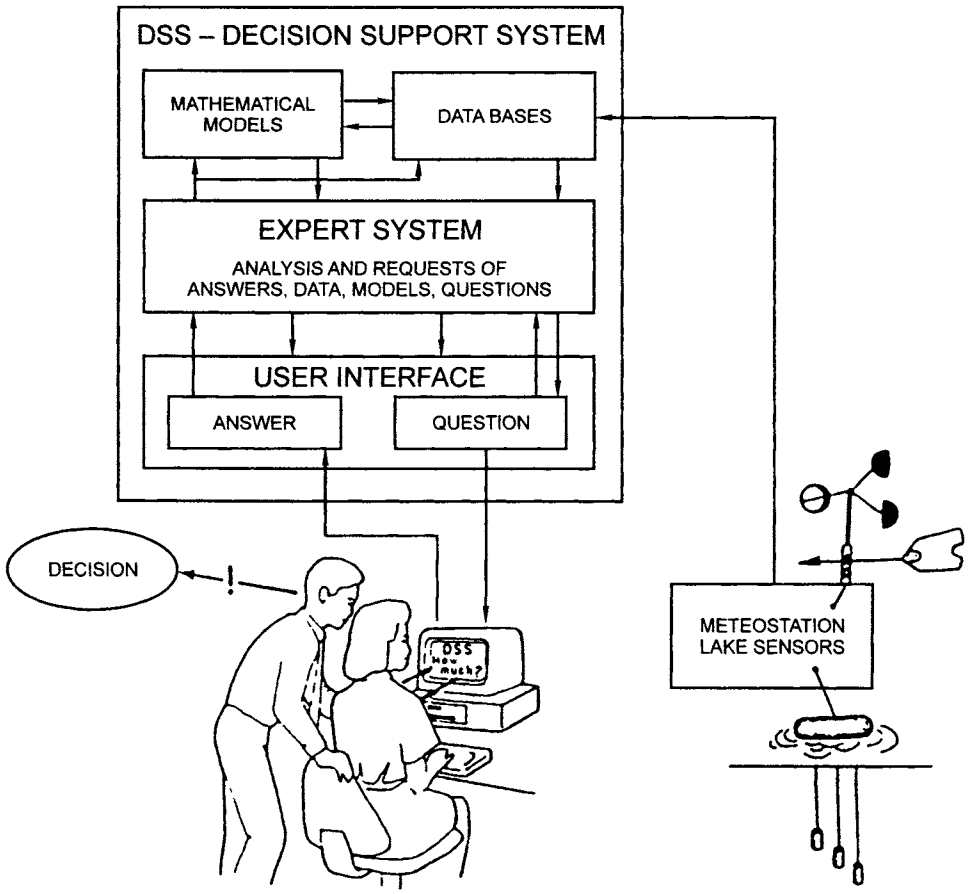

Fig. 5.8. A Decision Support System for water quality, combined with automatic recording.

Figure 5.8 provides an example of the structure and organization of a DSS. This DSS is connected to a meteorological monitoring station and to an in-lake monitoring system that measures some water quality variables in a lake or reservoir. Thus, actual information and past records of the situation are available for inspection in a transparent form. The database stores the past data, both recorded automatically or taken by hand sampling and analyzed biologically or chemically. It also contains a knowledge base of the expert system, which gives the questions what should be specified by the user in order to get the correct management advice. The latter comprise the decisions that experts would suggest in a particular situation. The DSS also incorporates a selection of water quality models that can be automatically set into operation, or suggested to the model user to be set into operation, since they will assist the manager in getting an idea of the consequences of specific management decisions before they are implemented.

Table 5.5. Expert and decision support systems for water quality management

Model name	Purpose	Author
• No name	Selection of control strategy for lake eutrophication	Grobler et al., 1987
• REH	Localization of pollution sources on a river that cause minimum deterioration of water quality	Gnauck et al., 1988
• No name	DSS for environmental decisions, combining a modelling system with GIS	Fedra, 1990a, 1990b
• CMSS	Analysis of environmental catchment policies	Davis et al., 1991; Davis and Farley, 1997
• AQUATOOL	Water resources management	Andreu et al., 1991
• DELAQUA	Prototype expert system for lake water quality management	Recknagel et al., 1991
• HEC-3	Multipurpose quantitative operation of reservoir systems (no water quality)	Haestad Methods, 1993
• GEO-WAMS	Modelling support system for integrating GIS with watershed analysis	DePinto and Rodgers, 1994
• MASAS	Evaluation of micropollutants	Ulrich et al., 1991, 1995
• WATERWARE	Water resource planning in the European Union, based on the No name DSS by Fedra given above, as well as on object-oriented simulation models for predicting the impact of water quantity and quality management strategies like IRAS (Loucks et al., 1995), RIBASIM and PCRSS	Fedra and Jamieson, 1996; Jamieson and Fedra, 1996a, 1996b
• BEKWAAM	Expert system for reservoir design and management; not directly water quality but using relevant information	Benoist et al., 1998
• ODE	Software tool for rapid building of DSS which can handle multiple issues across different scales	Reed et al., 1999
• RMU	Development of a catchment management DSS for Thailand	Scoccimarro et al., 1999

5.5 OVERVIEW OF MODELS APPLICABLE FOR VARIOUS MANAGEMENT PROBLEMS

5.5.1 Eutrophication Models

The complexity of eutrophication problems was previously discussed in Section 2.2.2—*Eutrophication*, and the relations with nonpoint-source nutrient loads in Section 4.2. Eutrophication models represent a particularly wide spectrum of complexity. Table 5.6 reviews various eutrophication models representing the spectrum of complexity and the characteristics of the models (i.e., number of state variables, nutrients considered, number of lake segments or number of water layers, whether constant stoichiometric or independent nutrient cycles were applied, whether the model has been calibrated and validated,

Table 5.6. Range of eutrophication models

Model name or developer	Number of state variables per layer or segment	Nutrients	Segments	Dimension (d) or layer (l)	CS or NC*	C and/or V†	Number of case studies
Vollenweider	1	P (N)	1	1 l	CS	C + V	Many
Imboden	2	P	1	2 l, 1 d	CS	C + V	3
O'Melia	2	P	1	1 d	CS	C	1
GIRL	3	P	1	1–2 d	CS	C + V	Many
Larsen	3	P	1	1 l	CS	C	1
Lorenzen	2	P	1	1 l	CS	C + V	1
Thomann 1	8	P, N, C	1	2 l	CS	C + V	1
Thomann 2	10	P, N, C	1	2 l	CS	C	1
Thomann 3	15	P, N, C	67	2 l	CS	—	1
Chen and Orlob	15	P, N, C	Sev.	2 l	CS	C	2 min.
Patten	33	P, N, C	1	1 l	CS	C	1
Di Toro	7	P, N	7	1 l	CS	C + V	1
Biermann	14	P, N, Si	1	1 l	NC	C	1
Canale	25	P, N, Si	1	2 l	CS	C	1
Jørgensen	17	P, N, C	1	1–2 l	NC	C + V	21
CLEANER	40	P, N, C, Si	Sev.	Sev. l	CS	C	Many
Lavsoe	7	P, N	3	1–2 l	NC	C + V	25
ASTER/MELODIA	10	P, N, Si	1	2 l	CS	C + V	1
Baikal	> 16	P, N	10	3 l	CS	C + V	1
Chiemsee	> 14	P, N, C, S	1	Profile	CS	C + V	Many
3DWFGAS	> 70	P, N, C, S	Many	Many	CS	C + V	135
Reward	16	P, N	1	Profile	CS	C + V	5
Mahamah	8	C, P, N	1	1–2 l	CS	C + V	2
LAKE ECOSYSTEM	11	C, P, N	1	1	CS	C + V	1
MINLAKE	9	P, N	1	1	CS	C + V	> 10
SALMO	17	P, N	1	2 l	CS	C + V	16

*CS means constant stoichiometric and NC means independent nutrient cycle.

†C means calibrated and V means validated.

number of case studies to which the model has been applied, etc.). It is assumed, particularly for more complex models, that some modifications from case to case to reflect specific lake conditions or properties should be reflected in the model (also see discussion in Section 5.4 on model generality).

The simple calculation modelling approach is exemplified by the relation between phosphorus, which can easily be calculated on the basis of the relation between the phosphorus load (corrected by the fraction trapped in the sediment) and chlorophyll (e.g., see OECD, 1982; Ryding and Rast, 1989; Rast and Thornton, 1996). Such empirical relations do have shortcomings. They are not necessarily general and, therefore, should be used with proper caution. The differences between the various empirical relationships indicates that a high standard deviation can be expected by application of empirical relationships.

As seen in Table 5.6, the complex dynamic models represent a range of complexity, given that the different models include a different number of submodels. Three possible core submodels that should be considered for inclusion in dynamic models are presented here. They will be discussed further when it is necessary to apply these submodels in an overall eutrophication model. The characteristics of each case study, as discussed above, should determine whether these three submodels should be included or not. They represent typical considerations for selecting the complexity for eutrophication models.

The application of independent nutrient cycles inevitably increases the complexity of a model, as this situation requires that nitrogen, phosphorus, carbon and perhaps silica may be included as state variables in each trophic level. In most models that include independent nutrient cycles, however, only one state variable is considered for zooplankton and fish. The application of independent nutrient cycles implies that the growth of phytoplankton is described as a two-step process, as follows:

- Phytoplankton nutrient uptake, in accordance with Monod's kinetics,
- Phytoplankton growth determined by the internal substrate concentration.

This complication obviously requires that the underlying data are of sufficient quality and quantity. Di Toro (1980) has shown that the application of independent nutrient cycles is particularly important when the model is used for shallow, very eutrophic lakes. In contrast, this complication can be omitted for deep, mesotrophic or oligotrophic lakes.

Because *lake bottom sediments* accumulate nutrients, it is important to describe quantitatively the processes determining the mass flows from sediment to water. This is of particular importance when the mass flows sediment to water are significant, compared with the other mass flows. As the relative amount of nutrients stored in the sediment is most significant for shallow, eutrophic lakes, the more detailed description presented below should always be included in models for such types of lakes.

The sediment–water submodel attempts to answer the following crucial question: To what extent will accumulated compounds in the sediment be redissolved into the lake water? Because these processes are important for lake eutrophication, the phosphorus and nitrogen exchange processes between mud and water have been extensively studied. Chen and Orlob (1975) ignored the exchange of nutrients between mud and water; as pointed out by Jørgensen et al. (1975), this will inevitably give a false prognosis. Ahlgren (1973) applied a constant flow of nutrients between sediment and water, while Dahl-Madsen and Strange-Nielsen (1974) used a simple first-order kinetic to describe the nutrient exchange rate.

A more comprehensive submodel (Fig. 5.9) for the exchange of phosphorus has been developed by Jørgensen et al. (1975). The settled material, S, is divided into S_{detritus} and S_{net}, the first being mineralized by microbiological activity in the lake, and the latter being the material actually transported to the sediment. S_{net} can also be divided into two flows, as follows:

$$S_{\text{net}} = S_{\text{net,s}} + S_{\text{net,e}}, \tag{5.1}$$

where $S_{\text{net,s}}$ = flow to the stable nonexchangeable sediment,

$S_{\text{net,e}}$ = mass flow to the exchangeable unstable sediment.

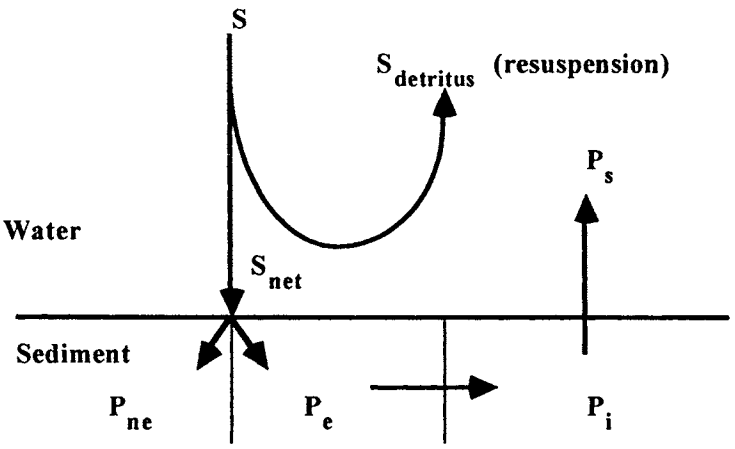

Fig. 5.9. Sedimentation, S, divided into S_{detritus} and S_{net}; P_{ne} nonexchangeable phosphorus in unstabilized sediment: P_{e} exchangeable phosphorus in unstabilized sediment; P_{i} phosphorus in interstitial water; P_{s} dissolved phosphorus in water.

Correspondingly, the nonexchangeable, P_{ne}, and exchangeable, P_{e}, phosphorus concentrations, both based on the total dry matter in the sediment, also can be distinguished. Increases in the stabilized sediment can be found by numerous methods. The analysis of lead isotopes, for example, is a fast and reliable method.

The exchangeable phosphorus is similarly mineralized to detritus in a lake, and a first-order reaction gives a reasonably good description of the conversion of P_{e} into interstitial phosphorus, P_{i}.

Finally, the interstitial phosphorus, P_{i}, will be transported by diffusion from the pore water in the sediment to the lake water. This process, which has been studied by Kamp-Nielsen (1975), can be described by means of the following empirical equation (valid at 7°C):

$$\text{Phosphorus release} = 1.21(P_{\text{i}} - P_{\text{s}}) - 1.7 \text{ (mg P m}^{-2} \text{ day)}, \tag{5.2}$$

where P_{s} = the dissolved phosphorus in the lake water.

This submodel of water–sediment exchange was validated in three case studies (Jørgensen et al., 1975), based on examining sediment cores in the laboratory. Kamp-Nielsen (1975) has added an adsorption term to these equations.

A similar submodel for sediment nitrogen release has been developed by Jacobsen and Jørgensen (1975). The nitrogen release from sediment is expressed as a function of the nitrogen concentration in the sediment and the temperature, under both aerobic and anaerobic conditions.

Figure 5.10 shows a sediment profile from these examinations, illustrating the interpretation of the profile that can be used in the model to distinguish between exchangeable and nonexchangeable sediment phosphorus.

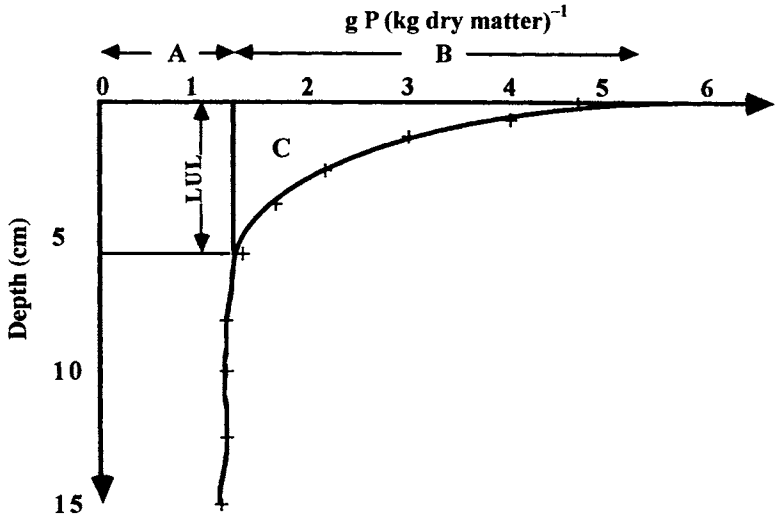

Fig. 5.10. Analysis of sediment core from Lake Esrom. Phosphorus concentration (mg P g^{-1} dry matter) is plotted against the depth. The area C represents exchangeable phosphorus. $f = (B \cdot A - 1)$, LUL is the unstabilized layer.

Grazing of phytoplankton by zooplankton (Z), and the predation of zooplankton by fish (F) are both expressed by a modified Monod expression, which considers a threshold concentration, KT, below which grazing or predation does not occur. The expression for phytoplankton grazing by zooplankton (Steele, 1976) is expressed as follows:

$$\mu Z = \mu Z_{\max} \cdot \frac{\text{Phyt} - KT}{\text{Phyt} + KM}, \tag{5.3}$$

where KM = Michaelis–Menten constant.

A zooplankton carrying-capacity must often be introduced to give a better simulation of zooplankton and phytoplankton. Although carrying capacities are often observed in ecosystems, the need to introduce them in this case may be due to a too-simple representation of the grazing process. Phytoplankton might not be grazed, for example, by all the zooplankton species present, and some zooplankton species might use detritus as a food source. The zooplankton growth rate, μZ, is computed in accordance with these modifications as:

$$\mu Z = \mu Z_{\max} \cdot \text{FPH} \cdot \text{FT2} \cdot \text{F2CK}, \tag{5.4}$$

where FPH = the expression in equation (5.4),
FT2 = a temperature regulation expression,
F2CK = accounts for the carrying capacity.

Now,

$$\text{F2CK} = \frac{CK - \text{ZOO}}{CK}, \tag{5.5}$$

where CK = carrying capacity.

If the data are not sufficient to include the three important submodels presented above, or other relevant submodels that an individual case study might require, it is recommended that the needed data be obtained with an intensive measuring effort that can provide high-quality data for the specific time period when the eutrophication processes are most dynamic.

An intensive measuring period, with several sets of measurements each week during the spring and summer bloom period, can first of all be applied to improve parameter estimation, which is often a focal problem in developing ecological models. The experience from conducting intensive measuring periods has identified the following advantages:

- Different optional expressions of simultaneously-limiting factors were tested, and only two gave an acceptable maximum growth rate for phytoplankton and an acceptably low standard deviation. These were (i) multiplication of the limiting factors, and (ii) averaging the limiting factors.
- The previously applied expression for the influence of temperature on phytoplankton growth gave unacceptable parameters, with standard deviations that were too high. A better expression (Equation 1) was introduced as a result of the intensive measuring period.
- It was possible to improve the parameter estimation, which gives more realistic values for some parameters. Whether this would give an improved validation when observations from a period with drastic changes in the nutrients loading are available could not be determined.
- The other expressions applied for process descriptions were confirmed.

It is important to validate models against independent set of measurements. Table 5.7 gives the results of a typical validation for a model with a medium to high complexity, developed on the basis of good data. R and A are the standard deviations for the mean and maximum value, respectively, of the considered state variables. Y, R and A give the errors in relative terms. Multiplying them by 100 gives the errors expressed as percentages (%). As shown in the table, the standard deviation, Y, for all measured state variables is 16%. It is the standard deviation for one comparison of modelled and measured values. As the standard deviation for a comparison of n sets of modelled and measured values is $\hat{u}n$ times smaller, and n is in the order of 200, the average picture of the lake is provided, with a very acceptable standard deviation of about 1%. Y is generally 5–10 times larger, for example, for hydrological models (WMO, 1975).

The relative errors of the mean values, R, are 3% for production, 8% for phytoplankton and 2% for nitrogen, all of which are very acceptable values. The relative error for total

Table 5.7. Numerical validation of the described model

Validation criterion	State variable	Value
Y	All	0.16
R	P total	0.18
R	P soluble	0.16
R	N total	0.02
R	N soluble	0.14
R	Phytoplankton	0.08
R	Zooplankton	0.20
R	Production	0.03
A	P total	0.12
A	P soluble	0.15
A	N total	0.07
A	N soluble	0.03
A	Phytoplankton	0.15
A	Zooplankton	0.00
A	Production	0.08

phosphorus, however, is 18%, and that for zooplankton is 20%, both of which must be considered too large. The relative errors of the maximum values, *A*, range from 0% to 15%, an acceptable range. The ability of the model to predict maximum production and maximum phytoplankton concentrations has special interest within the context of a eutrophication model, with the relative errors being 8% and 15%, respectively—both of which are very acceptable.

A prognosis for the development of eutrophication in Lake Glumsø (the validation results referred to in Table 5.7 are based on this case study) by different removal efficiencies for phosphorus, nitrogen, or phosphorus and nitrogen simultaneously, have been made. The validation of this prognosis is presented here to illustrate the reliability of prognoses made on the basis of well-developed eutrophication models.

It was previously stated that nitrogen removal had little or no effect on the lake, while phosphorus removal would give substantial reductions in the phytoplankton concentration. The results of two cases are summarized in Table 5.8, as follows:

Case A. The treated wastewater has a concentration of 0.4 mg P l^{-1}, corresponding to about 92% removal efficiency, which should be achieved with proper chemical precipitation.

Case B. The treated wastewater has a concentration of 0.1 mg P l^{-1}, corresponding to about 98% removal efficiency, which will require chemical precipitation, for example, in combination with ion exchange.

As seen in Table 5.8, the water quality will improve significantly, in accordance with the predictions. Case B, with a 98% removal of phosphorus, is obviously preferred. In the third year, Case B will give a reduction in production from 1100 g C m^{-2} yr to 500 g C m^{-2} yr, with the water transparency increasing from a minimum value of 20–60 cm. The 9th year would even result in reduction of the production to 320 g C m^{-2} yr, corresponding to a

Table 5.8. Model predictions for two concentrations of treated wastewater: Case A—0.4 mg P l^{-1}; Case B—0.1 mg P l^{-1}

	Third year		Ninth year	
	Case A	Case B	Case A	Case B
g C m^{-2} yr	650	500*	500	320*
Minimum Transparency (cm)	50	60	60	75

*An error of 3% on this value can be expected if the validation results hold, see *R* for production in Table 5.7.

mesotrophic lake, which is an acceptable improvement for a shallow lake situated in an agricultural area.

The prognosis gives a pronounced effect of 98% phosphorus removal, which could therefore be recommended to the appropriate environmental authorities. Further improvements after nine years should not be expected with this case study.

Conveyance of the wastewater also was considered, but has the following disadvantages:

- It is slightly more expensive than the Case B solution, taking interests, depreciation and running costs into consideration.
- The phosphorus is *not* removed but only transported to the downstream Susaa River, where its effects have not been considered.
- The sludge produced at the biological treatment plant will be less valuable as a soil conditioner, since the phosphorus concentration will be lower than when phosphorus removal is included.
- The freshwater is not retained in the lake, from which it could have been reclaimed, if needed, after storage for some time. Freshwater supply is not presently a problem in this area, but it is foreseen that it might be in 20–40 years.

In spite of these observations, the community in this case study chose to convey its wastewater to the Susaa River, due to a preference for traditional methods. The pipeline was constructed in 1980 and began operation in April 1981, which has enabled a validation of the presented prognosis.

Lake Glumsø was ideal for these studies due to its limited depth and size, but also because a reduced nutrient input to the lake could be foreseen. The limited retention time (about six months) makes it realistic to obtain a validation of a prognosis within a relatively short time interval (a few years). On April 1, 1981, the direct input of wastewater to the lake was stopped. Because the capacity of the sewage system is still too small, however, a minor input of mixed rain water and wastewater is discharged into the lake from time to time through an upstream tributary. Thus, the phosphorus loading is not reduced by 98%, but rather only by 88% (determined by a phosphorus balance). The prognosis in Case A, therefore, can be used for comparison.

During the third year after the reduction in phosphorus load occurred, a pronounced effect on the lake was observed. Table 5.9 compares some of the most important data of the prognosis. It also includes data obtained during the first two months of the third year. The

Table 5.9. Comparison of predicted and measured data

	Predicted (Case A, 92% P reduction)	Measurements (approximately 88% reduction)
Minimum transparency		
First year	20 cm	20 cm
Second year	30–	25–
Third year	45–	50–
Production, g C m^{-2} day, maximum		
First year	9.5 ± 0.8	5.5 ± 0.5
Second year		
(spring)	6.0 ± 0.5	11 ± 1.1
(summer)	4.5 ± 0.4	3.5 ± 0.4
(autumn)	2.0 ± 0.2	1.5 ± 0.2
Third year		
(spring)	5.0 ± 0.4	6.2 ± 0.6
Chlorophyll in spring, mg m^{-3}, maximum		
First year	750 ± 112	800 ± 80
Second year	520 ± 78	550 ± 55
Third year	320 ± 48	380 ± 38

table identifies errors as ± for g C m^{-2}day and chlorophyll maximum (mg m^{-3}). For the predicted values, the results from Table 5.7 (8% for production and 15% for phytoplankton concentration) are used to determine standard deviations. For the measured values, an error of 10% was estimated.

The lake was previously dominated by *Scenedesmus*. After the conveyance of the wastewater, it was dominated by diatoms, which have a lower optimum temperature and, therefore, typically bloom earlier in the spring than *Scenedesmus*. This seems to explain the discrepancy between the predicted and measured values regarding this parameter. The model, therefore, might improve its predictions if it was possible to account for shifts in species composition. Results published by Jørgensen (1981), Jørgensen and Mejer (1981a, 1981b) and Jørgensen (1992a, 1992b) indicate this would be possible by introducing a maximum growth rate for phytoplankton (see Section 5.6.7). Such models are called "structurally dynamic models" (Jørgensen, 1986a). They have given such promising results in recent times that Section 5.5.9 is devoted to discussion of this type of model.

In the Lake Glumsø case, however, since diatoms take up silica, it would probably also be necessary to introduce a silica cycle into the model. The other production and chlorophyll values are well predicted, except the spring production in the second year (Table 5.9). The predictions of minimum transparency are acceptable, as they show a difference of 5 cm or less. The general trends in the nutrient concentrations exhibit a good correlation between predicted and measured values.

This case study shows that it is possible to make reliable predictions using eutrophication models, provided that data of sufficient quality and quantities are available. On the other hand, an attempt should always be made to develop a eutrophication model, even if

the available data are not sufficient to construct a complex model, because the model results can be used to compare different management strategies with an indication of the uncertainty resulting from the validation. If the uncertainties are not acceptable, the model can be used to assess the weak points and help identify modifications that should be introduced to improve the model results.

Thus, the model should be considered a tool that is able to synthesize the knowledge available on a lake ecosystem of concern and, by following the recommendations in Section 5.4, should be able to obtain the best possible model predictions under given circumstances.

5.5.2 *Toxic Substance Models*

Over approximately the last 20 years, models of toxic substances have emerged because of the increasing interest in the environmental management of toxic substances that can cause water pollution. The topic of ecotoxicology was discussed in Section 3.2.6.

Toxic substance models attempt to model the fate and/or effects of toxic substances in ecosystems. Toxic substance models are most often biogeochemical models because they are meant to describe the mass flows of the toxic substances being considered. There also are models of population dynamics, which include the influence of toxic substances on the birth rate, growth rate and/or mortality and, therefore, which should also be considered toxic substance models.

Toxic substance models have some characteristic properties:

- The need for parameters to cover all possible toxic substance models is great. Thus, general estimation methods are widely used. Methods based on the chemical structure of chemical compounds are developed; the so-called QSAR and SAR methods.
- The safety margin should be high, for example, when expressed as the ratio between the actual concentration and the concentration that causes undesired impacts.
- The possible inclusion of an effect component, which relates the output concentration to its effect. It is easy to include an effect component in the model. However, it often is a problem to find a well-examined relationship upon which to base it. Rather, it will require the use of good knowledge of the properties, particularly the toxicological properties of the component of concern.
- The possibility and need of simple models, based on points 1 and 2 above, and of our limited knowledge of the processes, parameters, sublethal effects, antagonistic and synergistic effects.

The decision regarding which model class to apply is based on the ecotoxicological problem that one wishes to solve with the model. Figure 5.11 shows a model of lead contamination, with bioaccumulation through the food chain. This model requires detailed data about the lead concentrations in the various biological components as a function of time, which are rarely available.

However, it often is only the toxic substance concentration in one trophic level that is of concern. This includes the zero trophic level, which is understood to be the medium—lake

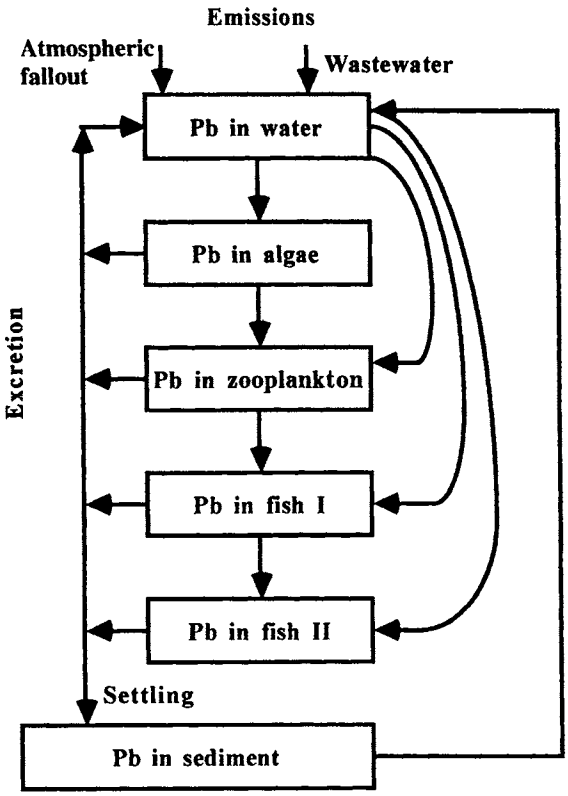

Fig. 5.11. Conceptual diagram of the bioaccumulation of lead (Pb) through a food chain in an aquatic ecosystem.

water, as illustrated with the example in Figure 5.12. It is a model of copper contamination in a lake ecosystem. The main concern is the copper concentration in the water, since it might reach a toxic level for the phytoplankton. Zooplankton and fish are much less sensitive to copper contamination, so the initial concern focuses on the concentration level harmful to phytoplankton. However, only the ionic form of copper is toxic and, therefore, it is necessary to model the partitioning of copper in its ionic form, complex-bound form, and adsorbed form. The exchange between copper in the water phase and the sediment also is included because the sediment is able to accumulate relatively large amounts of heavy metals. The amount released from the sediment may be significant under certain circumstances (e.g., low pH).

The acknowledgment of the uncertainty is of great importance for all models, but it is particularly important for ecotoxicological models. It may be taken into consideration either qualitatively or quantitatively. Another problem is: Where does one take the uncertainty into account? Should the economy or the environment benefit from the uncertainty?

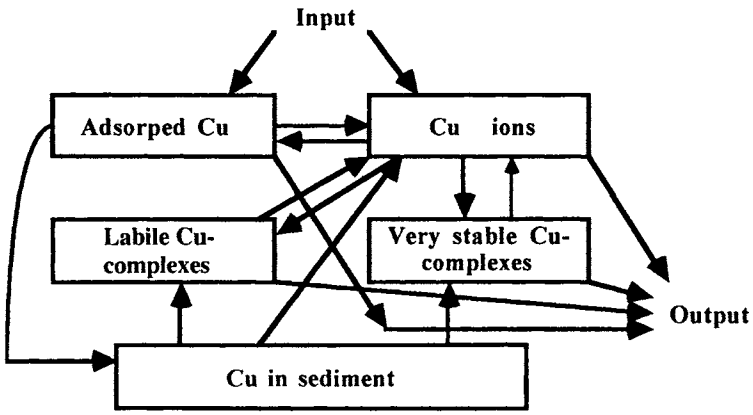

Fig. 5.12. Conceptual diagram of a simple copper (Cu) model.

Unfortunately, most decision-makers up to now have used the uncertainty to the benefit of the economy. This is a completely unacceptable approach, since the same decision-makers would, for example, never consider whether uncertainty should be used for the benefit of the economy or the strength of a bridge in a civil engineering project. Table 5.10 gives an overview of a number of ecotoxicological models applied to lake and reservoir management.

Ecotoxicological models are widely used to perform environmental risk assessments, *ERA* (see Section 5.5.8). This is of particular interest for lakes and reservoirs used as drinking water supplies, or for which the fisheries are significant. *ERA* typically answers such questions as: What is the risk of contaminating drinking water or fish for a given application of pesticides in an agricultural project adjacent to a lake or reservoir?

5.5.3 Acidification Models

Lake acidification is caused by acid rain, which originates from emissions of sulfur and nitrogen oxides into the atmosphere (see Section 2.2.2—*Acidification*). Thus, assessment of acidification for management purposes requires a chain of models, linking the emissions to the atmosphere to the effects of acid rain on soil chemistry in the lake's catchment area, and further to the pH changes in a lake. This is illustrated in Figure 5.13, which illustrates the model linkages between energy policy and lake and reservoir acidification.

In this context, only the last submodels of the chain (i.e., lake models and soil models) will be mentioned. These latter models determine the composition of the drainage water flowing into lakes and reservoirs. Those interested in entire model chains are referred to Alcamo et al. (1990) and Jørgensen (1994).

Several models have been developed to translate the emissions of sulfur and nitrogen compounds into changes in soil chemistry (in the first hand to changes in the pH of soil

Table 5.10. Examples of ecotoxicological lake models

Toxic subst.	Model characteristics	Reference
• Cadmium, mercury	Food chain as in a eutrophication model 6 state variables: water, sediment, suspended matter, invertebrates, plant and fish	Thomann et al., 1974 Miller, 1979
• Vinyl chloride	Chemical processes in water	Gillet, 1974
• Methyl parathion	Chemical processes in water, microbial degradation, adsorption, 2–4 trophic levels	Lassiter
• Heavy metals	Concentration factor, excretion, bioaccumulation	Ayoma et al., 1978
• Pesticides in fish: DDT and methoxychlor	Ingestion, concentration factor, adsorption on body, defecation, excretion, chemical decomposition, natural mortality	Leung, 1978
• Lead	Hydrodynamics, precipitation, toxicity of ionic lead on algae, invertebrates and fish	Lam and Simons, 1976
• Radionuclides	Hydrodynamics, decay, uptake and release by various aquatic surfaces	Gromiec and Gloyna, 1973
• Polycyclic aromatics	Transport, degradation, bioaccumulation hydrocarbons	Bartell et al., 1984
• Cadmium, PCB	Hydraulic overflow rate (settling), sediment interactions, steady state food chain submodel	Thomann, 1984
• Hydrophobic organic	Gas exchange, sorption/desorption, hydrolysis compounds, photolysis, hydrodynamics	Schwarzenbach and Imboden, 1984
• Mirex	Water–sediment exchange processes, adsorption, volatilization, bioaccumulation	Halfon, 1984
• Toxins (aromatic hydrocarbons, Cd)	Hydrodynamics, deposition, resuspension, volatilization, photooxidation, decomposition, adsorption, complex formation (humic acid)	Harris et al., 1984
• Persistent organic chemicals	Fate, exposure and human uptake	Paterson and Mackay, 1989
• pH, calcium and aluminium	Survival of fish populations	Breck et al., 1988
• Pesticides and surfactants	Fate in rice fields	Jørgensen et al.
• Toxicants	Migration of dissolved toxicants	Monte, 1998
• Growth promoters	Fate, agriculture	Jørgensen
• Toxicity	Effect on eutrophication	Legovic, 1997
• Pesticides	Mineralization	Fomsgaard et al., 1997
• Mecoprop (3)	Mineralization in soil	Fomsgaard et al., 1999

water). Kauppi et al. (1984) used knowledge about buffer-capacity and velocity to relate the emissions to soil water pH. A critical pH value of 4.2 is usually applied to interpret the results.

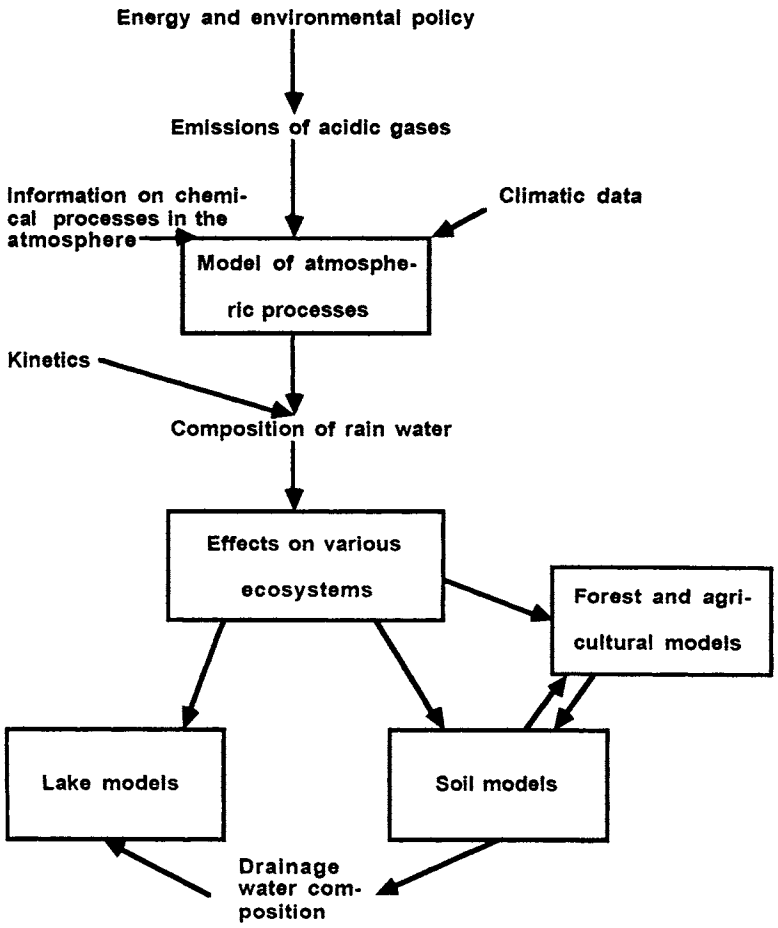

Fig. 5.13. A series of models must be used to relate energy and environmental protection policy to effects on soil, plants, water chemistry and aquatic ecosystems, which serve as feedback to political issues.

From the results of the atmospheric deposition calculations, it is possible to estimate the acid load in equivalents of hydrogen ions per square meter per year. In the European model, RAINS, the acid load is computed from the deposition, after accounting for forest filtering and atmospheric deposition of cations (for details, see Alcamo et al., 1990).

The Soil Map of the World classifies European soils into 80 soil types. The fraction of each soil type within each grid element is computerized to an accuracy of 5%. The resolution of the European RAINS model is such that each grid element includes one to seven soil types, with a mean number of 2.2. The model goal is to keep track of the development of soil pH and buffer capacity. Further development of soil models is still needed, as the soil model must be considered the weakest model in the chain.

It can be concluded that models of soil processes and chemical composition, including the concentrations of various ions and pH of the drainage water, are complex. It is not the intention here to present the models in detail—they are far too complex to do so—but rather to mention the difficulties and a few of the basic ideas behind them. Further details can be found in the references given in this section.

Henriksen (1980) and Henriksen and Seip (1980) developed an empirical model for the relationship between lake water pH and sulfur load. They plotted related values of pH and sulfur loads for a given catchment area with specific sensitivities for acidification. The resulting curves look like a titration curve. The sensitivity is dependent on the calcium concentration (low calcium concentration, high sensitivity due to low buffer capacity). For a sensitive area, a sulfur load of less than 0.7, or even 0.5 g m^{-2} · year is needed to insure a pH of 5.3 or higher.

These simple empirical approaches are used without consideration of the drainage water. Weathering processes, however, can be incorporated in the empirical approaches, although the results have little generality since they are based on regression analysis of local measurements. The presented modelling approach has been used on Scandinavian lakes with good results.

Most biological models of lake acidification focus on fish. On the basis of data from 719 lakes, Brown and Salder (1981) developed an empirical model relating the fish population to the pH of the water. For their study lakes in southern Norway, they found that a 50% reduction of the sulfate emissions will give an average increase in pH of 0.2, which will only improve the fish populations in 9% of the lakes. However, a criticism of the model is that it underestimates the relationship between the reduction of sulfate emissions and pH.

Muniz and Seip (1982) developed another empirical model, in which they distinguished between lakes of different conductivity. Chen et al. (1982) developed a very comprehensive pH-effect model, which considers the effects on all levels in the food chain and the total effects on the ecosystem.

5.5.4 Wetland Models

Nitrogen and phosphorus balances have shown that agricultural runoff and other nonpoint sources contribute significantly to overall lake and reservoir pollution, and particularly to the eutrophication problem. The results imply that environmental technology alone is not sufficient to cope with nonpoint pollutant sources, but must be supplemented with other methods. The results of comparative studies have shown that the use of wetlands is often a very effective method for reducing pollution (see Section 4.2.4).

Mitsch (1976, 1983) provided a more comprehensive review of wetland models than can be presented here. He distinguished between energy/nutrient models, hydrological models, models of spatial ecosystem, models of tree growth, process models, causal models and regional energy models. Mitsch et al. (1988) also reviewed several types of wetland models.

A nitrogen balance for agricultural regions revealed that nitrogen from nonpoint sources plays a major role in lake pollution, and that a solution to the eutrophication problem of freshwater and marine ecosystems cannot be realized without solving the problems asso-

ciated with nonpoint sources of pollution. The entire spectrum of ecological engineering methods identified in Chapter 4 has been implemented in various cases to solve the problems. As indicated above, the methods may have different effects in different situations, dependent on the actual mass balance and general properties of the lake or reservoir in question. In this context, there obviously is a need for a model that can be used to make predictions on the nutrient removal capacity of a wetland on the basis of certain information about an existing or a planned wetland. The goal is to develop as general a model as possible. However, because ecological models only have a certain generality, it is necessary to distinguish between the general relations and the more site-specific parameters and forcing functions. Thus, it is not possible to achieve a complete generality for wetland models.

Jørgensen (1994) presents a relatively general wetland model able to predict nitrogen removal by wetlands. A wide spectrum of wetland models has been proposed lately (e.g., see Jørgensen et al., 1995). The various models that only focus on nitrogen removal can easily be expanded to also cover heavy metal and phosphorus removal by adsorption. A simple adsorption isotherm can be added to consider the removal of phosphorus and nitrogen by harvest at day m of the wetland. The climatic information and some site specific properties of the focal wetland(s) (e.g., content of organic matter, plant species, hydraulic conductivity of the soil) must be assessed before a calibration, a validation and a prediction with use of the model can occur.

5.5.5 *Fisheries Models*

Augmented exploitation of freshwater fish resources by sport and commercial fishery (see Section 2.1.4), and the deterioration of water quality, has stimulated concern about the depletion of fish stocks.

This reality has intensified the development models which take into account the effects of harvesting and water quality on the fish population. Models with a wide spectrum of complexity attempt to provide a management tool to assess an optimum fishery strategy.

For lakes with important commercial fisheries, landing records are often available for periods of multiple decades, and may open the possibilities of developing a statistical fisheries model. However, a statistical model generally does not take into account a number of important factors, such as interactions among species, water quality and changes in the concentrations of fish food. A statistical model would build on the assumption that present and past properties of the environment and the fish populations will be maintained. Statistical models will not be discussed further here, primarily because they do not consider the influences of water quality. It should be mentioned, however, that the International Lake Environment Committee (ILEC) has developed a software that contains among several models, a simple eutrophication model with four state variables. It also computes the fish population with a simple regression equation relating primary production and the fish population.

The simplest approaches assume that the entire fish population is homogeneous, and does not consider the population dynamics and related age structure, which is essential for

fishing policy. The more complex approaches consider the influences of water quality on the population dynamics and the age structure of the fish populations.

5.5.6 *Models of Biomanipulation*

Success with biomanipulation varies considerably from case to case, depending on the specific circumstances (see Section 4.3.1). Thus, modelling seems an obvious tool to use in selecting biomanipulation as a control measure, since the primary task of management models is always to predict the results of alterations in an ecosystem. However, biomanipulation implies that the structure of the ecosystem (i.e., a lake) is changed, which is much more difficult to simulate with a model than is a simple change in forcing functions. On the other hand, structurally dynamic models are emerging (e.g., see Jørgensen, 1992a, 1992b). Models are increasingly used as an experimental tool that can sometimes also be used to explain ecosystem behavior associated, for example, with chaos and catastrophe theories (Jørgensen, 1992b).

Models based on case studies with structural changes are still rare. However, we know that ecosystems have the ability to adapt to changed forcing functions, and to shift to species better suited to emerging conditions. Because radical changes are imposed on ecosystems, which inevitably will lead to the most pronounced changes in ecosystem structures, it is particularly interesting to apply models with dynamic structures, which are becoming increasingly important in environmental management. Thus, this type of model is discussed in this section in relation to lake and reservoir biomanipulation.

Biomanipulation is based on changes in ecosystem structure imposed by intentional changes in fish populations. In this context, it is of interest to explain when and why top-down control measures are working (i.e., when the imposed structural changes can be predicted to work). This is also possible with the use of catastrophe theory on lake eutrophication models.

The short-term results of biomanipulation have been encouraging. It is unclear, however, whether or not a manipulated ecosystem will ultimately return to the initial eutrophic and turbid conditions. Some observations suggest that, if low nutrient concentrations are combined with a relatively high concentration of predatory fish, a stable steady state will be attained, while high nutrient concentration and high predatory concentration will lead to an unstable clear water state (see Hosper, 1989; Van Donk et al., 1989). On the other hand, turbid conditions may prevail even at medium nutrient concentrations, provided that the predatory fish concentration is low. By introducing more predatory fish, however, the conditions may improve significantly, even at medium nutrient concentrations.

Willemsen (1980) distinguishes in the temperate region into two possible conditions:

- A "bream state" characterized by turbid water, and a high degree of eutrophication relative to the nutrient concentration. Submerged vegetation is largely absent from such systems. Large amounts of bream are found, while pike are rarely found.
- A "pike state" characterized by clear water, and a low degree eutrophication relative to the nutrient level. Pike are abundant, while significantly fewer breams are found, compared with the "bream state". Willemsen's work shows that the pike/bream ratio

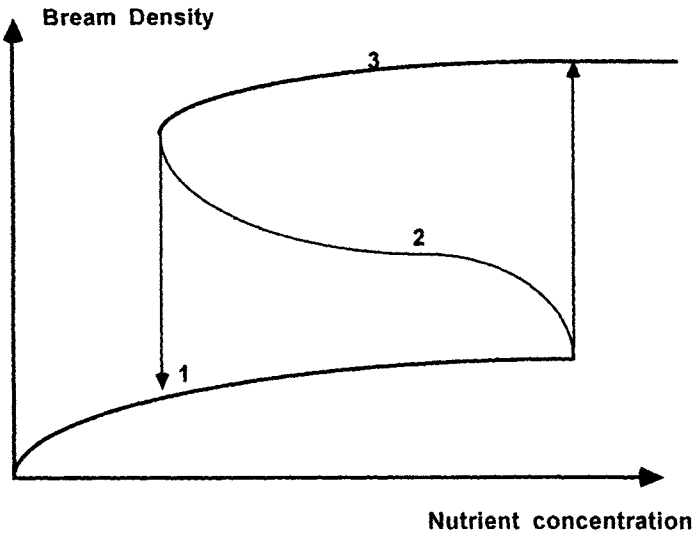

Fig. 5.14. A catastrophe fold shown by means of a projection of the intersection line of isocline planes of bream and pike on the nutrient–bream plane.

is strongly correlated with water transparency and that the separation between the two states is relatively distinct.

This behavior is clearly analogous to other examples described by catastrophe theory applied to biological systems (Jørgensen, 1992a, 1994). Figure 5.14 shows the catastrophe fold, where a bream isocline is plotted in relation to the nutrient concentration, assuming that the pike population is in a steady state. The isocline consists of the stable parts, 1 and 3. The unstable part, 2, corresponds to the "jump" between the two stable points.

The discontinuous response to increasing and decreasing nutrient levels implies that decreased nutrient levels will not cause a significant decrease in lake or reservoir eutrophication, and a significant increase in water transparency, before a rather low level has been attained. It may be possible, however, to "push" the equilibrium from point 3 to point 1 with the addition of predatory fish. This modelling example illustrates that two different concentrations of planktivorous fish can coexist with a certain nutrient concentration, which explains the hysteresis reaction shown in Figure 5.14. The general modelling experience is that a given set of forcing functions will give a certain set of state variables, including the concentration of planktivorous fish. However, when the set of equations that describe the ecosystem has a formulation causing catastrophic behavior in the mathematical sense, the reactions described above are observed.

To further explain these observations, models have been used as an experimental tool in the sense that the model description is in accordance with well-working lake models, but for which simulations with forcing functions for which there are no data available to control the model output, are carried out. The model used for these experiments is shown in Figure 5.15. Only phosphorus is considered as a nutrient in this case, although it is

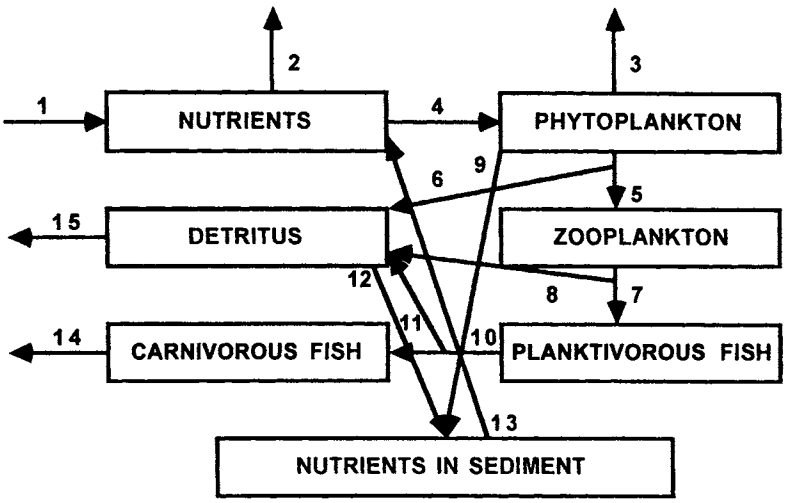

Fig. 5.15. The model used as an experimental tool. The state variables are nutrients (only phosphorus is considered in this case), phytoplankton, zooplankton, planktivorous fish, carnivorous fish, nutrients in sediment and detritus. The processes are: 1—inflow of nutrients, 2—outflow of nutrients, 3—outflow of phytoplankton, 4—uptake of nutrients by phytoplankton for growth, 5—grazing, 6—loss of detritus by grazing, 7—predation on zooplankton, 8—loss of detritus by this predation, 9—settling of phytoplankton, 10—predation by carnivorous fish, 11—loss of detritus by this predation, 13—release of nutrients from the sediment, 14—catch of fish, 15—outflow of detritus.

feasible to consider both nitrogen and phosphorus. The model encompasses the entire food chain. The modelling problem in the case of different inputs of nutrients, however, is that the phytoplankton, zooplankton, planktivorous and carnivorous fish are all able to adjust their growth rates within certain ranges. Thus, it is necessary to test a series of simulations with different combinations of growth rates to find which combination can give the highest probability of survival for all four classes of species.

The results of these simulations can be summarized in the following points:

- Between a total phosphorus (TP) concentration of 60–125 $\mu g\ l^{-1}$, two levels of planktivorous fish give a stable situation, with a high probability of survival for all four classes of species. The level with the lowest level of planktivorous fish give the highest concentration of zooplankton and carnivorous fish, while the phytoplankton concentration is lowest. This interval from 60–125 $\mu g\ l^{-1}$ is, of course, dependent on the model descriptions of the lake and must not be taken as fixed values for all lakes. Rather, they only indicate that there is an interval corresponding approximately to mesotrophic conditions and two stable situations.
- The stable situation with the lowest level of planktivorous fish corresponds to the lowest growth rate of zooplankton and phytoplankton, which normally implies species that are larger in size (see Peters, 1983).

- Only one stable level is achieved at total phosphorus concentrations below 60 $\mu g\ l^{-1}$ or above 125 $\mu g\ l^{-1}$. The zooplankton, relative to the level of phytoplankton, are present in highest levels at total phosphorus concentrations below 60 $\mu g\ l^{-1}$ and at relatively low levels above 125 $\mu g\ l^{-1}$.
- When the planktivorous fish are present at low concentrations either below total phosphorus concentrations of 60 $\mu g\ l^{-1}$, or between 60–125 $\mu g\ l^{-1}$, the phytoplankton is controlled by the relatively high zooplankton level (i.e., the grazing pressure), while phytoplankton at a high planktivorous level above total phosphorus concentrations greater than 60 $\mu g\ l^{-1}$ is controlled by the nutrient concentration.

As already underlined, this exercise should only be considered qualitatively. However, the results suggest that the use of biomanipulation only seems to be successful at an intermediate nutrient level, which is consistent with the results of many biomanipulation experiments (see Section 4.3.1). The range at which biomanipulation can be used successfully is most probably dependent on the specific conditions in the considered lakes, which unfortunately makes it problematic to use results described in this section more qualitatively. The model example here uses a test of many combinations of growth rates to find the best combination of parameters from a survival perspective. This adjustment of the parameters corresponds to adaptation within some ranges, and for more radical changes of the parameters to a change in the species composition in the lake. If models are to be used as management tool in cases where significant changes in nutrient levels will occur, or where biomanipulation is being considered, it is necessary to develop models that can account for structurally dynamic changes. However, this type of model development is still in its infancy, and only limited experience is available.

Our present models have generally rigid structures and a fixed set of parameters, indicating that no changes or replacements of the components are possible. However, it is necessary to introduce parameters (properties) that can change according to changing general conditions for the state variables (components). The current idea is to test if a change of the most crucial parameters produces a higher so-called goal function of the system and, if so, to use that set of parameters.

The type of models that can account for changes in species composition, as well as for the ability of the species (i.e., the biological components in the models) to change their properties (i.e., to adapt to the prevailing conditions imposed on the species), are as indicated in the introduction to this section; namely, the so-called *Structurally Dynamic Models* (see Fig. 5.16). They also may be called the next or fifth generation of ecological models, in order to emphasize that they are radically different from previous modelling approaches and can do more; namely describing changes in species composition.

It can be argued that the ability of ecosystems to replace present species with better-fitted species, can be considered by constructing models that encompass all the actual species for the entire period the model attempts to cover. However, this approach has two essential disadvantages. First, the model becomes very complex, since it will contain many state variables for each trophic level. It implies the model will contain many more parameters that have to be calibrated and validated, and which will introduce a high uncertainty to the model predictions, rendering the application of the model very case-

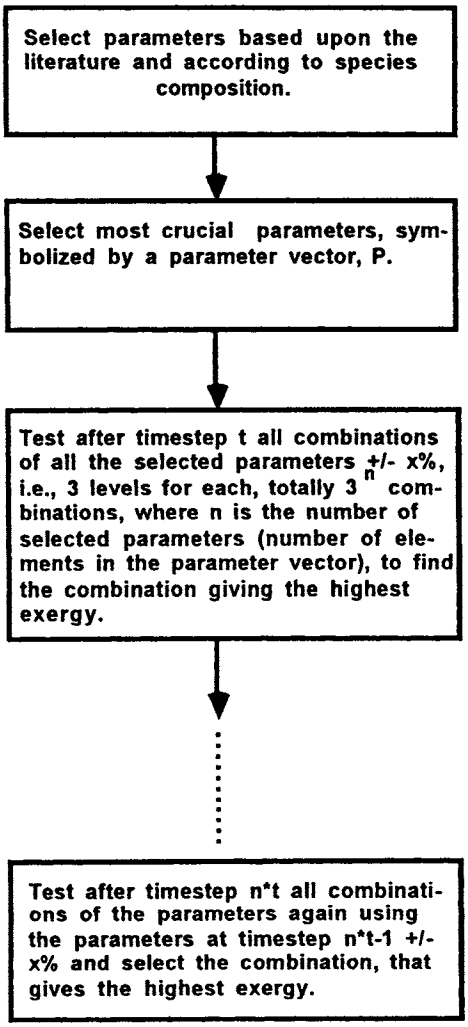

Fig. 5.16. The procedure used to develop structurally dynamic models.

specific (Nielsen, 1992a, 1992b). In addition, the model will still be rigid and not give the model the ecosystem property of having continuously changing parameters even without changing the species composition (Fontaine, 1981).

Structurally Dynamic Models can be developed by a current change of some of the most crucial parameters, reflecting the change of species. These changes may be based on expert knowledge, or may be determined with the use of a goal function. In the first case, the changes of parameters are made in accordance with good knowledge of the dominant species under different conditions (i.e., different combinations of forcing functions).

Reynolds (1996) illustrates this approach. In the latter case, the parameters currently are changed according to goal functions. Several goal functions have been proposed, but only a few models accounting for changes in species composition, or for the ability of species to change their properties within some limits, have been developed. Straškraba (1979) used a maximization of biomass as the governing principle (i.e., the above-mentioned goal function). The model computes the biomass and adjusts one or more selected parameters to achieve the maximum biomass at every instance. The model has a computation program that computes the biomass for all possible combinations of parameters within a given realistic range. The combination that gives the maximum biomass is selected for the next time step, etc. However, biomass can hardly be used in models with more trophic levels, and it will lead to biased results by, for example, adding together the biomass of fish and phytoplankton. The thermodynamic variable, exergy, has been used most widely as a goal function in ecological models; see Jørgensen (2002) and Section 5.5.9.

The modelling experience shows that models can help explain why biomanipulation works under some circumstances, and why it does not work under other circumstances. The applications of catastrophe theory and/or structurally dynamic models are able to explain the appearance of hysteresis in the relations between nutrient level and eutrophication (see Fig. 5.17). The results can be used to help explain that this hysteresis relationship exists in an intermediate nutrient level, which explains why biomanipulation in this range of nutrient concentrations has worked properly (i.e., with long-term effects), but not above or below this intermediate range.

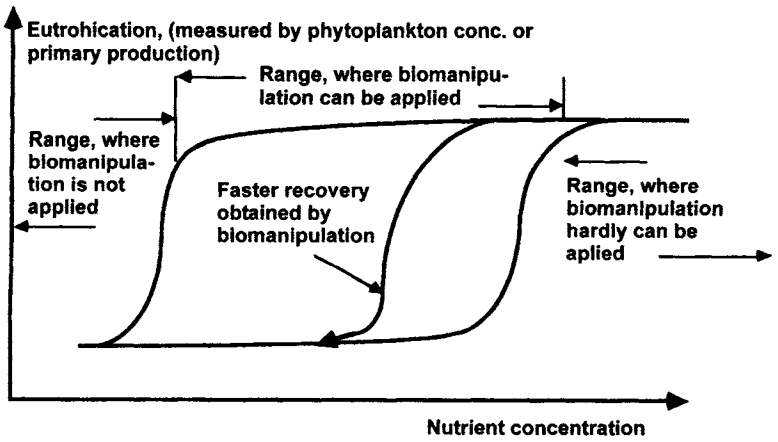

Fig. 5.17. The hysteresis relation between nutrient level and eutrophication measured by the phytoplankton concentration or the primary production. The possible effects of biomanipulation are shown. As shown, will it be able to short cut between the high eutrophication structure and the low eutrophication structure? An effect of biomanipulation can hardly be expected above a certain concentration of nutrients, as indicated on the diagram. Below a certain nutrient concentration, biomanipulation will not be applied, since eutrophication is too low to expect any effect.

Models have been an applicable tool in efforts to understand biomanipulation results. The results may be summarized in the following recommendations for using models for managing biomanipulation:

- Attempt either to use a structurally dynamic model or catastrophe theory to examine the possibilities of using biomanipulation.
- Consider the results only as approximations, unless very good data for applying structural dynamic models are available.
- Consider intermediate nutrient levels, between approximately 60 $\mu g\ l^{-1}$ and 125–140 $\mu g\ l^{-1}$ of total phosphorus, or 7 times higher concentrations for nitrogen if it is the limiting nutrient, as the range within which biomanipulation will most probably work.

The results obtained by modelling and in-lake biomanipulation experiments may be explained by the presence of ecological buffer capacities and time lags in structural changes. When the nutrient level is increased (see Fig. 5.17), the degree of eutrophication will initially not increase significantly. The lake ecosystem has an ecological buffer capacity, which can be explained by increased grazing and settling of the phytoplankton resulting from increased nutrient levels. At a certain nutrient level, however the zooplankton can no longer control the phytoplankton concentration, which becomes limited only by the nutrient level. The result is that the eutrophication level increases considerably with increased nutrient levels. The entire structure of the ecosystem is changed because phytoplankton is now limited by nutrients, zooplankton are limited by predation from planktivorous fish rather than by the available food source (phytoplankton), and the planktivorous fish are now limited by the food source (zooplankton) rather than by the carnivorous fish.

This implies that other properties are selected (e.g., other growth rates). Further, the carnivorous fish will be scarce since they mostly hunt by sight, with the increasing eutrophication causing an increased turbidity and, therefore, making hunting more difficult.

If nutrient levels are now decreased, for example, by discharging wastewater with significantly lower nutrient concentrations, will this "high eutrophication structure", characterized with a low concentration of carnivorous fish, high concentration of planktivorous fish, low concentration of zooplankton, and high concentration of phytoplankton, change immediately?

Thus, the low transparency will still make an increase in the carnivorous fish difficult to achieve, and grazing will still not able to control the phytoplankton concentration. This is because they are present in relatively low concentrations, since they are still under stress from considerable predation pressure by planktivorous fish. In this situation, will biomanipulation either by removal of planktivorous fish and/or introduction of more carnivorous fish, give a clear effect, as shown in Figure 5.17? Biomanipulation simply provides a faster recovery to the "low eutrophication structure", where grazing controls the phytoplankton concentration. Outside the intermediate nutrient level, the forcing functions (input of nutrients) determine the state of eutrophication.

Models are a useful tool for trying to understand the function of biomanipulation, including the fact that it sometimes gives positive results, and sometimes negative results. Models generally should be used as a tool to try to qualitatively understand the behavior of complex systems (e.g., lake ecosystems). When a good data base is available, mod-

Table 5.11. Some sediment oxygen demand values (g O_2 m^{-2} day)

Bottom type	Range	Average
Filamentous bacteria (10 g m^{-2} dry wt.)	5–10	7
Municipal sewage sludge—out fall vicinity	2–10	4
Municipal sewage sludge—downstream of outfall	1–2	1.5
Estuarine mud	1–2	1.5
Sandy bottom	0.2–1.0	0.5
Mineral soils	0.05–0.1	0.07

els can sometimes be used quantitatively in environmental management, an example being the control of eutrophication by wastewater management (e.g., see Jørgensen and Vollenweider, 1988; Jørgensen, 1986b, 1994). The use of models in a quantitative sense for biomanipulation efforts is possible by applying structural dynamic models. However, because our experience with this latter type of models is limited, the modelling results should not be the sole management decision criteria, although the results may be used in a qualitative way. Thus, there is a clear need for the use of models in management and selection of biomanipulation techniques to try to answer such questions as: Can biomanipulation give the desired results? How many planktivorous fish must be removed and/or how many carnivorous fish must be added? How many times, and with which frequency, should biomanipulation be used to ensure the anticipated results? Such questions can only rarely be answered today with the use of models, primarily because the data requirements would be too great for most case studies. Thus, it is recommended that more case studies on the use of models under such conditions be developed and supported with good data sets. Only with increased experience in using models for biomanipulation purposes can the urgently needed management tools be developed.

5.5.7 *Most Commonly-Applied Dynamic Water Quality Models and DDS*

Some of the commonly-applied models for practical water quality management of lakes and reservoirs, particularly deep, stratified ones, belong to the category of coupled hydrodynamic–ecological models (Orlob, 1983, 1984; Varis, 1994). The reason for coupling detailed hydrodynamics (Martin and McCutcheon, 1999) and basic chemical and biological processes is that hydrodynamic conditions vary widely, depending on changes in inflows and meteorology. The variability is particularly great in reservoirs under various operational regimes. The depth and time distribution of the chemical compounds in them is highly affected by currents and other movements of water masses, and the biological processes react on physical conditions both directly and indirectly via chemistry.

The coupled hydrodynamic–ecological models are used to simulate time-dependent water quality conditions under different meteorological conditions, eutrophication or its abatement, and increasing or decreasing pollution, in order to evaluate the consequences of different management strategies. Further, the conditions existing shortly after a reservoir is filled (the aging process—see Section 6.5.4) can be simulated, and also the conditions in reservoirs subject to different operation regimes, undergoing dam reconstruction and/or

turbine repair. With modern personal computers, the simulation of one-year cycles can be done in a few minutes, and the *scenario analysis* (comparative analysis of a number of model runs) can be used as a basis for making decisions. The manager can see, with the graphical model outputs, the probable consequences of different variants of management actions under different hydrological and meteorological situations.

The input conditions needed to run the models are lake morphometry, annual cycles of hydrology and meteorology, and chemical and biological conditions of the inflows. Particularly important is the knowledge (or reasonable assumptions about) the inflow water density, particularly as determined by temperature and salinity. The morphometry is characterized particularly by the area and volume curves. In the case of reservoirs, it also is characterized by the slope of the bottom and sides of the reservoir. The character of the outflow structure and operation regimes are important as well.

The *hydrodynamic part* of the model provides information on the physical structure of the water masses under different external conditions. Its final output is usually the water temperature stratification. However, for the chemical and biological components, the intensity of mixing and exchange among different strata is the decisive output used. The hydrodynamic models are categorized according to the space dimensions being considered, as one-, two- or three-dimensional.

One-dimensional models provide the depth distribution of the physical properties in the deepest part of the waterbody and the water movements. In addition, *two-dimensional models* provide the longitudinal profile, which is important for reservoirs. The most complicated are the *three-dimensional models*, which treat the full volume of a waterbody in both the horizontal and vertical directions. The one-dimensional models are adequate for most management purposes, but two-dimensional models may be necessary if the knowledge of the longitudinal distribution in a reservoir is important for a manager. The use of a three-dimensional model may be necessary for large lakes, as well as lakes and reservoirs with complicated shapes.

The *ecological part* of the model provides information on the chemical and biological components of interest to the manager. The biological part need not be directly used by the manager, but must be considered because of the close interactions between water chemistry and biology. Only the conservative chemical components (e.g., salinity) do not strongly interact with the biological components, although most chemical variables are either directly used and/or released by organisms, or are affected by other chemical changes produced during photosynthesis, respiration and decomposition. As an example, changes in pH and oxygen conditions in a lake or reservoir can affect most chemical reactions. There also is a feedback between lake thermics and phytoplankton, in that higher radiation adsorption by phytoplankton can lead to more heat accumulation in the upper water layer, surface temperatures increase and the thermocline will be located at a shallower depth. Phytoplankton growth is enhanced by the higher temperature (Straškraba, 1998a).

Few of the existing models have found broad application (Table 5.12). In Russia and Ukraine, similar models have been developed by Oleg Vasiliev and co-workers (Vladivostok), mainly from the hydrodynamic perspective, and by Vladimir Lavrik (Kiev) mainly from the mathematical perspective (e.g., Lavrik et al., 1990). In addition to the

Table 5.12. Examples of coupled hydrodynamic–ecological models

- LAKE ONTARIO model (Scavia and Chapra, 1977) is a multi-purpose ecological model developed specifically for the Great Lakes, particularly Lake Ontario.
- SALMO (Benndorf and Recknagel, 1982) includes schematic distinction into epilimnion and hypolimnion, interactions between phytoplankton biomass and changing external nutrient load, temperature, light, mixing and zooplankton. SALMOSED (Recknagel and Benndorf, 1995) includes exchange of phosphorus between water and sediments.
- RESQUAL by Stefan and Cardoni (1982) was applied to Lake Chicot and was the basis for further models designed by the group associated with Heinz Stefan at the University of Minnesota (see MINLAKE).
- CE-QUAL-RIV1 is a derivative of the model CE-QUAL for water quality in larger rivers (Bedford et al., 1983; Anonymous, 1986—manual for application). The model was originally destined "for crude planning analysis of reservoir eutrophication" (Wlosinski and Collins, 1985), but was continuously extended into two-dimensional forms. The model is distributed free by the USEPA and is broadly used, particularly in the Americas (e.g., Anonymous, 1995; Diogo and Rodrigues, 1997).
- FINNISH THREE DIMENSIONAL WATER QUALITY–TRANSPORT MODEL by Virtanen et al. (1986) concentrates first of all on longitudinal flows in complex shaped reservoirs (Koponen et al., 1998).
- WASP4 (Ambrose et al., 1988) includes hydrodynamics, conservative mass transport, eutrophication, oxygen and toxic chemical-sediment dynamics. The model is also distributed free by USEPA, including documentation. The model is used in the USA for many predictions, a recent list mentioned, for example, by Tufford et al. (1998).
- MINLAKE (Riley and Stefan, 1988) was recently extensively modified to allow estimation of the effect of climate changes on USA lakes (Stefan and Fang, 1994a) and dissolved oxygen conditions for regional lake analysis (Stefan and Fang, 1994b).
- MIKE (Anonymous, 1998a) is originally a model with a simplified two-layer representation. A new version MIKE11 was presented by the Danish Hydraulic Institute (Agern Alle 5, Horsholm) and represents a two-dimensional vertical hydrodynamic flow model coupled with an eutrophication model covering 12 state variables, including inorganic nutrients, phytoplankton, zooplankton, detritus and dissolved oxygen. Used in Denmark and England, but also applied elsewhere. A number of additional models for estimating the loads from watershed (CATCHMENT, LOAD, WETLAND) and other water quality processes are also available (Anonymous, 1998a).
- ASTER and MELODIA (Salençon and Thèbauld, 1994a, 1994b, 1995) were applied in France to model stratification and biological conditions in Pareloup Reservoir. The hydrodynamic part represents a separate model, EOLE (Salençon, 1997).
- DYRESM–WQ, the DYnamic REServoir Model–Water Quality (Schladow et al., 1994; Hamilton and Schladow, 1997; Schladow and Hamilton, 1995, 1997; Hamilton and De Stasio, 1998; Hamilton, 1999) is based on the hydrodynamic model DYRESM by Imberger and Patterson (1981). The water quality model simulates stratification and flow conditions, phytoplankton, nutrients (different forms of phosphorus and nitrogen), oxygen, biochemical oxygen demand (BOD), iron and manganese, and sedimentation. It is being systematically extended, with CE-QUAL the most widely used water quality model. However, the cost of the model available from the Water Research Centre (University of Western Australia, Nedlands, Western Australia) is high. A standard one-dimensional, a two-dimensional hydrodynamic (Hocking and Patterson, 1988, 1991), and most recently a three-dimensional water quality version (Romero and Imberger, 1999), also exist. An extension of the model to simulate the consequences of artificial destratification was formulated by Schladow and Hamilton as used, for example, by Lindenschmidt and Chorus (1997) and Schlenkhof (1997).

Table 5.12 (*continued*)

- BEEKWAM is intended for nonstratified embankment reservoirs in The Netherlands. It combines an empirical equilibrium temperature model with differential equations for nutrients and algal growth. Matlab® and Simulink® are used as simulation tools (Benoist et al., 1998).
- PROTECH–C (from Phytoplankton RespOnses To Environmental Change) is a two-dimensional model directed to detailed representation of species specific phytoplankton reactions on external effects, including the meteorological, hydrological and anthropogenic effects (Anonymous, 1998b). The model from the Algal Modelling Unit (Institute of Freshwater Ecology, Far Sawrey, Ambleside, Cumbria, UK) is based on extensive scientific phytoplankton studies by Reynolds (1987, 1992, 1998, 1999a, 1999b) and is used by a number of water quality agencies in UK.

models listed in Table 5.12, some of the more complex ecological models without elaborate hydrodynamics have been used for water quality management decisions, particularly for the more simple, shallow waterbodies, including:

- The model of Jørgensen et al. (1978), which was first applied to Lyngby Lake during 1952–1958. The model also closely matched the conditions which later changed during 1959–1975.
- AQUAMOD, the AQUAtic MODel by Straškraba (1976) is a simple eutrophication-oriented model. In the extended version, the model GIRL OLGA (mentioned below) was used for Czechoslovakian reservoirs. The model also exists in a two- and three-layer version, including sediments (Straškraba and Gnauck, 1985; Dvorkov and Kozerski, 1980). Gnauck et al. (1990) have used the modelling system SONCHES to apply AQUAMOD in Germany.
- BLOOM, particularly in the form of BLOOM II (Los and Brinkman, 1988; Los, 1991), examines the eutrophication of shallow lakes, and was systematically extended into DELWAG-BLOOM-SWITCH for control of eutrophication of lake and channel systems in The Netherlands (van der Molen et al., 1994).
- The CONSTANT SEDIMENT FEEDBACK PHOSPHORUS MODEL and WATER–SEDIMENT MODEL by Chapra and Canale (1991) concentrates on phosphorus conditions, particularly its exchange with the sediments. Thus, they are relevant for evaluating the consequences of phosphorus abatement strategies.
- PCLAKE, the shallow lake model designed specifically by Janse et al. (1993) for use on personal computers is systematically being extended to increase its usefulness for managing shallow lakes, particularly with respect to eutrophication and attempts to treat it using biomanipulation (Janse et al., 1995). It is also being applied to the problem of two multiple stable states of shallow lakes—the phytoplankton state and macrophyte state (Janse, 1997; Janse et al., 1998).
- The BALATON model by Kutas and Herodek (1986) is a complex model specifically designed to aid in the management of shallow Lake Balaton, characterized by high calcium content low amounts of zooplankton and high importance of bacterial processes.

These complex models are often framed into decision support systems (DSS), as described in Section 5.4. Presented below is a list of some DSS which may prove useful to a lake or reservoir water quality manager (Table 5.5). One part of a DSS often is the

GIS-based determination of pollutant loads, as well as evaluation of a lake water quality model, as discussed further in a following section.

5.5.8 *Environmental Risk Assessment (ERA)*

ERA can be defined as the process of assigning magnitudes and probabilities to the adverse effects of human activities. The process involves identification of hazards (e.g., the release of toxic chemicals to the environment) by quantification of the relationship between an activity associated with an emission to the environment and its impacts. The entire ecological hierarchy is considered in this context, implying that the impacts on the cellular level, organism level, population level, ecosystem level and the entire ecosphere should be considered.

The application of environmental risk assessment is rooted in the recognition that:

- The cost of elimination of all environmental effects is impossibly high,
- The decision in practical environmental management must always be made on basis of incomplete information.

Humans use about 100,000 chemicals in such quantities that they may threaten the environment. However, we only know a small fraction about what we must know about these chemicals to be able to make a proper and complete environmental risk assessment of them.

ERA is a process complementary to environmental impact assessment, EIA (Jørgensen, 1991), with the latter used to assess the impacts of a human activity. EIA is predictive, comparative and concerned with all possible effects on the environment, including secondary and tertiary (indirect) effects, while ERA attempts to assess the probability of a given (defined) adverse effect resulting from a considered human activity.

Both ERA and EIA use models to find the *expected environmental concentration* (EEC), which is translated into impacts for EIA, and to risks of specific effects for ERA.

Uncertainty plays an important role in risk assessment. Risk is the probability that a specified harmful effect will occur or, in the case of a graded effect, the relationship between the magnitude of the effect and its probability of occurrence.

Risk assessment has emphasized risks to human health, ignoring ecological effects to a certain extent. However, it has now been acknowledged that some chemicals with little or no risk to human health can cause severe effects to aquatic and other organisms. Examples include chlorine, ammonia and certain pesticides. An up-to-date risk assessment, therefore, comprises consideration of the entire ecological hierarchy, which is the ecologist's perspective in terms of level of organization. Organisms interact directly with the environment, and they are exposed to toxic chemicals. The reproducing population is the smallest meaningful level in the ecological sense. However, populations do not exist in vacuum, but rather within a community of other organisms of which the population is a part. The community occupies a physical environment, with which it forms an ecosystem.

Moreover, both the various adverse effects and the ecological hierarchy have different scale in time and space, which must be included in a proper environmental risk assessment (Fig. 5.18). For example, oil spills occur at a spatial scale similar to those of populations,

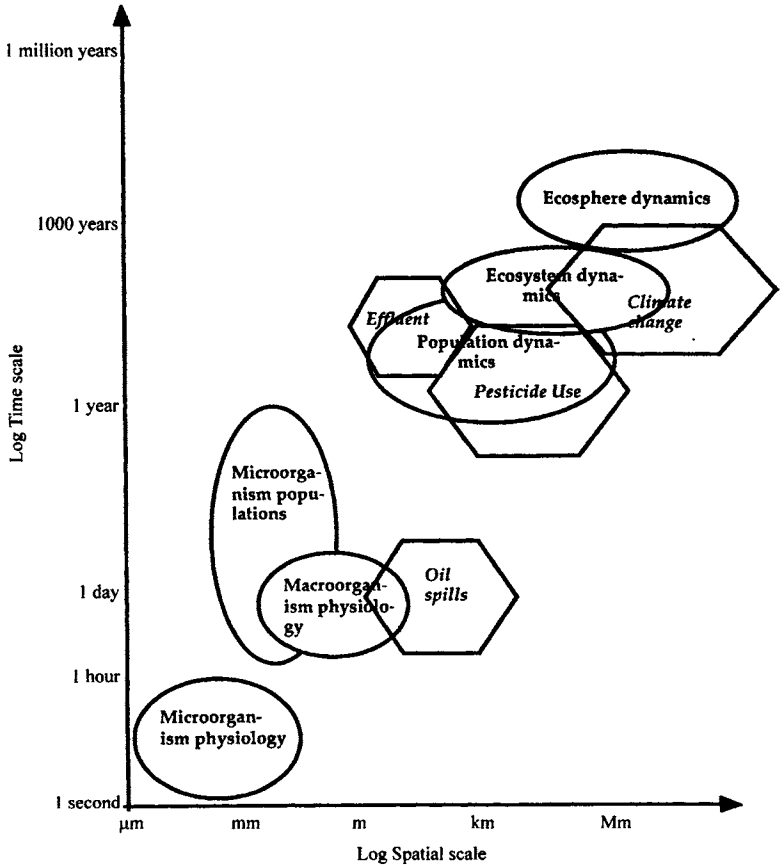

Fig. 5.18. The spatial and time scale for various hazards (hexagons, italic) and for the various levels of the ecological hierarchy (circles, nonitalic).

but they are briefer events than population processes. Thus, a risk assessment of a oil spill requires considerations of reproduction and recolonization that typically occur on a longer time scale than the spill, and that determine the magnitude of the population responses and its significance to natural population variance safety factors. Uncertainties have three basic causes:

- The inherent randomness of the world (i.e., stochasticity),
- Errors in execution of assessment,
- Imperfect or incomplete knowledge.

The inherent randomness refers to the uncertainty that can be described and estimated, but cannot be reduced because it is a characteristic of the system. The meteorological factors (e.g., rainfall, temperature, wind) are effectively stochastic at levels of interest for risk

assessment. Many biological processes, such as colonization, reproduction and mortality, also must be described stochastically.

Human errors are inevitably attributes of all human activities. This type of uncertainty includes incorrect measurements, data recording errors, computational errors, etc.

Lack of knowledge results in undefined uncertainty that cannot be described or quantified. It is a result of practical constraints on our ability to accurately describe, count, measure or quantify everything relevant to an estimate of risks. Prominent examples are an inability to test all toxicological responses of all species exposed to a pollutant, and simplifications needed in a model to predict the expected environmental concentration.

The most important feature distinguishing risk assessment from impact assessment is the emphasis in risk assessment on characterizing and quantifying uncertainty. Thus, it is of particular interest in risk assessment to be able to analyze and estimate the analyzable uncertainty. They include natural stochasticity, parameter errors and model errors. Statistical methods may provide direct estimates of uncertainties, and are widely used in model development (e.g., see Jørgensen, 1994).

The use of statistics to quantify uncertainty is complicated in practice by the need to consider errors in both the dependent and independent variables, and to combine errors when multiple extrapolations should be made. Monte Carlo analysis is often used to overcome these difficulties (e.g., see Bartell et al., 1984).

Model errors include inappropriate selection or aggregation of variables, incorrect functional forms and incorrect boundaries. The uncertainty associated with model errors are usually assessed by field measurements utilized for calibration and validation of the model (Jørgensen, 1994).

Risk assessment of chemicals can be divided into nine steps (Fig. 5.19). The nine steps correspond to questions the risk assessment attempts to answer in order to quantify the risk associated with the use of a chemical, as follows:

Step 1. Which hazards are associated with the application of the chemical? Answering this question involves gathering data on the types of hazards, including possible environmental damages and human health effects. The health effects include congenital, neurological, mutagenic and cancerogenic effects. It may also include characterization of the behavior of the chemical within the body (interactions with organs, cells or genetic material). What is the possible environmental damage, including lethal effects and sublethal effects on growth and reproduction of various populations?

A variety of toxicity tests has been devised to attempt to quantify the potential danger posed by chemicals. Some recommended tests involve experiments with subsets of natural systems (i.e., microcosms) or with entire ecosystems. The majority of the testing of new chemicals for possible effects, however, has been confined to laboratory studies on a limited number of test species. Results from these laboratory assays provide useful information for quantifying the relative toxicity of different chemicals. They are used to forecast effects in natural systems, although their justifications have been seriously questioned.

Step 2. What is the relation between dose and responses of the type defined above in Step 1? It implies knowledge of no effect concentration (NEC), LD_x-, LC_y- and

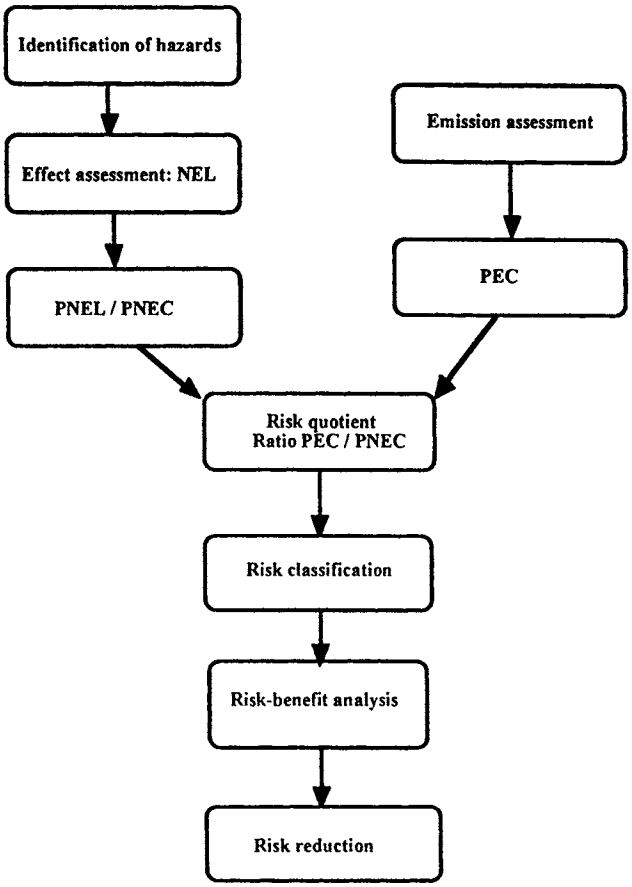

Fig. 5.19. The procedure for a nine-step risk assessment of chemical compounds. Steps 1–3 require extensive use of ecotoxicological handbooks and ecotoxicological estimation methods to assess the toxicological properties of the considered chemical compounds, while Step 5 requires a selection of a proper ecotoxicological model (PEC—predicted environment concentration; PNEL—predicted non-effect level; PNEC—predicted no effect concentration).

EC_z-values, where x, y and z express a probability of harm. The answer can be found by laboratory examinations or estimation methods. Based on these answers, a most probable *level of no effect, NEL*, is assessed.

Data needed for Steps 1 and 2 above can be obtained directly from scientific libraries. They also are increasingly being found via online data searches in bibliographic and factual databases. Data gaps should be filled with estimated data (e.g., see Jørgensen et al., 1997).

Step 3. Which uncertainty (safety) factors reflect the degree of uncertainty that must be taken into account when experimental laboratory data or empirical estimations methods

are extrapolated to real situations? Safety factors ranging from 10 to 10,000 are typically used. If adequate knowledge about a chemical is available, a safety factor of 10 may be applied. On the other hand, if the available information has a high uncertainty, a safety factor of 10,000 may be appropriate. Safety factors ranging between 100–1000 are most frequently applied. The result of NEL_x, the safety factor, is called the *predicted non-effect level, PNEL.* The complexity of environmental risk assessment is often simplified by deriving *predicted no effect concentration, PNEC,* for different environmental compartments (e.g., water, soil, air, biota, sediment).

Step 4. What are the sources and quantities of emissions? The answer to this question requires a complete knowledge of the production and use of the chemical compounds of concern, including an assessment of how much of the chemical is wasted to the environment by production and use? The chemical also may be a waste product, making it very difficult to determine the amounts involved. The very toxic dioxins, for example, are waste products of the incineration of organic waste.

Step 5. What is (are) the actual exposure concentration(s)? The answer to this question is called the *predicted environmental concentration, PEC.* Measuring environmental concentrations can assess exposure. It also may be predicted with a model when the emissions are known. The use of models is necessary in most cases, either because we are considering a new chemical, or because the assessment of environmental concentrations require a very high number of measurements to determine the variations in concentrations over time and space. Further, it always provides an additional degree of certainty to compare model results with measurements, implying that it is always advisable both to develop a model and to make at least a few measurements of concentrations in the ecosystem components, where the highest concentrations are expected. Most models will require an input of parameters which describe the properties of the chemicals and the organisms, and which also will require an extensive application of handbooks and a wide range of estimation methods.

The development of an environmental, ecotoxicological model, therefore, requires an extensive knowledge of the physical–chemical–biological properties of the considered chemical compound(s). The selection of a proper model is discussed in Section 5.4.

Step 6. What is the ratio *PEC/PNEC*? This ratio is often called the risk quotient. It should not be considered an absolute assessment of risks, but rather a relative ranking of risks. The ratio is usually found for a wide range of ecosystems (e.g., aquatic ecosystems, terrestrial ecosystems, ground water).

Step 7. How will one classify the risk? The valuation of risks are made in order to decide on risk reductions (Step 9). Two risk levels are defined:

- The upper limit (*maximum permissible level, MPL*), and
- The lower limit (*negligible level, NL*). It may also be defined as a percent of the *MPL.*

The two risk limits create three zones: A black, unacceptable, high risk zone > *MPL,* a gray, medium risk level, and a white, low risk level < *NL.*

Step 8. What is the relation between risk and benefit? This analysis involves examining socioeconomic, political and technical factors, which is beyond the topic of this volume.

The cost-benefit analysis is also difficult, because the costs and benefits are often of a different order.

Step 9. How can the risk be reduced to an acceptable level? The answer to this question requires a thorough technical, economic and legislative investigation before it can be given. Assessment of alternatives is often an important aspect in risk reduction.

Steps 1–3 and 5 require knowledge of the properties of the chemical compounds of concern, which again implies an extensive literature search and/or selection of the best feasible estimation procedure.

5.5.9 Structurally Dynamic Models

Our present models are built on generally-rigid structures and a fixed set of parameters. No change or replacement of components is usually possible. However, we also may need to introduce parameters (properties) which can vary according to changing general conditions for the state variables (components). The idea currently is to test whether a change of the most crucial parameters produces a higher so-called goal function of the system and, if so, to use that set of parameters.

As indicated in the introduction to this section, models that can account for change in species composition, and for the ability of the species (i.e., the biological components of the models) to change their properties (i.e., to adapt to the prevailing conditions imposed on them), are called *Structurally Dynamic Models*. (This model type was mentioned in Section 5.5.6 as they can explain success and failure of biomanipulation.) They also may be called the *next* or *fifth generation* of ecological models, in order to underline that they are radically different from previous modelling approaches and can do more, including describing changes in species composition.

It could be argued that the ability of ecosystems to replace current species with others that are better adapted to the ecosystem can be addressed by constructing models which incorporate all possible species for the entire study period. However, there are two essential disadvantages. First, such models become very complex, since they will contain many state variables for each trophic level. Thus, many more of them need to be calibrated and validated, which will introduce a high uncertainty, and render application of the model very case-specific (Nielsen, 1992a, 1992b). In addition, the model will still be rigid and not replicate the ecosystem property of parameters that are continuously changing without changing species composition (Fontaine, 1981).

Several goal functions have been proposed, but only a few models have been developed that can account for change in species composition, or for the ability of the species to change their properties within some limits. Straškraba (1979) used maximization of biomass as the governing principle (the goal function). The model adjusts one or more selected parameters, in order to achieve maximum biomass at every instance. A modelling software routine is included which computes biomass for all possible combinations of parameters within a given realistic range. The combination that gives the maximum biomass is selected for the next time step, etc. However, the biomass can hardly be used in models with more

trophic levels. To add the biomass of fish and phytoplankton together, for example, will lead to biased results.

The thermodynamic variable, exergy, has been used as a goal function in some ecological models. One of the few lake case studies available is discussed below. There are two pronounced advantages of exergy as a goal function, compared to entropy and maximum power (Odum, 1983). These are that (1) it is defined far from thermodynamic equilibrium, and (2) it is related to state variables which are easily determined or measured. However, because exergy is not a common thermodynamic function, it is first necessary to describe it.

Exergy expresses energy with a built-in measure of quality, quantifies natural resources, and can be considered as fuel for any system that converts energy and matter in a metabolic process (Schrödinger, 1944). Thus, ecosystems convert exergy, with exergy-flow through the system being necessary to keep it functioning. Exergy (as the amount of work the system can perform when brought into equilibrium with its environment) measures the distance from the "inorganic soup" in energy terms, as will be explained further below. Thus, exergy is dependent both on the environment and the system, rather than the system alone. This means, for example, that it is not a state variable like free energy and entropy.

If we assume a reference environment representing an ecosystem at thermodynamic equilibrium, the configuration illustrated in Figure 5.19 is valid. All components are inorganic, at the highest possible oxidation state, and homogeneously distributed in the system. Thus, as much free energy as possible is utilized to perform work (no gradients). As the chemical energy embodied in the organic components and the biological structure contributes the most by far to the exergy content of the system, there seems to be no reason to assume a (minor) temperature and pressure difference between it and the reference environment. Under these circumstances, we can calculate the exergy content of the system provided entirely by chemical energy as $\Sigma_c(\mu_c - \mu_{ceq})N_i$. We can also determine its exergy, compared with that of a similar system at the same temperature and pressure, but in the form of an inorganic soup without any life, biological structure, informational or organic molecules. Because $(\mu_c - \mu_{ceq})$ can be found from the definition of the chemical potential (replacing activities by concentrations), the following expressions for the exergy can be obtained:

$$Ex = RT \sum_{i=0}^{n} C_i \ln \frac{C_i}{C_{i,eq}}. \tag{5.6}$$

As seen, exergy measures the difference between free energy (given the same temperature and pressure) of an ecosystem, and that of the surrounding environment. If the system is in equilibrium with its surroundings, exergy is zero, with $n = 0$ accounting for inorganic compounds, and $n = 1$ corresponding to detritus.

Since the only way to shift systems away from equilibrium is to perform work on them, and since the available work in a system is a measure of its ability to do so, we need to distinguish between the system and its environment (or thermodynamic equilibrium alias the inorganic soup). Thus, it is reasonable to use the available work (i.e., exergy) as a measure of the distance from thermodynamic equilibrium.

Survival implies the maintenance of biomass, while growth means its increase. Exergy is needed to construct biomass, which then possesses exergy transferable to support other processes. Thus, survival and growth can be measured by use of the thermodynamic concept exergy, which may be understood as *the free energy relative to the environment* (see Equation 9.31).

Darwin's theory of natural selection (1859), therefore, may be reformulated in thermodynamic terms and expanded to an ecosystem level as follows: *The prevailing conditions of an ecosystem steadily change. The system will continuously select those species which contribute most to the maintenance, or even to the growth of the exergy of that system.*

Notice that the thermodynamic translation of Darwin's theory requires *populations* to possess properties of reproduction, inheritance and variation. The selection of species that contribute most to the exergy of the system under the prevailing conditions requires that there are sufficient individuals with different properties for selection to take place. Reproduction and variation must be high and, once a change has taken place, it must be conveyed to the next generation via better adaptation. It is also noted also that a change in exergy is not necessarily $\geqslant 0$, but rather depends on the resources of the ecosystem. However, the above proposition claims that an ecosystem attempts to reach the highest possible exergy level under the given circumstances with the available genetic pool (Jørgensen and Mejer, 1979).

It is not possible to measure exergy directly. However, it is possible to compute it if the composition of the ecosystem is known. C_i represents the ith component expressed in a suitable unit (e.g., for phytoplankton in a lake, C_i mg nutrient in the phytoplankton/liter of lake water) and $C_{i,\text{eq}}$ is the concentration of the ith component at thermodynamic equilibrium. For detritus, exergy can be found on basis of equilibrium constants, which give the ratio between the concentration of detritus in the ecosystem and that at thermodynamic equilibrium. The exergy content of detritus is approximately 18.7 kJ g^{-1}, which can be compared with the exergy (chemical energy) content of mineral oil (about 42 kJ g^{-1}).

For more complex compounds (e.g., unicellular organisms), $C_{i,\text{eq}}$ will be smaller. The probability of forming one *coli* bacterium or a simple phytoplankton cell can be estimated from the number of genes, which again determine the sequence of amino acids. It has been found by this method (Jørgensen et al., 1994) that the exergy content of phytoplankton is 3.4 times greater than that of detritus, because of their information content. Of course, the probability of forming multi-cell organisms at thermodynamic equilibrium is even lower, in that additional exergy is required to make up the more complex structure and to provide the information embedded in its structure. Thus, the exergy content of zooplankton is provisionally estimated to be around 35 times that of detritus, and fish to be more than 300 times. Such conversion factors for several classes of organisms are listed in Table 5.13.

Of course, proposals for the concentrations of various biological components at thermodynamic equilibrium do not lead to any exact value of exergy, or even of its exact relative change. However, they will account for relative changes caused by variations in the properties (parameters) of *organisms*. The inorganic constituents of an ecosystem do not create similar computational difficulties, but the thermodynamic equilibrium concentrations will be the total concentrations of the various elements, corresponding to the fact that all chem-

Table 5.13. Approximate number of nonrepetitive genes (Cavalier-Smith, Li and Grauer, Lewin)

Organisms	Number of information genes	Conversion factor*
Detritus	0	1
Minimal cell (Morowitz, 1992)	470	2.7
Bacteria	600	3.0
Algae	850	3.9
Yeast	2000	6.4
Fungus	3000	10.2
Sponges	9000	30
Moulds	9500	32
Plants trees	10,000–30,000	30–87
Worms	10,500	35
Insects	10,000–15,000	30–46
Jellyfish	10,000	30
Zooplankton	10,000–15,000	30–46
Fish	100,000–120,000	300–370
Birds	20,000	390
Amphibians	120,000	370
Reptiles	130,000	400
Mammals	140,000	430
Human	250,000	740

*Based on number of information genes and the exergy content of the organic matter in the various organisms, compared with the exergy contained in detritus; 1 g detritus has about 18 kJ exergy (= energy which can do work).

ical compounds in the primeval soup were in inorganic form, which we often use as the reference state for our exergy calculations.

The last few pages have presented the theoretical background for the application and development of structurally dynamic models. These are important tools in environmental management, as they account for current changes of species composition and the properties of the organisms in the focal ecosystem. The idea of the new generation of models presented here is to find a new set of parameters (limited for practical reasons to the most crucial, i.e., the most sensitive) better suited to the prevailing conditions of the ecosystem, as defined in the Darwinian sense by the ability of the species to survive and grow. As indicated above, this may be measured by the use of exergy (Jørgensen, 1986b, 1994; Jørgensen and Mejer, 1977, 1979). Figure 5.16 illustrates the proposed modelling procedure which has been applied in the cases presented.

The use of exergy calculations continuously to vary parameters has only been employed in nine case studies of biogeochemical modelling. One of these (Søbygaard Lake) is described here as an illustration of what can be achieved with this approach. The results (Jeppesen et al., 1989) are particularly fitted to test its applicability to structural dynamic models.

Søbygaard is a shallow lake (depth of 1 m) with a short retention time (15–20 days). The phosphorus nutrient load was significantly lowered in 1982, from 30 g to 5 g P m^{-2} yr.

However, the decreased load did not result in reduced nutrient and chlorophyll concentrations during the period 1982–1985 because of internal loading of stored nutrients in the sediment (Jeppesen et al., 1989).

Radical changes were then observed during the period 1985–1988. Recruitment of planktivorous fish was significantly reduced during the interval 1984–1988 because of a very high pH. The zooplankton increased, and the phytoplankton decreased in concentration, with the average summer chlorophyll-a concentration reduced from 700 $\mu g\ l^{-1}$ in 1985 to 150 $\mu g\ l^{-1}$ in 1988. The phytoplankton population even collapsed during shorter periods because of extremely high zooplankton concentrations.

Simultaneously, phytoplankton species increased in size. Their growth rates declined and higher settling rates were observed (Kristensen and Jensen). In other words, this case study illustrates that pronounced ecosystem structural changes were caused by biomanipulation-like events. However, the primary production was not higher in 1985 than in 1988, because of pronounced self-shading by smaller algae. Thus, it was very important to include a self-shading effect in the model. Simultaneously, sloppier feeding of zooplankton was observed, with a shift from *Bosmina* to *Daphnia* taking place.

The model contains six state variables, all of which represent different forms of nitrogen, including fish, zooplankton, phytoplankton, detritus nitrogen, soluble nitrogen and sedimentary nitrogen. The model equations are given in Table 5.14. Because nitrogen is the limiting nutrient for eutrophication in this particular case, it may be sufficient to only include this element in the model.

The aim of the study is to describe, by use of a structural dynamic model, the continuous changes in the most essential parameters, using the procedure shown in Figure 5.16. The data from 1984–1985 were used to calibrate the model. The two parameters which it was intended to change for the period 1985 to 1988 received the following values:

Maximum phytoplankton growth rate:	2.2/ day
Phytoplankton settling rate:	0.15/day

The state variable, fish nitrogen, was kept constant at 6.0 during the calibration period. During the period 1985–1988, however, an increased fish mortality was introduced to reflect the increased pH. Thus, fish stock was reduced to 0.6 mg N l^{-1}; notice the equation "mort = 0.08 if fish > 6 (may be changed to 0.6) else almost 0". A time step of $t = 5$ days and $x\% = 10\%$ was applied (Fig. 5.16). This means that nine runs were needed for each time step, in order to select the parameter combination giving the highest exergy. Changes in parameters from 1985 to 1988 (summer) are summarized in Table 5.15. It may be concluded that the proposed procedure (Fig. 5.16) can approximately simulate the observed change in ecosystem structure.

The maximum phytoplankton growth rate is reduced by 50% from 2.2/day to 1.1/day, approximately in accordance with to the increase in size. It was observed that the average size was increased from a few 100 μm^3 to 500–1000 μm^3, a factor of 2–3 (Jeppesen et al., 1989). This would correspond to a specific growth reduction by a factor $f = 2^{2/3} - 3^{2/3}$ (Jørgensen, 1994; Jørgensen et al., 2000).

Table 5.14. Model equations for Søbygaard Lake

fish = fish + dt × (−mort + predation)
INIT(fish) = 6
$na = na + dt$ × (uptake − graz − outa − mortfa − settl − setnon)
INIT(na) = 2
$nd = nd + dt$ × (−decom − outd + zoomo + mortfa)
INIT(nd) = 0.30
$ns = ns + dt$ × (inflow − uptake + decom − outs + diff)
INIT(ns) = 2
nsed = nsed + dt × (settl − diff)
INIT(nsed) = 55
$nz = nz + dt$ × (graz − zoomo − predation)
INIT(nz) = 0.07
decom = nd × (0.3)
diff = (0.015) × nsed
exergy = total_n × (Structural-exergy)
graz = (0.55) × na × $nz/(0.4 + na)$
inflow = 6.8 × qv
mort = IF fish > 6 THEN 0.08 × fish ELSE 0.0001 × fish
mortfa = (0.625) × na × $nz/(0.4 + na)$
outa = na × qv
outd = qv × nd
outs = qv × ns
pmax = uptake × 7/9
predation = nz × fish × $0.08/(1 + nz)$
qv = 0.05
setnon = na × 0.15 × (0.12)
settl = (0.15) × 0.88 × na
Structural-exergy = (nd + $\text{nsed}/\text{total}_n$) × (LOGN($nd$ + $\text{nsed}/\text{total}_n$) + 59) + ($ns/\text{total}_n$) × (LOGN($ns/\text{total}_n$) − LOGN($\text{total}_n$)) + ($na/\text{total}_n$) × (LOGN($na/\text{total}_n$) + 60) + ($nz/\text{total}_n$) × (LOGN($nz/\text{total}_n$) + 62) + ($\text{fish}/\text{total}_n$) × (LOGN($\text{fish}/\text{total}_n$) + 64)
$\text{total}_n = nd + ns + na + nz$ + fish + nsed
uptake = $(2.0 - 2.0 \times (na/9)) \times ns \times na/(0.4 + ns)$
zoomo = 0.1 × nz

Thus:

$$\text{the growth rate in 1988} = \text{the growth rate in 1985}/f, \tag{9.32}$$

where f is between 1.58 and 2.08. In the above table, the value of 2.0 is found with the use of the structurally dynamic modelling approach. Kristensen and Jensen observed that settling was 0.2 m day^{-1} (range 0.02–0.4) during 1985, but 0.6 m day^{-1} (range 0.1–1.0) in 1988. Using the structurally dynamic modelling approach, the increase was found to be 0.15 m to 0.45 m day^{-1}, a slightly lower set of values. However, the same (3) phy-

Table 5.15. Parameter combinations giving the highest exergy

	Maximum growth rate (day^{-1})	Settling rate ($m\ day^{-1}$)
1985	2.0	0.15
1988	1.2	0.45

toplankton concentration as chlorophyll-a was simultaneously reduced from 600 $\mu g\ l^{-1}$ to 200 $\mu g\ l^{-1}$, approximately in accord with observations.

In this case, it may be concluded that structurally dynamic modelling gave an acceptable result. Validation of the model, and the procedure in relation to structural changes, was positive. Of course, the approach is never better than the model applied, and the model presented here may be criticized for being too simple, and not accounting for changes in zooplankton.

For further elucidation of the importance of introducing parameter shifts, an attempt was made to run data for 1985 with parameter combinations for 1988, and vice versa. These results (Table 5.16) show that it is of great importance to apply the appropriate parameter set to given conditions. If those for 1985 are used for 1988, significantly less exergy is obtained, and the model behaves chaotically. The parameters for 1988 used under 1985 conditions give significantly less exergy.

Experience mentioned previously in this chapter shows that models can be applied to explain why biomanipulation may work under some circumstances, and not others. Qualitatively, the results can be used to explain that hysteresis exists over an intermediate range of nutrient loadings, so that biomanipulation has worked properly over this range, but not above or below it.

Another hysteresis behavior obtained with the use of structurally dynamic models for lakes have recently been published (Zhang et al., 2003a). It focuses on the structurally change between a dominance of submerged vegetation and phytoplankton in shallow lakes. The model results show that between about 100 and 250 $\mu g\ P\ l^{-1}$, both structures can exist—they show hysteresis in this range. This result is in accordance with observations from many shallow lakes.

Ecosystems are very different from physical systems, due mainly to their enormous adaptability. Thus, it is crucial to develop models that are able to account for this property, in order to derive reliable model results. The use of exergy as goal functions to cover the concept of fitness seems to offer a good possibility for developing a new generation of models, which are able to consider the adaptability of ecosystems and to describe shifts in species composition. The latter advantage is probably the most important, because a description of the dominant species in an ecosystem is often more essential than assessing the level of the focal state variables.

The structurally dynamic approach has also recently been used to calibrate eutrophication models. It is known that the different phytoplankton and zooplankton species are dominant in different periods of the year. Thus, a calibration based upon one parameter set for the entire year will not capture the succession which did take place over the year. By using exergy optimization to capture the succession (i.e., the parameter giving the best

Table 5.16. Exergy and stability by different combinations of parameters and conditions

Year	Parameter 1985	Conditions 1988
1985	75.0—Stable	39.8 (average)—Violent fluctuations, chaos
1988	38.7—Stable	61.4 (average)—Only minor fluctuations

survival for phytoplankton and zooplankton over the year), it has been possible to improve the calibration results (see Jørgensen et al., 2002).

The structurally dynamic modelling approach generally has been most widely applied in eutrophication models. A software package named Pamolare, and launched by the International Lake Environment Committee (ILEC) and the United Nations Environment Programme's International Environment Technology Centre (UNEP-IETC) also contains a structurally dynamic model, in addition to a conventional two-layer model. A test of this model has shown that it is calibrated and validated faster than the conventional model and gives better results, understood as a smaller standard deviation.

In other words, models are an appropriate tool in our efforts to understand the results of structural changes to ecosystems. In addition to the use of a goal function, it also is possible to base the structural changes on knowledge, for example, of what conditions under which specific classes of phytoplankton are dominant. This knowledge can be used to select the correct combination of parameters, as well illustrated by Reynolds (1996). That the combined application of expert knowledge and the use of exergy as a goal function will offer the best solution to the problem of making models work more in accordance with the properties of real ecosystems, cannot be ruled out. Such combinations would draw upon the widest possible knowledge at this stage.

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