NITROGEN TMDL DEVELOPMENT IN THE NEUSE RIVER WATERSHED: AN IMPERATIVE FOR ADAPTIVE MANAGEMENT

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The Neuse River estuary in North Carolina (Figure 1) is a typical example of a stressed coastal system. The estuary has been experiencing characteristic symptoms of nutrient overload including excessive algal blooms, low levels of dissolved oxygen, large fish kills, and outbreaks of toxic microorganisms (Burkholder et al., 1995; Paerl et al., 1998). These problems have been attributed to the high nutrient loading that generally results from the kinds of changes that have occurred in the watershed over the past several decades (NC Senate Select Committee on River Water Quality and Fish Kills, 1996; McMahon & Woodside, 1997) . The upper portion of the Neuse River drainage basin includes much of North Carolina's Research Triangle (defined by the cities of Raleigh, Durham, and Chapel Hill), an area that has experienced economic prosperity and rapid population growth since the 1970s. Population expansion and development are also occurring in lower portions of the basin with an increasing coastal population and a growing commercial hog-farming industry. Municipal wastewater treatment plants, urban runoff, and confined animal feeding operations, together with agricultural fertilizers, are considered to be major sources of nutrients in the Neuse watershed.

Violation of the chlorophyll a standard and growing public concern over water quality led the North Carolina Division of Water Quality (NC DWQ) to list the Neuse River estuary as an impaired water body under Section 303(d) of the Clean Water Act. Once a water body is listed on the Federal 303(d) list, the state must identify the pollutant causing the water quality impairment (in this case, chlorophyll a standard violations) and then develop a total maximum daily load (TMDL) for that pollutant. TMDLs are quantitative estimates of the pollutant loading that will still allow the water body to meet its water quality standards (while incorporating a "margin of safety"). The impaired condition of waters across the nation underlies the requirement that thousands of TMDLs for pollutants must be developed in the next ten years (NRC, 2001). As in many other marine systems, nitrogen has been identified as the pollutant of concern in the Neuse estuary because it is the nutrient believed to be stimulating the excessive algal growth that is the root of other eutrophication symptoms. Therefore the TMDL management decision to be made is: What percent nitrogen reduction is required to bring the estuary into compliance with the chlorophyll a water quality standard? Also of general interest is: How will these reductions address the concerns of the public? As in most such cases, because reducing nitrogen loading comes at an economic cost to some of the affected stakeholders, there are conflicting objectives influencing this decision.

UNCERTAINTY IN WATER QUALITY MODELING AND MANAGEMENT

For years after the passage of the 1972 Clean Water Act (CWA), the cornerstone of EPA strategy for surface water quality management was a phased schedule of increasingly stringent point source discharge controls through the National Pollutant Discharge Elimination System (NPDES). While water quality standards were established by the states, and total maximum daily loads were proposed in the 1972 CWA, point source controls were emphasized to achieve the goal to eliminate pollutant discharges to navigable waters by 1985. The consequences were less emphasis on the linkage between pollutant sources and effects, and a diminished need for water quality modeling because NPDES permits were typically technology, rather than water-quality, based. However, recent emphasis on the TMDL program as the focus of surface water quality management has greatly expanded the need for reliable water quality models.

To develop an effective TMDL, all significant sources of the pollutant must be identified, and predictive linkages must be established between the identified sources of pollution and the water quality standard variable. With the emergence of the TMDL program, it has been believed that mathematical water quality models would provide the scientific basis to quantify the pollutant-effect relationship. While models of increasing complexity have been developed and applied in the intervening years, there is increasing evidence that little confidence can be attached to the predictions of such models (NRC, 2001). One problem is that these detailed process-based models are over parameterized, meaning the model parameters cannot be uniquely determined from available data. This situation forces modelers to select parameter values from technical guidance documents (Bowie et al., 1985) with perhaps some ad hoc revision based on a visual comparison of predictions and observations. However, parameter values, such as reaction rates, are variable and depend on the spatial and temporal scale of observation (Adams & Reckhow, 2001). Choosing a single parameter value that is appropriate for the scale of the model application is problematic.

Indeed, while calibration studies may sometimes show a close fit between predictions and the observations to which models are calibrated, verification studies against different sets of data suggest that prediction errors may be large, particularly for models of higher resolution and greater mechanistic detail (Reckhow, 1994). This result should not be surprising, considering the complexity of natural systems relative to even the most sophisticated simulation models. We cannot possibly define all the mechanisms of aquatic systems and expect to construct accurate models based on a complete understanding of all parts (Pace, 2001).

Additionally, there is an increasing recognition that ecosystems behave as complex adaptive systems (Levin, 1999). Forecasting behavior in complex aquatic ecosystems is an inherently uncertain endeavor (Huisman & Weissing, 2001). Reconciling the proportion of the variance of future behavior that is predictable in complex ecosystems is an emerging frontier for researchers (Clark et al., 2001). The remaining variance, which captures the unpredictable system behavior, should be regarded as information that is characterized, quantified, and conveyed to decision-makers for explicit consideration in the decision process (Ludwig et al., 1993).

ADAPTIVE MANAGEMENT

Viewing environmental decisionmaking as a one-time event that will either succeed or fail depending on the predictive accuracy of a model may lead to management paralysis as decision-makers wait for better predictions. However, a large amount of uncertainty may be unavoidable, even with continued data collection and model development. Therefore, the "wait and see" approach will be less valuable than we intuitively expect. If instead we view decisionmaking as an ongoing, flexible process, preliminary actions can be taken that will improve our knowledge of system response and make simultaneous progress toward management objectives. After all, the true response of a natural system to management can only be learned through experience. This "learning by doing" approach is a pragmatic attempt to deal with growth, change, new information, and imprecise forecasting. This strategy, labeled "adaptive management," should not be an ad hoc game of trial and error, but rather an articulated succession of judgment-based decisions, followed by implementation, feedback, and readjustment (Holling, 1978; Walters, 1986). A flexible, updateable model that quantifies information on uncertainty can serve as the organizing principle behind this set of actions.

BAYESIAN PROBABILITY NETWORKS

The need for scientific modeling that will support adaptive decision-making under uncertainty suggests the use of a decision-analytic tool called a Bayesian probability network (Reckhow, 1999). Also known as causal networks, belief nets, Bayes nets, and influence diagrams, probability networks are graphical models that depict the nature of relationships among a number of uncertain variables. These relationships are quantified using models, data, or expert opinion that capture the aggregate effect of the dominant processes. The effects of secondary processes are summarized with probabilistic expressions. Such models are a more honest representation of our true knowledge of natural systems than deterministic simulation models that strive to include processes at very fine scales, offering the illusion of precision.

Fundamental to developing and using probability networks is depicting the model as a graph. In the graph, round nodes represent important system variables, and an arrow from one node to another represents a dependency between the corresponding variables. These dependencies may reflect causal relationships or the aggregate effect of more complex associations. For example, the classic phosphorus loading approach, successfully used to anticipate and control lake eutrophication in the 1970s (Chapra, 1980), can be described by a simple probability network (Figure 2). Algal density, measured by chlorophyll a concentration, is dependent on in-lake phosphorus concentration, which in turn is dependent on phosphorus loading and lake depth. The interesting point that is made explicit in the graph is that once the value of phosphorus concentration is known, the values of depth and phosphorus loading are not required to predict chlorophyll concentration. This conditional independence indicated by the lack of a connecting arrow between depth or phosphorus loading and chlorophyll concentration greatly simplifies the modeling process by allowing separate submodels to be developed for each conditional relationship. As in the original phosphorus loading approach, these submodels may represent any combination of process-based equations, statistical relationships, or expert judgment. However, unlike most integrated water quality modeling, probability networks make the assessment of uncertainty explicit by using probabilistic, rather than deterministic, representations. Each relationship indicated by an arrow in a probability network is quantified by a conditional probability distribution that describes the relative likelihood of each value of the down-arrow node, conditional on every possible combination of values of its predecessors. A node that has no incoming arrows is said to have no predecessors, and such a variable can be described probabilistically by a marginal (or unconditional) probability distribution.

The use of an inherently probabilistic model to represent a complex physical process may initially be uncomfortable to both scientists and decision-makers. However, one must take the view that, "the probabilistic model is a model, not of the physical process itself, but rather a coherent set of beliefs about it. Those beliefs incorporate knowledge of the physical process when that knowledge exists, but focus more on linkages among physical processes about which deterministic knowledge does not exist, but experience and opinion do. Such models therefore represent a compromise between pure judgment in probabilistic form and deterministic modelling" (Abramson et al., 1996).

This philosophy is consistent with the Bayesian approach to inference and decision (Winkler, 1972) which combines the formal properties of probability theory with the belief that probabilities, rather than being a physical trait of the system, are a way of expressing one's degree of knowledge about the system. With this view, key known or expected relationships can be represented without the full complexity, or information needs, of process-based models. Any additional variability or uncertainty not resulting from known processes is then described by probabilistic expressions that are either assessed using historical relative frequencies or the elicited judgment of an expert. The use of expert opinion is a common trait of Bayesian modeling and well-developed protocols exist for eliciting such opinions in probabilistic form (Morgan & Henrion, 1990; Meyer & Booker, 1991).

The domain of water quality modeling and management is ideally suited for the application of probability networks. Water quality data are often abundant, but not at the spatial and temporal scale required by detailed simulation models. Scientific understanding of mechanisms is advanced, but only to the point of being able to identify the existence of aggregate causal relationships, not to quantify all of the small-scale dynamics. Physical, chemical, and biological processes in aquatic environments are complex and chaotic, making representation by probability distributions appropriate. Probability networks provide a methodology for combining expert knowledge of causal structure and aggregate ecosystem response with condensed models that are identifiable from available data. The formal structure of a network makes the reasoning and assumptions of the analysis explicit, so that they can be challenged and revised as necessary. The probabilistic predictions give stakeholders and decision-makers a more honest appraisal of the chances of achieving desired outcomes. The result is an integrative model that can be used effectively within an adaptive decision-making process.

BAYESIAN NETWORK FOR THE NEUSE ESTUARY

A Bayesian probability network model has been developed for the Neuse Estuary eutrophication problem (Borsuk, 2001) (Figure 3). Predictive endpoints include algal density, as measured by chlorophyll a concentration, abundance of the toxic microorganism *Pfiesteria*, fish population health, frequency of fish kills, and shellfish abundance. Because intermediate variables and relationships are included in the model only if they contribute to our ability to predict model endpoints, the model structure can be best explained by starting with the endpoints and proceeding in the "up-arrow" direction.

As revealed by a stakeholder study (Borsuk et al., 2001a), fish kills are an attribute of significant interest to the public and decision-makers of the Neuse basin. The current scientific belief is that fish kills are predominantly caused by a combination of low oxygen bottom water (hypoxia) and wind conditions which force that bottom water to the surface, trapping fish along the shores where they suffocate (Crowder, 1998). Fish are generally more susceptible if they are already in poor health. Therefore, a probabilistic prediction of fishkills depends on the health of the fish population, the temporal extent to which the estuary experiences hypoxic conditions, and the frequency of cross-channel, "trapping" wind conditions. The frequency of cross-channel winds can be considered to be a marginal node, without parents, since historical data and observation exist on their occurrence, but, they cannot be controlled by management. Prediction of the temporal extent of hypoxia, however, is conditional on the pattern of bottom water oxygen concentrations. Oxygen concentration is determined by both the rate of sediment oxygen consumption by bacterial respiration and the duration that the bottom waters are separated from the surface due to salinity stratification (Stanley & Nixon, 1992; Paerl et al., 1998). It is generally believed that stratification occurs whenever cross-channel winds are calm enough to avoid mixing for more than one day (Luettich, 1998). Therefore, a variable describing the number of consecutive days between winds of sufficient strength to mix the system is the only variable relevant to stratification. This variable, like fish kills, is dependent on the frequency of strong cross-channel winds. Freshwater flow into the estuary may also influence the strength (and, therefore, duration) of stratification (Luettich, 1998), but its overall effect is not clear at this time. Therefore, the effect of flow has not been included.

Sediment oxygen demand is dependent on the decay rate of organic matter in the sediments, which, in turn, is dependent on the amount of organic matter available (Rizzo & Christian, 1996). In a eutrophic estuary such as the Neuse, most of the sediment organic matter is believed to be internally derived via carbon fixation by algae, rather than externally derived via river loading of terrestrial material (Alperin et al., 1998). Because regular measurements are not made of the organic matter decay rate or the sediment organic carbon content, these intermediate steps are not included in the model, and a direct link is shown between sediment oxygen demand and algal carbon production. This is an instance where the aggregate effect may be more well known than the sum of a number of individual, uncertain processes.

Algal carbon production is primarily determined by algal density, although water temperature also plays an important role (Mallin et al., 1991). Additionally, light intensity and photic depth have been shown to be significant factors (Cole & Cloern, 1987; Boyer et al., 1993). However while these are both observable variables (in that they can be measured), they are neither manageable by nitrogen controls nor predictable from other known factors (as water temperature is from the seasonal cycle). Therefore they are not explicitly included, and the variability they cause becomes part of the model uncertainty.

Among the factors believed to control algal density are nitrogen inputs and water temperature (Pinckney et al., 1997). Additionally river flow has been shown to be an important factor (Mallin et al., 1993), perhaps because of its influence on estuarine salinity and water residence time. Detailed measurements of water temperature, river flow, and river nitrogen concentration exist, making these suitable marginal nodes. To test the effects of future nitrogen reductions with the model, river nitrogen concentrations were adjusted accordingly. Another model endpoint is fish population health (Figure 3). While a number of factors affect the health of the Neuse estuary fish population, only the harmful effects of hypoxia can be controlled through nitrogen reductions. The situation is similar for shellfish. However, because shellfish are sessile, it is not only their health, but their abundance, that is threatened by long term exposure to low oxygen conditions. Thus, both the duration and severity of hypoxia are important considerations, prompting the arrows from nodes representing both duration of stratification and dissolved oxygen concentration.

The presence of the toxic dinoflagellate, *Pfiesteria piscicida*, is a concern to the public, in part, because of the large amount of media attention it has received in the past five years. It has been blamed for a having a major role in the occurrence of fish kills both by directly attacking the fish and by making them more susceptible to harsh conditions (Burkholder, 1999). *Pfiesteria* has also been found to adversely impact the health of laboratory researchers studying the organism by causing respiratory and neurological distress (Glasgow et al., 1995). However, the potential threat to people exposed to *Pfiesteria* under natural conditions is highly controversial (Griffith, 1999), and the distinct role the organism plays in fish kills is uncertain (Stow, 1999). Many of the scientists we spoke with felt that *Pfiesteria* was just one of many stressors that fish faced, and if *Pfiesteria* were not present in the estuary, other opportunistic organisms would be. Therefore, to satisfy the interests of the stakeholders, *Pfiesteria* abundance was included as an endpoint in the model, but it was not linked to fish population health or fishkills. Nor was a human health effect included. Perhaps as more laboratory research, field-work, and health studies are conducted, the role of *Pfiesteria* in the network can be modified accordingly

Development of the quantitative relationships among the variables in the probability network is described by Borsuk et al. (2001a, 2001b, 2001c, in review).

PROBABILITY NETWORKS FOR ADAPTIVE MANAGEMENT

Development of the probability network was undertaken not to create a more realistic representation of the Neuse system, but rather to develop a model that more realistically represents our *knowledge* about that system. In particular, we wanted to represent current scientific knowledge about the linkage between nitrogen inputs and the ecosystem variables that are of interest to the public and decision-makers. In this sense, the probability network should not be seen as a suggested replacement for other models, but rather as an integrator of many forms of knowledge, whether expressed as a process-based model, an empirical relationship, or a quantification of expert judgment. To the extent that an existing complex simulation model appropriately represents our level of understanding about the functioning of the system, that model can be used as the basis for a set of dependencies in a probability network. However, because knowledge in all forms is inherently uncertain, and probability networks represent that uncertainty using conditional distributions, the predictive accuracy of the process description must be fully quantified. While progress has been made recently in characterizing the uncertainty of complex models (Poole & Raftery, 2000; Brun et al., 2001; Kennedy & O'Hagan, 2001; Reichert et al., 2001), most commonly used water quality models have not undergone a rigorous uncertainty analysis (Reckhow, 1994). Therefore, when process models were used as an expression of knowledge in the probability network, they were applied at a considerably more aggregate scale.

Rather than creating an elaborate model *a priori* and basing all subsequent decisions on predictions from that model, adaptive management emphasizes updating the model based on observation and learning as time passes. Updating the parameters in the probability network in response to observation, learning, and change over time is relatively straightforward using Bayes' Theorem (Bernardo & Smith, 1994). The parameter distributions developed in the current study can be used as the *prior* beliefs, to be combined with the *likelihood* derived from any new information, to result in an updated *posterior* distribution. This distribution can then be used in the probability network, as well as to serve as the starting point for subsequent updates. In turn, management actions can adapt based on results from the updated model. This process may involve repeated cycles of prediction, decision, management action, and evaluation. Such an approach is particularly appealing in environmental applications where population growth, land use change, and variability in climatic forcing functions exceed the limited range of observation and experience.

The probability network is structured to allow the uncertainty arising from random fluctuations to be separated, at least in part, from the uncertainty that arises from knowledge uncertainty in the form of uncertain parameter values. This is important information for decision-makers. Stochastic variability is a property of the system that must be accounted for but, for a given model, cannot be reduced. Knowledge uncertainty, on the other hand, can generally be reduced through the gathering of additional information (Hession & Storm, 2000). Estimates of the net benefit of such information using expected value theory can provide the basis for choosing preliminary actions or data collection that will be most valuable (Clemen & Reilly, 2001).

CONCLUSIONS

The probability network is one of several estuarine response models currently being used to inform the near-term selection of a TMDL for the Neuse River. Compared to the other models, its process-representation is simple. Complex physical, chemical, and biological processes are combined into aggregate components described by measurable, operationally defined variables. The model does not invoke more detail than necessary, emphasizing the fact that it should not be considered an attempt to describe all the processes operating in the system, but instead is a simplification for a specific purpose. In this case, the purpose is to serve as a framework for decision-making by organizing current scientific understanding and assumptions. By focusing on attributes of the system that are meaningful to the public and decision-makers, the model provides the opportunity for hydrodynamists, chemists, and biologists to understand the linkages that are required between their research fields to develop meaningful environmental policy. The probability network can incorporate both quantitative and qualitative information, facilitating the practical integration of information from the multiple contributing fields.

Ecosystem management requires the prediction of ecosystem responses to alternative management actions. There are essentially four tools to guide such predictions: 1) microcosm experiments, 2) mesocosm experiments, 3) whole-ecosystem experiments, and 4) numerical experiments (models), all of which are imperfect, imprecise, or impractical. The concept of adaptive management was developed with the recognition that our ability to predict the response of ecosystems to management actions is inherently uncertain. However, management actions can be regarded as ecosystem-scale experiments that provide an opportunity to learn about system behavior and reduce uncertainty. Information from monitoring studies can then be formally assimilated into our knowledge base using Bayes theorem (Reckhow, 1990). While the concept of adaptive management is not new, to our knowledge the water quality literature contains no examples where it has been explicitly applied within a rigorous framework for assimilating new data and updating model information and predictions. A Bayesian probability network is an ideal framework for implementing adaptive management and, with appropriate follow-through; the Neuse River TMDL will be an excellent test case.

AUTHORS

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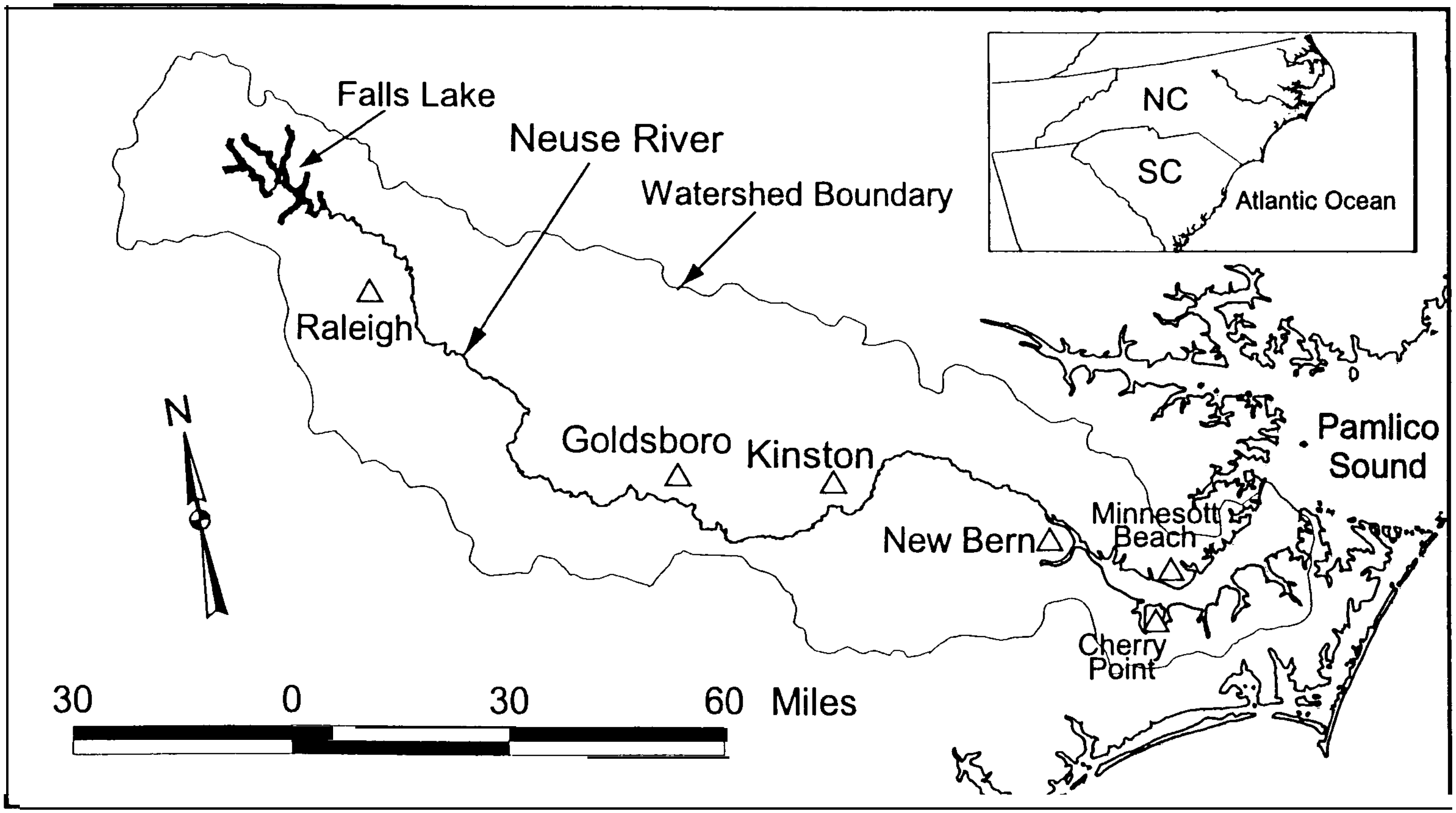

FIGURE 1. The Neuse River and Estuary, North Carolina.

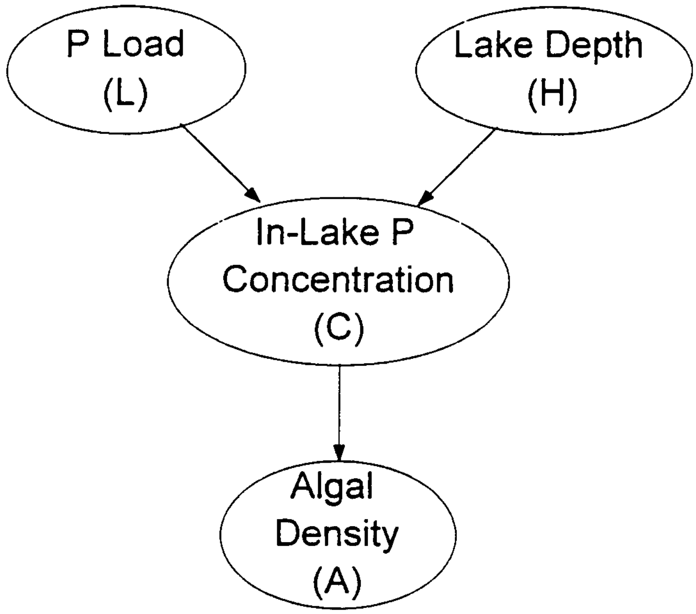

FIGURE 2. Graphical representation of a probability network for the phosphorus loading model.

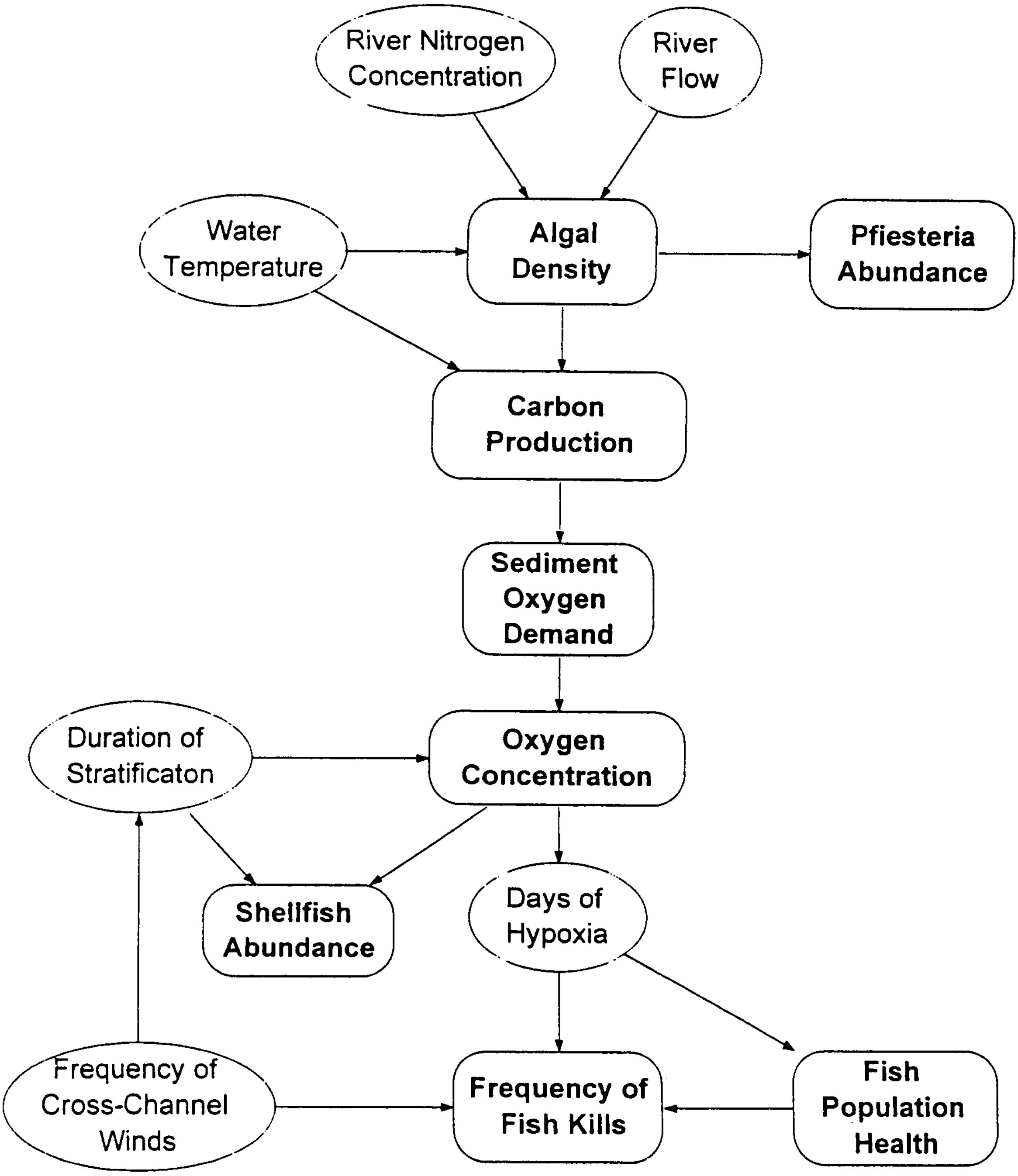

FIGURE 3. Schematic representation of the probability network for Neuse eutrophication. Rounded boxes represent sub-networks of several more detailed nodes.