# AN ABSTRACT OF THE THESIS OF

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Title: Development of a Decision Support System for Pond Aquaculture.

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Decision support systems (DSS) have been used to a very limited extent in pond aquaculture. This study documents the development of a DSS (POND) which allows representation of an entire pond aquaculture facility, and provides analysis capabilities in the form of simulation models and an economics package. Simulation tools in POND include temperature, water budget, fertilization, and fish bioenergetics models. Verification of the water temperature model at sites in Thailand, Honduras and Rwanda indicated that it would accurately predict daily temperatures over entire seasons or diurnal temperatures over one day intervals if complete input weather datasets are available. Similarly, adequate estimates of water requirements can be obtained from the water budget model. Sensitivity analysis with the former model, and results obtained from the latter, indicate that input weather datasets should include air temperature, relative humidity, short-wave solar radiation, precipitation and wind speed measurements. The fertilization model estimates fertilizer application rates on the basis of nutrient concentrations, gross primary productivity and nutrient recycling processes. Model output was more conservative compared to rates used in Honduras, Thailand and the Philippines, suggesting that responsive fertilization strategies which account for ambient pond water conditions are more efficient than fixed input strategies.

The bioenergetics model accounts for the effects of size, water temperature, photoperiod, dissolved oxygen and unionized ammonia on fish growth. The model was calibrated and validated for Nile tilapia (*Oreochromis niloticus*), tambaqui (*Colossoma macropomum*), pacu (*Piaractus mesopotamicus*), common carp (*Cyprinus carpio*), and channel catfish (*Ictalurus punctatus*). Model experiments generated useful information regarding supplemental feed initiation and fish feeding rates. A resource substitution function was also used in this model to analyze the consumption of endogenous and exogenous food resources by Nile tilapia. This function suggests that adding supplemental feed to tilapia ponds may increase phytoplankton biomass because feed is preferentially consumed. A genetic algorithm-based technique was developed to automatically calibrate the bioenergetics model. This technique generates best-fit parameters by comparing results of multiple model runs to observed data. In general, results obtained from all the models suggest that POND should be a useful tool for managers, planners and researchers involved with pond aquaculture.

# Development of a Decision Support System for Pond Aquaculture

by

Shree S. Nath

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# CONTRIBUTION OF AUTHORS

Dr. John Bolte was involved in the conceptualization and implementation aspects of the overall POND decision support system, and thus contributed to each of the manuscripts presented in this dissertation. Douglas Ernst was involved with the design of POND (Chapter 1), with the development and implementation of the water temperature model (Chapter 2), and with various aspects of fish growth modeling (Chapters 5 and 6).

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# DEDICATION

For my family, all of whom have made sacrifices to ensure that I would get the educational opportunities that they could not.

# DEVELOPMENT OF A DECISION SUPPORT SYSTEM FOR POND AQUACULTURE

## INTRODUCTION

It is generally well accepted that marine and many inland fishery resources are heavily exploited, or overexploited. Aquaculture is widely perceived as having the potential to meet at least in part the ever-increasing global demand for fishery products. The combined contribution of cultured finfish and shellfish to the overall output of global fisheries has increased steadily since 1984 (Rana et al., 1996). In 1994 (the year for which most recent global statistics are available), aquacultural production of finfish and shellfish amounted to 18.6 million metric tonnes (mt) out of a total global fisheries output of 109.6 mt, a proportion of nearly 17% (Rana et al., 1996). In terms of growth rates, aquaculture has been outpacing livestock meat production two- to four-fold since 1984, with an estimated increase of about 10.2% per year (Tacon, 1996).

As with other agricultural activities, the rapid increase in both the overall aquaculture output as well as area that is being farmed has raised concerns regarding the long-term sustainability of such production systems (Pillay, 1992; New et al., 1995). In reviewing global aquaculture trends, Tacon (1996) concluded that the keys to long-term sustainability and growth of aquaculture are improved efficiency of resource use and the development of environmentally friendly, economically viable, and socially acceptable production systems.

Among the various types of aquaculture systems, pond aquaculture is by far the most prevalent both in terms of the overall output as well as area under production. Improved resource use efficiency in such systems is therefore particularly important. The most important resources used in pond aquaculture include water, feeds, fertilizers, liming materials, fish fingerlings (for stocking) and energy (e.g., for pond aeration) (Schaeperclaus, 1933; Hickling, 1962; Boyd, 1990). In general, the intensity at which one or more of these resources are used at a given location may be based either on initial experimentation at the site or adapted on a trial and error basis from the experience of practitioners in the same or other regions. However, pond aquaculture technology that has been found to be appropriate at one location may not necessarily be applicable elsewhere (Colt, 1986). The failure of such types of technology transfer is attributable to a variety of reasons.

Firstly, fish production in earthen ponds is a function of water and soil quality, as well as climatic characteristics (Lannan et al., 1986). For example, fish species such as tilapia and carps which derive a substantial portion of their dietary requirements from natural or endogenous food (i.e., resources such as phytoplankton, zooplankton and benthos) will thrive better in ponds that respond positively to management practices such as liming and fertilization (Hepher, 1978; Boyd, 1979). It is important to note that water and soil quality can be radically different even within relatively small geographic areas, implying that fine-tuning of the aquaculture practices prevalent in the region may be necessary for a particular location. For example, Batterson et al. (1988) reported that source water alkalinities in two adjacent drainage basins in West Java (Indonesia) were 20 and 180 mg $CaCO_3$ $L^{-1}$ respectively; because the principal source of inorganic carbon for photosynthesis in fresh water is the carbonate-bicarbonate alkalinity (Arce and Boyd, 1975), ponds located in the two drainage basins will likely have different productivities and require different fertilization and lime application rates. Climatic characteristics typically exert their influence over larger regions. Thus, ponds located in the tropics are more productive than those in the sub-tropics because year round warm temperatures in the former will likely enhance both endogenous food as well as fish productivity compared to those located at the higher latitudes (Boyd, 1979). It follows that management practices will likely be different between these two broad geographic regions even if the target fish species are identical.

Direct transfer of technology may also not produce acceptable results because of differences in the availability and costs of resources (e.g., liming materials, fertilizers, feed, fingerlings, etc) among locations. Thus, it would be somewhat inappropriate to attempt the production of a fish species such as the channel catfish (*Ictalurus punctatus*) which requires high quality protein in its diet (typically met by the use of artificial feeds; Lovell, 1989) in a region where such feeds are either not available or are very expensive. Similarly, Molnar et al. (1996) reported that subsistence farmers in Rwanda typically avoid the use of synthetic fertilizers and manures in tilapia ponds because the former nutrient source is expensive and the latter a scarce commodity. Introduction of pond management practices from other locations where such sources are plentiful and inexpensive into Rwanda is therefore not appropriate.

Finally, marketing and socio-economic factors are also extremely important in determining the suitability of a production technology for a new region. Examples of marketing factors include demand for fish species, proximity of the farms to actual markets, and the potential for farm gate sales (Allen et al., 1983; Kapetsky, 1994). Socio-economic factors include ownership rights, cultural issues, reluctance of farmers to adopt new technologies, goals of individual fish farmers, and interactions of the farmers within a community (Chambers et al., 1989; Harrison, 1994; Molnar et al., 1996). The degree of importance of marketing and socio-economic factors varies according to whether fish farming is primarily a commercial or a subsistence operation. Effects of marketing and socio-economic factors on pond aquaculture systems are not considered in this dissertation.

It is relevant to point out that the current propensity for pond production technology to be transferred without taking into account differences among locations may very well be due to the lack of appropriate tools that would help decision makers in rapidly assessing fish production potential under different environmental, management and economic conditions. Such tools, termed decision support systems (DSS), integrate various types of knowledge (e.g., quantitative models, heuristics, and/or databases) into user-friendly software focused on developing, analyzing and optimizing management strategies (Hopgood, 1991). DSSs that have been developed for aquaculture may be classified into two broad categories: farm management/planning tools (e.g., Gempesaw et al., 1992; Lannan, 1993; Ernst et al., 1993; Silvert, 1994; Itoga and Brock, 1995) and macro-economic tools (El-Gayar and Leung, 1996). Software in the former category deal primarily with decisions relevant to short- and medium-term farm management operations (e.g., fertilizer and lime recommendations for ponds as in Lannan, 1993; site selection for marine fish culture operations as in Silvert, 1994; fish disease diagnosis and treatment as in Itoga and Brock, 1995), as well as long-term planning tasks that may be required during the design phase of a physical farm (e.g., financial assessment relevant to the target fish species as in Gempesaw et al., 1992). Macro-economic tools, on the other hand, have been developed to assess the economic feasibility of aquaculture development of one or more culture species in larger regions varying in size from districts to perhaps entire countries (El-Gayar and Leung, 1996).

With the exception of the system described by Ernst et al. (1993), none of the farm management/planning DSSs were designed to serve as a framework for representing aquaculture facilities and providing capabilities for comprehensive analysis of these facilities under various management scenarios. An overview of a DSS (POND) that was developed to provide such functionality for pond aquaculture facilities is presented in Chapter 1 of this dissertation.

However, the primary focus of the work accomplished deals with the analysis of inter-relationships among environmental, management and economic variables via the use of a variety of simulation models. These variables are important in estimating fish production potential, and the simulation models that link them are expected to generate information that will likely be important in arriving at decisions pertinent to the operation and planning of individual pond aquaculture facilities. A family of simulation models ranging from relatively simple descriptions of pond systems to much more complex ones (see Chapter 1) have been developed and implemented in POND. However, the types of data needed to calibrate and validate the latter category of models are currently either not reported by aquaculture researchers or not collected during their experiments.

Therefore, it was decided to present only the more simplified simulation models that were verified for pond aquaculture systems during this research effort. These models include a water temperature model (Chapter 2), a water budget model (Chapter 3), a fertilization model (Chapter 4), a fish growth model (Chapter 5), and a model that describes natural food and supplemental feed consumption patterns by fish in ponds (Chapter 6). During the active phase of model development in this research work, it became evident that model parameter estimation would be greatly assisted by the development of an automated calibration technique. The final chapter of the dissertation (Chapter 7) deals with development of such a technique and its application to the fish growth model described in Chapter 5.

# CHAPTER 1

# AN OVERVIEW OF THE ARCHITECTURE, SIMULATION MODELS AND APPLICATIONS OF *POND*

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## ABSTRACT

Decision-making for pond aquaculture requires knowledge of the effects of management practices on fish performance, soil and water quality. It is also necessary to examine economic and environmental consequences of various practices. A decision support system POND[1] which enables definition of an entire aquaculture facility (in terms of location, ponds, fish populations, and species), and provides analysis capabilities in the form of simulation models and an economics package has been developed. The software requires an IBM-compatible personal computer running the Microsoft Windows operating environment. POND models can be used to examine the implications of management practices such as feeding, fertilization, liming, stocking and water exchange rates on facility-level fish production. Fish growth models in POND can be automatically parameterized for different species. Economic analysis is accomplished by the use of enterprise budgets which account for fixed, depreciable, and variable costs, as well as income based on fish yields predicted by the models. POND provides a useful framework for integrating various components that define a pond aquaculture facility. Applications of decision support systems such as POND for technology transfer, management, planning and research are discussed.

## INTRODUCTION

Pond aquaculture planners and managers are often confronted with a variety of decisions regarding site locations, target fish species and appropriate practices such as fish feeding, pond fertilization and liming, stocking densities, aeration, and water exchange (Hickling, 1962; Boyd, 1979; Allen et al., 1983; Colt, 1986; Hepher, 1988). These decisions typically have considerable effects on resource use efficiency and

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[1] POND is a copyright of Oregon State University.

therefore the economics of an aquaculture facility (Allen et al., 1983). The decision-making process typically requires some expertise on the part of the planner, manager or extension agent. Such expertise includes an understanding of the principles of pond aquaculture and the implications of various decisions on facility-level economics (Shang, 1981; Allen et al., 1983). In certain situations, it may also be necessary to address socio-economic issues such as receptivity of farmers to new technology, and alternative uses of available resources (Chambers, 1989; Harrison, 1994; Molnar et al., 1996). Decision-makers usually acquire the required knowledge via a combination of formal education and experience. Often, the immediate need for pond aquaculture technology may cause decision-makers to apply or recommend management practices developed and tested at one location to a new site.

The use of technology that has been found to be suitable for one location may very well be inadequate when applied elsewhere (Colt, 1986). This may be due to differences in fish production potential caused by the variability in climate, water and soil characteristics among sites (King and Garling, 1986), and because of differences in the availability and cost of resources used in pond production (Shang, 1981). For example, a decision as specific as the calculation of feed requirements for a pond requires consideration of fish biomass, natural food availability, and water temperature which vary both with time and among different locations (Hepher, 1988). Similarly, calculation of fertilizer application rates requires a basic understanding of soil and water chemistry both of which also vary among different sites (King and Garling, 1986). In both cases, availability and cost of appropriate inputs should be factored into the decision-making process (Shang, 1981).

The complexity of decision-making for an aquaculture facility suggests the need for analytical tools that can integrate biological, physical, environmental, economic, and social components of the knowledge base required to arrive at a decision. Such tools, termed decision support systems (DSS), integrate knowledge in the form of mathematical models, rule-based (expert) systems, and/or databases into user-friendly software systems focused on developing, analyzing and optimizing management strategies. These tools have emerged as powerful tools for capturing expert knowledge about particular domains and providing that knowledge in a friendly, easy-to-use manner to end users. In a broader sense, DSSs address the problem of packaging a large domain of scientific and technical knowledge into a form that is of practical value to a diverse audience, including non-scientists (Lannan, 1993). The power of such systems results from their capability for representing and manipulating both quantitative and qualitative knowledge that describe objects in the domain of interest and their inter-relationships.

A key component of any DSS is the knowledge base(s) upon which decisions are made. Expertise exists in many forms, ranging from highly qualitative 'rule of thumb' approaches useful for representing subjective information, to databases containing historical data, to more rigorous and quantitative mathematical algorithms that describe explicit relationships among components of the domain in question (Hopgood, 1991).

In agriculture, DSSs have been developed for the diagnosis of plant diseases (Michalski et al., 1982), crop production (Smith et al., 1985), analyzing marketing alternatives (Uhrig et al., 1986), selection of appropriate crop cultivars (Lodge and Frecker, 1989; Bolte et al., 1990), pesticide application (Ferris et al., 1992) and many other applications. DSSs that have been developed for aquaculture can be classified into two broad categories: farm management/planning tools (e.g., Lannan, 1993; Gempesaw et al., 1992; Silvert, 1994; Ernst et al., 1993; Itoga and Brock, 1995) and macro-economic tools (Pedini et al., 1995; El-Gayar and Leung, 1996). DSSs that fall into the former category deal primarily with decisions relevant to farm management operations (e.g., fertilizer and lime recommendations for ponds as in Lannan, 1993; site selection for marine fish culture operations as in Silvert, 1994; tilapia disease diagnosis and treatment as in Itoga and Brock, 1995), as well as long-term planning tasks that may be required during the initial design phase of a farm (e.g., financial assessment relevant to the target fish species as in Gempesaw et al., 1992). Macro-economic tools, on the other hand, have been developed to evaluate project proposals (e.g., Pedini et al., 1995) and to examine the economic consequences of aquaculture development of one or more culture species in larger regions varying in size from districts to perhaps entire countries (El-Gayar and Leung, 1996). The development of both categories of aquaculture DSSs are relatively recent, and the presently available tools should be considered to be more or less first generation products.

With the exception of the system described by Ernst et al. (1993), none of the farm management/planning DSSs were designed to serve as a framework for representing aquaculture facilities and providing capabilities for comprehensive analysis of these facilities under various management scenarios. This paper provides an overview of the design aspects, functional modules and application areas of POND, a decision support software that has been developed to specifically enable analysis of pond aquaculture facilities via a combination of simulation models and enterprise budgeting. The development of POND is supported by the Pond Dynamics/Aquaculture Collaborative Research Support Program (PD/A CRSP) funded in part by the U.S. Agency for International Development.

## GENERAL FRAMEWORK AND ARCHITECTURE

The main focus of the POND software is to provide a view of pond dynamics at both the individual pond as well as at the facility level. This involves providing capabilities for (i) representing a pond aquaculture facility, (ii) simulating processes within individual ponds, (iii) enabling users to impose certain management or planning decisions on a given facility prior to executing a specific simulation scenario, and (iv) undertaking economic analyses of simulation scenarios.

The term 'facility' is used in POND to describe a physical aquaculture system that consists of a specific geographical location, source water quality, pond(s) associated with

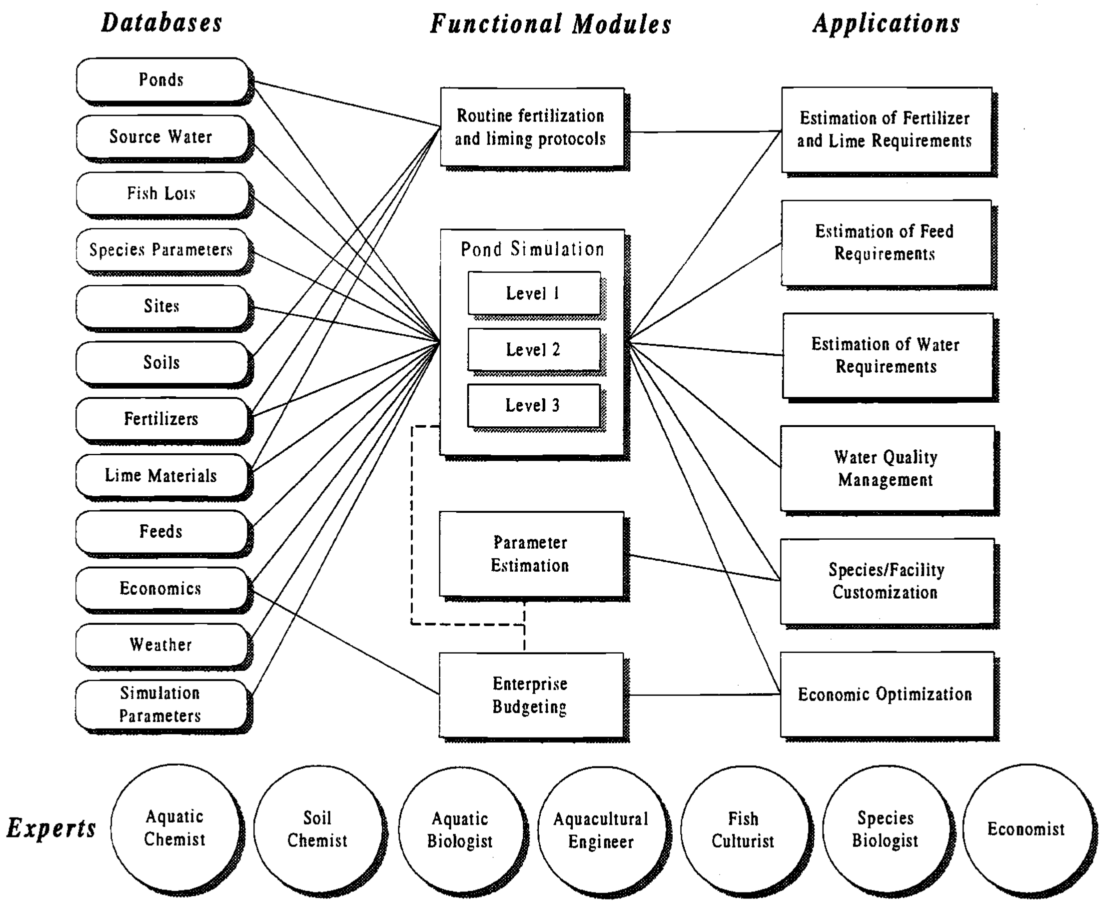

Figure 1.1. General architecture of POND indicating databases, functionality and applications. Experts involved in facility-level simulations are also shown.

the site, fish lot(s) or populations (comprising one or more species) associated with each pond, and a soil type for each pond. Mini-databases are maintained to record user-specified information for each of the above entities, and for other functional components of the software (Fig. 1.1). POND is programmed in Borland® C++, and requires an IBM-PC[2] compatible personal computer running the Microsoft Windows[3] (version 3.1 or higher) operating environment. It requires approximately 1.5MB of available hard disk space and a minimum of 4MB RAM. An 80386 CPU is required, and an 80486 or greater CPU is recommended.

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[2] IBM-PC is a trademark of IBM corporation.

[3] Windows is a trademark of Microsoft corporation.

In the POND software, information is encapsulated, exchanged and manipulated using an object-oriented programming (OOP) paradigm. OOP provides a powerful mechanism for representing real world entities in the form of objects or classes, which are self-contained collections of data and algorithms. Because these objects mirror reality at both conceptual and implementation levels, object-based software tend to be flexible, and are easier to design and maintain compared to conventional software. Code reusability is also promoted by the use of object-oriented principles. Further advantages of OOP may be found in Meyer (1988) and Budd (1991).

Use of the OOP approach for information representation and management in the context of aquacultural decision support systems has previously been demonstrated (e.g., Bolte et al., 1991; Ernst et al., 1993). In a manner similar to the management of actual farms, these authors conceptualized the simulation of aquaculture facilities to involve theintervention of various experts from areas such as aquatic biology, aquatic chemistry, soil chemistry, fish biology, fish culture, aquacultural engineering, and economics. In an actual simulation, methods available in these experts are used to manage specific components (such as ponds and associated fish populations) of the aquaculture facility. Simulations are conducted by the use of an object-oriented simulation environment (Bolte et al., 1993). A similar approach is used in POND, where the simulation of a pond facility is conducted by assembling instances of various 'experts' (Fig. 1.1) and a collection of facility entities (e.g., one or more fish pond instances, each representing a pond in the facility, and one or more fish lot instances, each representing a single fish population of a particular species). POND simulations are dynamic, providing time series results for a range of variables. During a simulation, time series data for each variable are stored; these data may be viewed in plots or tables at the end of the simulation run.

## FUNCTIONAL MODULES

The functionality of POND encompasses four general areas (Fig. 1.1): (i) routine fertilization and liming protocols, (ii) pond simulation capabilities, (iii) economic analysis, and (iv) parameter estimation. These modules are discussed in greater detail below.

### Routine Fertilization and Liming Protocols

POND provides simplified methods for estimating fertilizer and lime requirements of individual ponds without invoking more complex simulation methods. These methods are intended for routine management of actual ponds. Fertilizer requirements are assessed on the assumption that fish production in fertilized ponds can be enhanced by appropriate management of primary productivity levels (Boyd, 1979; Hepher, 1978; McNabb et al., 1990; Schroeder et al., 1990; Lannan, 1993). The methodology (see also Chapter 4) involves the use of a site-specific gross primary productivity level, calculation of primary plant (i.e., inorganic carbon, nitrogen and phosphorus) nutrient requirements based on ambient pond water quality conditions, and the generation of least cost fertilizer combinations that would meet these requirements.

Addition of lime to ponds with acid muds or water of low alkalinity is a widely accepted aquacultural practice. The amount of calcium carbonate required to neutralize the exchange acidity of a pond soil is called the lime requirement, which depends on ion exchange processes that occur on the surface of soil particles (Boyd, 1979). Bowman and Lannan (1995) developed a simple technique based on soil pH to estimate lime requirements. This approach is used to estimate the amount of lime to be added to a pond of a given soil type in the POND program.

## Pond Simulation Capabilities

Previous simulation modeling efforts for pond aquaculture have focused only on certain aspects of the pond ecosystem (e.g., water quality and natural food as in Svirezhev et al., 1984; water quality as in Piedrahita, 1990; fish bioenergetics as in Cuenco et al., 1985a and Cacho, 1990). Further, simulation models in the above studies were developed primarily to understand pond ecosystems. Use of these models for decision support has received very limited attention, both in terms of their relevance to actual management practices and their implementation in a manner that is accessible to decision-makers.

Simulation models were chosen as the primary analysis tool in POND for several reasons. Firstly, they provide an opportunity for *knowledge synthesis*, whereby a large body of knowledge about pond aquaculture can be integrated into a comprehensive representation of the system which can be used to explore the effects of different management scenarios. Simulation model development also imposes a rigorous framework on the model builder. This forces the model builder to clearly articulate knowledge of the fundamental relationships that govern a pond's response to external stimuli, simultaneously exposing gaps in the knowledge base. The rigorous nature of model specification results in a *testable hypothesis* about the pond system, i.e., the model can be run for a known set of pond management and environmental conditions to determine whether its output is adequate to represent our knowledge of systems processes, and useful in the context of decision-making.

Simulation models are also valuable tools for predicting system response to conditions that are either too complex or expensive to explore experimentally. Because model-based experiments can be completed in seconds on a computer, rather than in months or years in the field, models provide opportunity to explore a much larger set of operating conditions, environments, management strategies, and constraints compared to physical experiments. Results of numerical experiments are also useful in evaluating model assumptions, and refining the models. Further discussions about the general use of simulation models for biological systems can be found in Grant (1986) and Haefner (1996). Similarly, detailed descriptions of their applications in pond aquaculture systems are available in Cuenco (1989), Piedrahita (1991) and Piedrahita et al. (in press).

One of the design constraints of the POND software was that it should provide capabilities to meet the needs of pond aquaculture managers, planners and researchers alike. However, these three groups of potential users likely have very different needs. For example, in terms of fertilizer use in ponds, managers are more interested in determining regular application rates (e.g, at weekly or biweekly intervals) for different ponds. On the other hand, planners perhaps need rough assessments of the total fertilizer requirements for a given facility over longer time periods (e.g., one season). For the same problem, researchers are perhaps interested in examining the biological (e.g., plankton growth) and physico-chemical (e.g., changes in nutrient concentrations) responses of ponds to fertilizer additions. Moreover, the targer user groups of POND are likely to have different types of input data available for use in the software.

In order to enable the three target groups of POND users to perform different kinds of analyses based on output resolution requirements and differences in input data availability, simulation models in the software are organized hierarchically into three levels (Levels 1-3; Fig. 1.1) which are more fully discussed in a later section of this paper. A list of the various state variables and associated processes considered at each of the modeling levels is provided in Table 1.1.

POND simulation models are deterministic in nature, and are formulated as a set of ordinary differential equations which are solved numerically over time by the use of a Runge-Kutte integrator. The software supports both daily and diurnal simulations of pond facilities, and provides capabilities to address fish growth, water temperature and volume changes, water/sediment quality dynamics, and primary and secondary productivity under different pond management and environmental conditions.

Table 1.1. A summary of state variables maintained in POND and the source/sink processes considered at the three modeling levels. Processes directly manipulated by management practices are italicized. For some variables (e.g., nitrogen, phosphorus), mass balances may vary depending on the modeling level, and separate state variables are maintained for 'sub-components' (e.g., total ammonia-nitrogen, organic nitrogen, etc). In such cases, the table lists processes that may be considered at all the modeling levels, as well as the additional ones (e.g., atmospheric diffusion of ammonia-nitrogen) specifically affecting the sub-component.

| State Variable | Modeling Level | Sources | Sinks |
|---|---|---|---|
| Fish Mass | 1, 2, 3 | Natural food uptake | Feeding catabolism |
| | | *Artificial feed uptake* | Fasting catabolism |
| Water Temperature | 1, 2, 3 | Net short-wave solar radiation | Long-wave back radiation |
| | | Net long-wave atmospheric radiation | Evaporative heat loss |
| | | *Influent heat* | Conductive heat transfer[a] |
| | | | Non-flow related volume changes[a] |
| | | | *Effluent heat* |
| Water Volume | 1, 2, 3 | *Influent water* | *Effluent water* |
| | | Direct precipitation | Evaporative water loss |
| | | Runoff | Seepage[a] |
| | | | Overflow |
| Water-column Nitrogen (N) | 1, 2, 3 | *Influent water* | *Effluent discharge* |
| Total-N | 2, 3[b] | Fish respiration + excretion | Non-flow related volume changes[a] |
| Dissolved inorganic-N | 1 | Wasted feed | Phytoplankton uptake |
| | | Phytoplankton respiration + death | Bacterial uptake |
| | | Zooplankton respiration + death | Sediment exchange[a] |
| | | Bacterial respiration + death | Miscellaneous sinks/sources[a] |
| | | *Fertilization* | |
| Total Ammonia-N | 3 | Ammonification | Nitrification |
| | | | Volatilization[a] |
| Nitrate-N | 3 | Nitrification | |
| Organic-N | 3 | | Ammonification |

[a] Can be either a source or a sink.

Table 1.1, Continued.

| State Variable | Modeling Level | Sources | Sinks |
|---|---|---|---|
| Water-column Phosphorus (P) | 1, 2, 3 | *Influent water* | *Effluent discharge* |
| Total-P | 2, 3[b] | Fish respiration + excretion | Non-flow related volume changes[a] |
| Dissolved inorganic-P | 1 | Wasted feed | Phytoplankton uptake |
|  |  | Phytoplankton respiration + death | Bacterial uptake |
|  |  | Zooplankton respiration + death | Sediment exchange[a] |
|  |  | Bacterial respiration + death | Miscellaneous sinks/sources[a] |
|  |  | *Fertilization* |  |
| Inorganic-P | 3 | Mineralization |  |
| Organic-P | 3 |  | Mineralization |
| Water-column Carbon (C) | 1, 2, 3 | *Influent water* | *Effluent discharge* |
| Total-C | 2 | Fish respiration + excretion | Non-flow related volume changes[a] |
| Organic-C | 3 | Wasted feed | Phytoplankton uptake |
|  |  | Phytoplankton respiration + death | Bacterial uptake |
|  |  | Zooplankton respiration + death | Sediment exchange[a] |
|  |  | Bacterial respiration + death | Miscellaneous sinks/sources[a] |
|  |  | *Fertilization* |  |
| Dissolved Inorganic-C | 3 | Sediment respiration | Atmospheric diffusion[a] |
| Total Sediment-N | 2, 3 | Supply of water column material: | Water column exchange[a] |
| Sediment Inorganic-N | 1, 3[b] | From fish excretion, wasted feed, |  |
|  |  | and phytoplankton, zooplankton |  |
|  |  | and bacterial death. |  |
| Sediment Ammonia-N | 3 | Ammonification | Nitrification |
| Sediment Nitrate-N | 3 | Nitrification |  |
| Sediment Organic-N | 3 |  | Ammonification |

[a] Can be either a source or a sink.

[b] Calculated from concentrations of inorganic and organic forms at Level 3.

Table 1.1, Continued.

| State Variable | Modeling Level | Sources | Sinks |
|---|---|---|---|
| Total Sediment-P | 2, 3[b] | Supply of water column material:<br>From fish excretion, wasted feed, and phytoplankton, zooplankton and bacterial death. | Water column exchange[a] |
| Sediment Inorganic-P | 1, 3[b] | | |
| Sediment Inorganic-P | 3 | Mineralization | |
| Sediment Organic-P | 3 | | Mineralization |
| Total Sediment-C | 2, 3 | Supply of water column material:<br>From fish excretion, wasted feed, and phytoplankton, zooplankton and bacterial death. | Water column exchange[a] |
| Sediment Organic-C | 3 | | Sediment respiration |
| Carbonate-bicarbonate Alkalinity | 3[c] | *Influent water*<br>Phytoplankton uptake of nitrate-N<br>Ammonification<br>*Lime addition* | *Effluent discharge*<br>Non-flow related volume changes[a]<br>Nitrification<br>Bicarbonate uptake<br>Hydrogen ion production<br>Phytoplankton uptake of bicarbonate<br>Phytoplankton uptake of ammonium ion |
| Dissolved oxygen | 3 | *Influent water*<br>Phytoplankton growth<br>*Aeration*[d] | *Effluent discharge*<br>Non-flow related volume changes[a]<br>Respiration<br>Fish, phytoplankton, zooplankton, bacteria and sediments<br>BOD of organic fertilizers<br>Atmospheric diffusion[a] |

[a] Can be either a source or a sink.

[b] Calculated from concentrations of inorganic and organic forms at Level 3.

[c] Assumed to remain at steady-state levels for Level 1 and 2 models.

[d] Not currently supported.

Table 1.1, Continued.

| State Variable | Modeling Level | Sources | Sinks |
|---|---|---|---|
| Phytoplankton | 2, 3 | *Influent water* | *Effluent discharge* |
| | | Growth | Non-flow related volume changes[a] |
| | | | Respiration + death |
| | | | Fish consumption |
| | | | Zooplankton consumption |
| Zooplankton | 2, 3 | *Influent water* | *Effluent discharge* |
| | | Growth | Non-flow related volume changes[a] |
| | | | Respiration + death |
| | | | Fish consumption |
| Bacteria | 3 | *Influent water* | *Effluent discharge* |
| | | Growth | Non-flow related volume changes[a] |
| | | | Respiration + death |
| | | | Zooplankton consumption |
| | | | Fish consumption |

[a] Can be either a source or a sink.

Simulation models used in POND are based on principles of mass and energy (for water temperature calculations) balance. Ponds are assumed to be continuously stirred tank reactors (CSTR) with unsteady flow (Benefield and Randall, 1980). Real ponds seldom satisfy the assumption of fully mixed conditions required of CSTR's. For example, shallow earthen ponds are typically stratified, resulting in distinct vertical profiles of variables such as pond water temperature and dissolved oxygen levels (Cathcart and Wheaton, 1987; Losordo, 1988; Losordo and Piedrahita, 1991). However, simulation models that specifically account for stratification typically require a large number of weather data inputs collected over diurnal time intervals, are relatively computation-intensive, and difficult to use (e.g., Losordo and Piedrahita, 1991). Therefore, the assumption that actual ponds conform to CSTR conditions is retained in the POND models. The differential equation expressing the change in concentration of a state variable in such reactors (e.g., Benefield and Randall, 1980; McDuffie, 1991) is given by:

$$\frac{dC}{dt} = \frac{Q_i C_i}{V} - \frac{Q_o C_o}{V} + R_c - \frac{C}{V}\frac{dV}{dt} \tag{1}$$

where C = concentration of the material (e.g., g $m^{-3}$), $Q_i$ = influent rate ($m^3$ $d^{-1}$), $Q_o$ = effluent rate ($m^3$ $d^{-1}$), $C_i$ = material concentration in the influent (g $m^{-3}$), $C_o$ = material concentration in the effluent (g $m^{-3}$), V = pond volume ($m^3$) and $R_c$ = sum of the source and sink processes affecting the material (e.g., g $m^{-3}$ $d^{-1}$). Equation 1 addresses the three typical conditions (Boyd, 1990) under which aquaculture ponds are operated: (a) ponds with a constant volume (i.e, $Q_i$ , $Q_o$ and dV/dt = 0), where Equation 1 reduces to the form used for continuously stirred batch reactors (Benefield and Randall, 1980), (b) ponds without regulated flow (i.e., $Q_i$ and $Q_o$ = 0) but in which substantial volume changes may occur due to seepage, evaporation and/or runoff events, and (c) ponds in which significant flow is maintained. For the latter two conditions, volume changes can have important implications for fertilization and effluent quality management. Use of Equation 1 also implies that the POND simulation models can be used to analyze fish culture in tanks where flow considerations are particularly important.

As previously indicated, simulation models in POND are organized into three levels as follows:

*Level 1*: Simulation models at this level are fairly simple and require minimal data inputs. They are intended for applied management and rapid analysis of pond facilities. State variables simulated are fish growth, inorganic nitrogen and phosphorus in the pond water and sediments, water temperature, and pond volume (Fig. 1.2; Table 1.1). Weather data required for the latter two variables may either be generated by a simple weather generator embedded in POND (Appendix 1) or read from ASCII files provided by the user. Consumption of natural food by fish is assumed to be a function of fish biomass and appetite. Nutrient exchange between the pond water column and the underlying sediments is assumed to depend on the concentration gradient between these two components. Fertilizer and feed application rates may either be user-specified or optionally generated by the software.

*Level 2*: Models at this level provide a substantially more sophisticated view of pond dynamics, allowing prediction of phytoplankton, zooplankton and nutrient dynamics (total carbon, nitrogen and phosphorus) in the pond water, in addition to all the functionality of Level 1 (Fig. 1.3; Table 1.1). These models allow for more detailed pond analysis, management optimization and numerical experimentation. At Level 2, steady state bacterial concentrations are also maintained. Fish can feed from a pool of natural food resources and/or artificial feed. Consumption of natural food (phytoplankton, zooplankton and bacterial pools) by fish is predicted on the basis of a resource competition function (Tilman, 1982), and is dependent on the concentrations of the natural food pools and artificial feed (if specified), food preference of fish species, and fish appetite (see also Chapter 6). At this level, too, both fertilizer and feed requirements may be user-specified or optionally generated by the model.

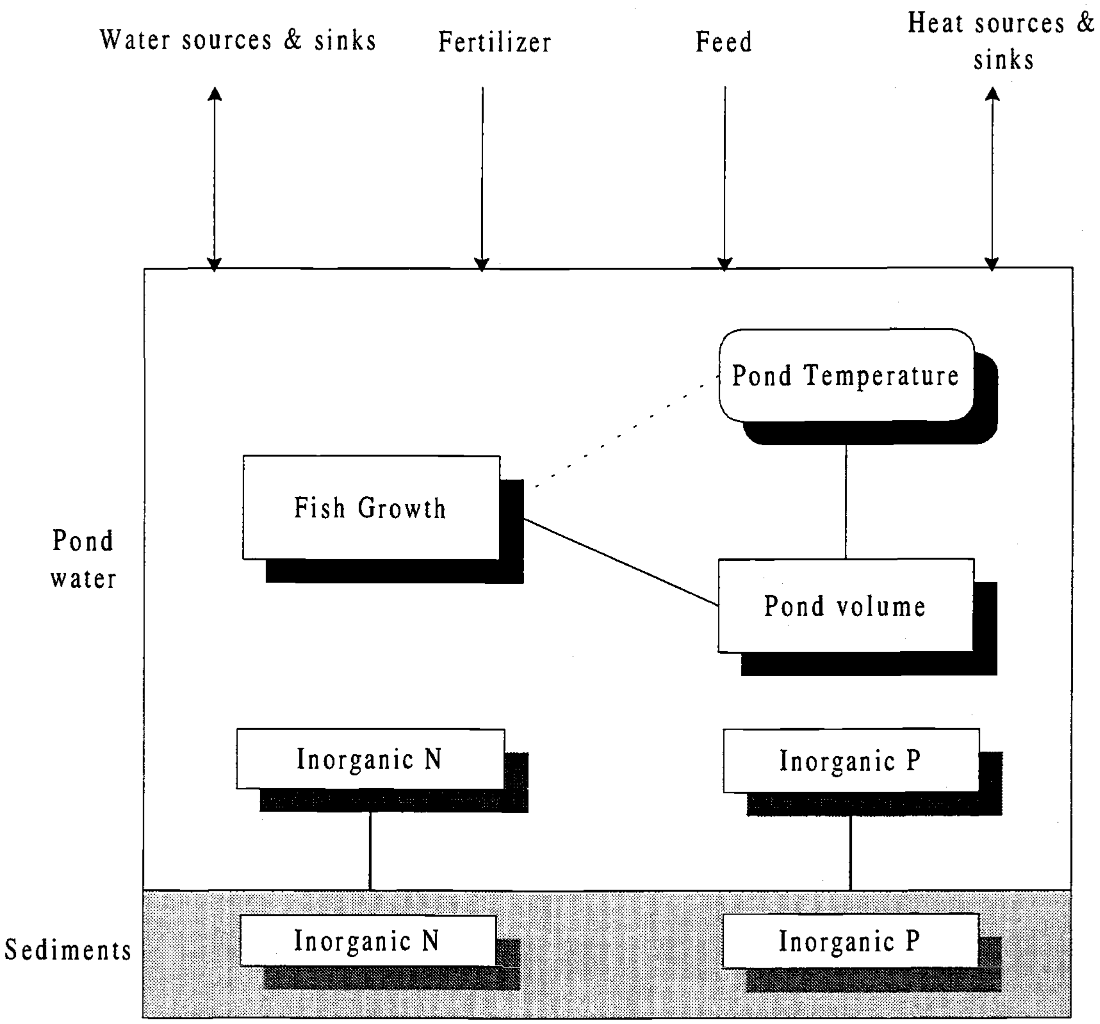

Figure 1.2. State variables and system inputs/outputs for Level 1 modeling in POND.

*Level 3*: Simulation models at this level include all the functionality of Level 2, and provide additional capabilities for simulating bacterial kinetics, and detailed pond water/sediment quality dynamics (Fig. 1.4; Table 1.1). These models are useful for exploring fundamental aspects of pond dynamics (e.g., detailed nutrient transformations in pond water and sediments, atmospheric diffusion, etc). Additional state variables for

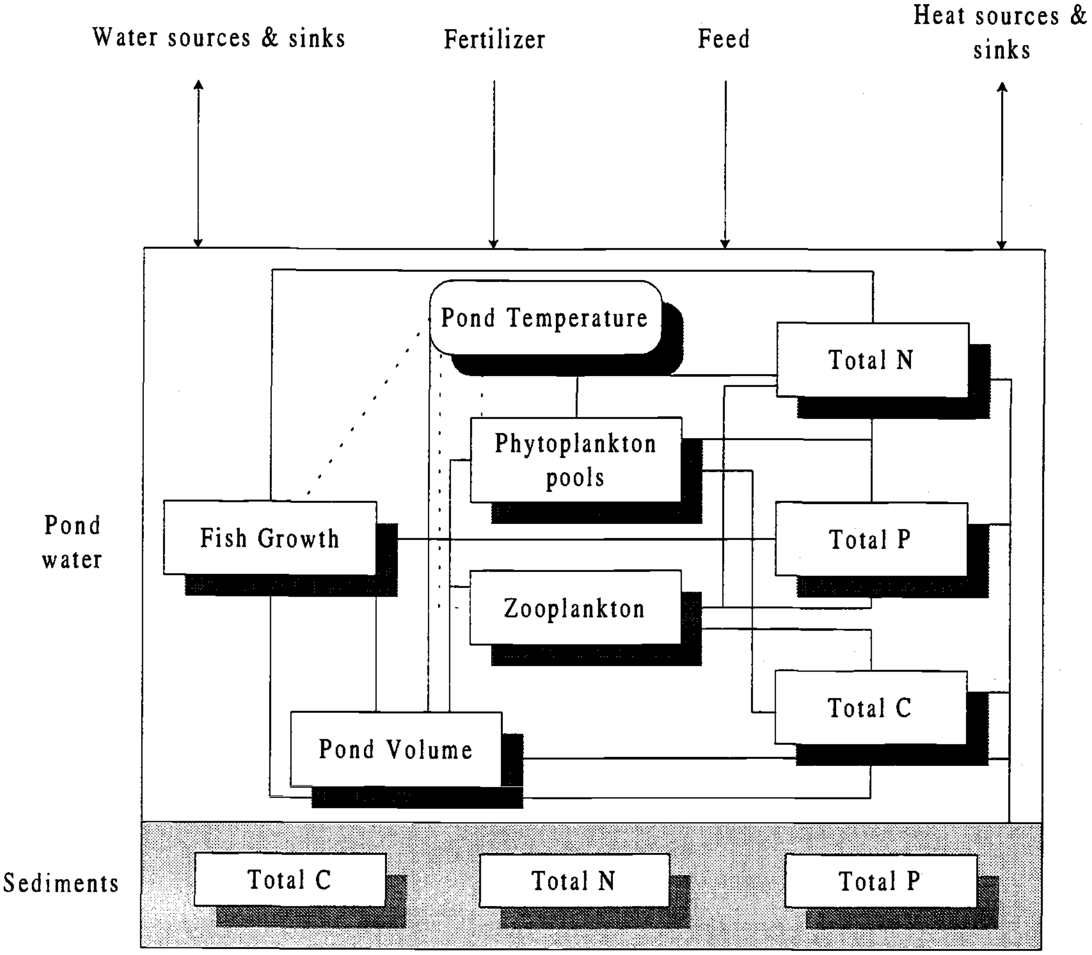

Figure 1.3. State variables and system inputs/outputs for Level 2 modeling in POND.

pond water include dissolved oxygen and alkalinity. Further, state variables are also maintained for organic, ammonia and nitrate nitrogen, as well as organic and inorganic phosphorus and carbon in both pond water and sediments. User-specified fertilization and feeding regimes, coupled to pond process-based nutrient mass balances, are used to estimate nutrient consumption and production rates.

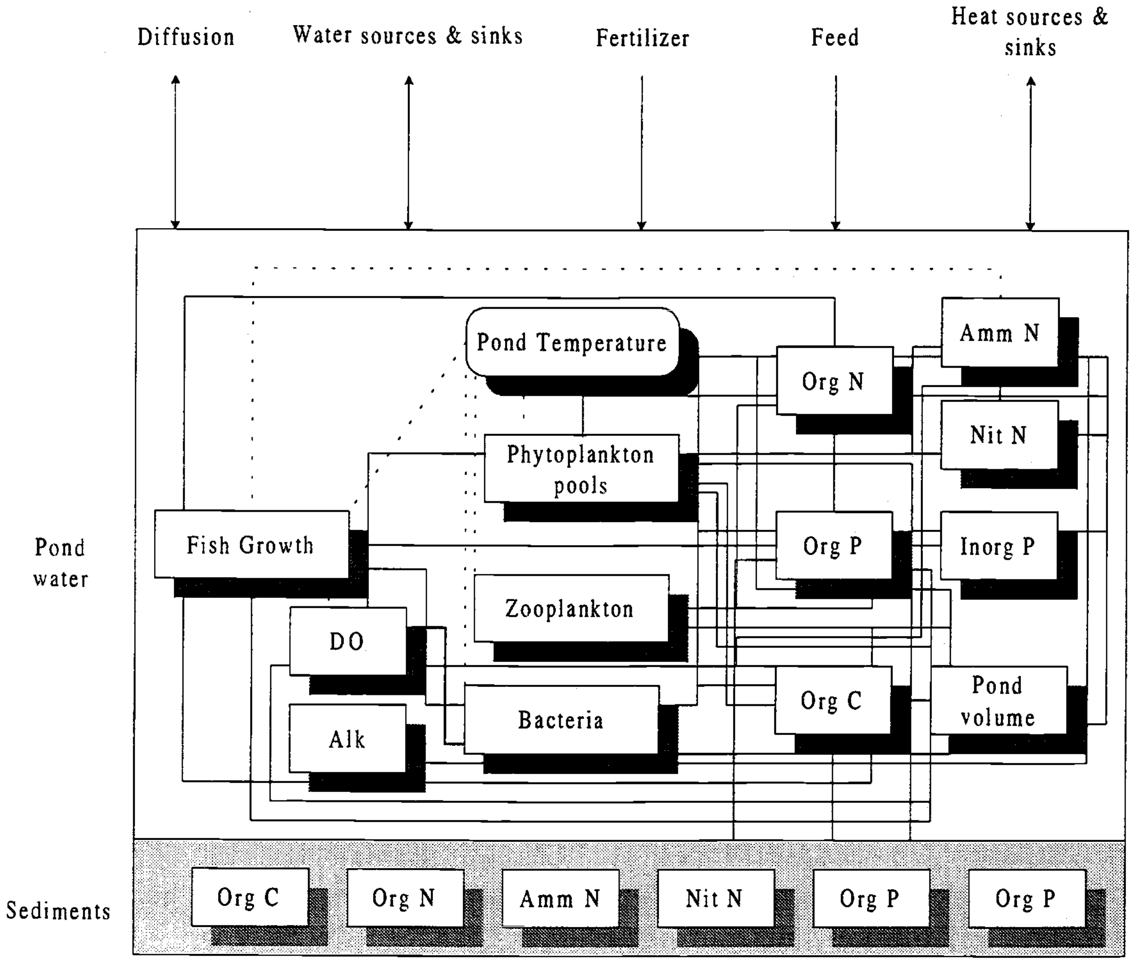

Figure 1.4. State variables and system inputs/outputs for Level 3 modeling in POND.

## Economic Analysis

POND enables economic analyses of facilities to be accomplished by the use of enterprise budgets. Although such budgets do not provide a comprehensive means of analyzing the economic viability of aquaculture enterprises, they do enable rapid comparisons of different management practices (Allen et al., 1983; Amir and Knipscheer, 1989). Enterprise budgets in POND allow definition of various types of cost and income items, and associated interest and depreciation expressions, all of which can be used to assess the overall economic viability of a particular production enterprise. Three cost categories are supported: (i) fixed, (ii) depreciable and (iii) variable costs. Fixed costs do not change over the course of facility operation (e.g., construction cost for a pond). Related to fixed costs are depreciable costs which apply to items such as equipment that may have a redeemable value after some period of time. POND incorporates depreciation schedules that describe the loss of value of the depreciable asset over time. Variable costs are neither fixed or depreciable, and typically vary according to the scale of production (e.g., labor costs, fertilizer and feed costs).

To generate an enterprise budget, income sources are also required. POND allows the specification of any number of income sources, based on either a per unit area, per unit of production, or per facility basis. Income sources relating to fish production are automatically fed to the economics package at the end of a simulation run. Finally, interest rates used for calculating fixed and variable investment costs are to be provided by the user. Once all the items to be included in the enterprise budget are specified and a simulation completed, the economics package in POND summarizes costs on an areal (e.g., per ha), per unit of production (e.g., per kg of fish produced) or overall facility basis, balances these costs against income, and reports the results in a tabular form. By including or excluding particular costs/incomes, or adjusting cost/income details, users can quickly 'experiment' with various facility configurations and/or management strategies to examine their effects on the economic performance of the facility.

### Parameter Estimation

Users of the POND software may often be interested in tailoring fish growth model (Chapter 5) to one or more species at a given location. This may be accomplished by calibrating (adjusting) model parameters such that the simulations result in fish growth profiles that are consistent with the user's experience or match their growth data adequately. Although the task of calibration can be accomplished manually, it is tedious because of the large number of parameters in the models. Therefore, a parameter estimation technique is embedded within the POND program. This technique involves the use of a non-linear, adaptive search algorithm (Chapter 7) that generates best-fit model parameters by comparing the results of multiple runs of the models with user-provided fish growth data.

## APPLICATIONS

DSSs such as POND can provide valuable information in the context of pond management, planning, extension (including technology transfer) and research. Specific applications where POND is likely to be useful within each of these broad focus areas are discussed in greater detail below (see also Fig. 1.1).

### Estimation of Water Requirements

Examination of water availability is one of the primary planning tasks that is undertaken at the time of assessing the suitability of a site for pond aquaculture (Yoo and Boyd, 1994). Because there may be costs associated with using a certain water source or procuring the amount of required water (e.g., via pumping), planners are likely to benefit from a tool that can be used to estimate water requirements over long-term periods. Such a tool has been implemented in POND in the form of a water budget model (Chapter 3). This model offers an alternative to site-specific water budgets (e.g., Szumiec, 1979a; Boyd, 1982) that require routine measurements of water sources and sinks into ponds. Moreover, the model can be applied to new locations where such measurements may be difficult or costly to conduct.

## Estimation of Fertilizer and Lime Requirements

Application rates of fertilizers to aquaculture ponds are typically arrived at by trial and error (Colt, 1986), or adapted from strategies that appear to be optimal at one location. However, the use of a fertilizer loading rate that is appropriate for a particular site can result in substantially different fish yields when applied elsewhere because of the variability among sites (Lannan, 1993). The approach used in POND to estimate fertilizer requirements takes into account ambient pond conditions and climatic characteristics (Chapter 4). This approach is expected to result in increased cost and fertilizer use compared to more traditional fixed input fertilization strategies. Generation of fertilization schedules as one of the outputs of the POND models is useful from the viewpoint of assessing fertilizer requirements for an entire facility and gauging the viability of certain pond aquaculture systems (e.g., subsistence farming) from a planning perspective.

Lime requirements recommended by POND take into account soil properties, and once again are expected to be more efficient compared to traditional approaches which involve the application of fixed amounts of liming materials without adequate consideration of such properties (Bowman and Lannan, 1995). However, the requirements obtained from the approach used in POND are likely to be more applicable to new ponds that have not accumulated substantial amounts of organic matter (Bowman and Lannan, 1995). Older ponds may have different lime requirements because the original nature of the soil is modified as organic matter accumulates (Boyd, 1979).

## Estimation of Feed Requirements

Artificial feeds often represent the single most important component of variable costs in an aquaculture facility (Allen et al., 1983; Hepher, 1988). Therefore, assessment of feed requirements (in terms of both quantity and quality) and subsequent effects on facility-level economics will likely be useful for various pond aquaculture user groups (e.g., managers, planners and extension agents). Estimation of feed requirements are required for large aquaculture operators (regardless of the target species) so as to manage feed inventory properly and gauge the economic benefits of different feeding rates.

### Water and Sediment Quality Management

Analyses of the effects of management practices on pond water/sediment quality are important from planning, extension and management perspectives in terms of resource flows, facility-level economics and verifying whether effluent standards (e.g., nitrogen, phosphorus and organic carbon levels) are met. It may also be possible to assess short-term aeration requirements for ponds by the use of Level 3 models once they are fully validated. Because many pond processes are not fully understood, the POND models may also be used to guide experimental work that specifically focuses on these processes. At the current time, Level 1 and 2 models provide some capabilities of predicting and estimating nutrient sources and sinks in ponds.

### Species/Facility Customization

The POND framework is generic in that it can be adapted for different species and culture conditions. This feature may be useful for pond managers who wish to explore the use of alternate species or want to compare model output and recommendations (e.g., feeding or fertilization rates) to their current practices. Such analyses may also be important for planning, research and extension activities (e.g., feasibility studies for different species and/or locations). Factoring in local costs for various resources by the use of the POND enterprise budgets as well as market factors should be of use to pond planners and managers in selecting the appropriate species and culture techniques for their location.

### Economic Optimization

The simulation and economic analysis capabilities of POND can be useful for economic optimization. From a management perspective, such analyses may focus on identifying suitable practices (e.g., levels of fertilization and feeding, water exchange) for an already existing facility. From a planning perspective, optimization may provide useful information for feasibility studies that focus both on facility configurations (e.g., combinations of ponds, lots and species) and management strategies. Optimization may also be of interest to researchers involved in the comparison of economic benefits from different pond aquaculture systems.

## CONCLUSIONS

POND represents the first effort to integrate simulation models and economic analysis capabilities into a comprehensive framework for analyzing pond aquaculture facilities. The approach of using 'experts' to manage ponds and lots in an aquaculture facility (derived from Bolte et al., 1991 and Ernst et al., 1993) has resulted in both a powerful and flexible mechanism of representing and simulating fish production in such facilities. The software appears to have considerable potential for meeting the needs of pond planners, managers, and researchers. However, further work is needed to verify the simulation models in the software at different geographical locations. Future research should concentrate on such types of model verification. Efforts should also be undertaken to address analyses of other types of pond farming systems (e.g., integrated farming systems) within the overall POND framework.

# CHAPTER 2

# A SIMULATION MODEL FOR WATER TEMPERATURE IN AQUACULTURE PONDS

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## ABSTRACT

A simulation model for water temperature in completely mixed aquaculture ponds has been developed. Heat gains considered include influent heat, net short-wave solar radiation, and atmospheric long-wave radiation, whereas heat losses include effluent heat, back radiation, and evaporation. Additionally, conductive transfer which may either be a heat gain or loss is considered. The model can be used to project both daily mean and diurnal profiles of water temperature in static ponds or those with regulated flow. Model performance has been verified at four geographical locations in Thailand, Honduras and Rwanda. Input weather data for model verification were obtained from weather records (RW) or estimated by the use of a weather generator (GW). The model accurately predicted seasonal profiles of daily mean water temperature at all the four sites; model accuracy was much better in the RW compared to the GW simulations. Further, the availability of daily relative humidity and cloud cover data for the two sites in Thailand apparently resulted in improved predictions of daily mean water temperatures compared to the sites in Honduras and Rwanda. One day simulations that were also conducted at all the four sites to examine diurnal temperature predictions suggested that the model would generate profiles that are consistent with actual measurements. However, predicted values tended to be lower that measured temperatures towards the end of the 24h simulation periods, perhaps a result of the lack of adequate data and the assumptions of constant weather conditions (e.g., cloud cover, relative humidity and wind speed over the course of a day). Sensitivity analyses indicate that predicted water temperatures for seasonal-long daily simulations were most sensitive to mean air temperature, followed by relative humidity, short-wave solar radiation, cloud cover, and wind speed. Similar trends were obtained for diurnal simulations, with the exception that temperatures were somewhat more sensitive to wind speed than to cloud cover. Improved model performance can be expected if existing weather data collection protocols for experimental facilities are expanded to include collection of humidity and cloud cover data. In general, the model is relatively robust, and should therefore be useful for a

variety of planning and management applications including assessment of aquaculture potential for species with different temperature preferenda, estimation of feed requirements and in routine water quality management.

## INTRODUCTION

Water temperature is a crucial driving variable for several biological (e.g., growth and respiration) and physico-chemical (e.g., nutrient transformations and gas diffusion) processes in earthen aquaculture ponds. Consequently, a number of management decisions (e.g., stocking and harvest rates, feed and fertilizer application rates) are also temperature-dependent (Wax et al., 1987). Further, knowledge of seasonal temperature profiles in ponds may also be useful for assessing the suitability of different sites in relation to temperature preferenda of one or more targeted culture species. Water temperature models can be a useful tool to assist aquaculture planners and managers with these decisions.

A variety of pond water temperature models have previously been developed. These include empirical formulations (e.g., Wax et al., 1987) and mechanistic models, which in turn can be categorized into models that assume ponds to be completely mixed reactors (e.g., Krant et al., 1982; de Jaeger and Walmsley, 1984; Klemetson and Rogers, 1985), as well as those that specifically account for temperature stratification in ponds (e.g., Cathcart and Wheaton, 1987; Losordo and Piedrahita, 1991; Culberson and Piedrahita, 1992). Empirical models such as those developed by Wax et al. (1987) rely on the availability of long-term, historical databases for pond and air temperatures which can be 'mined' to develop regression relationships between these variables. As pointed out by Wax et al. (1987), these empirical models are of limited use outside the regions for which they have been parameterized. Mechanistic models, although typically more complicated, attempt to avoid such limitations of empirical models.

It is well known that shallow aquaculture ponds tend to stratify, and that their stratification profiles vary both diurnally and seasonally (Cathcart and Wheaton, 1987). However, mechanistic pond temperature models that specifically account for stratification typically require a large number of weather data inputs collected over diurnal periods (e.g., Losordo and Piedrahita, 1991; Culberson and Piedrahita, 1992). Such datasets are rarely available, except from sophisticated research stations. Further, stratified models are also relatively computation-intensive and difficult to use.

Previously developed models that assume ponds to be fully mixed have either not been validated (e.g., Klemetson and Rogers, 1985), been subjected only to validation at one locality (e.g., Krant et al., 1982) or developed for somewhat different systems (e.g., plastic-covered ponds for algal culture as in de Jaeger and Walmsley, 1984). This paper documents a model that can be used to project both diurnal and seasonal trends in earthen ponds, and its verification for sites with different geographical characteristics.

## MODEL STRUCTURE

Earthen aquaculture ponds are typically analyzed assuming one of the following three conditions: (i) a constant volume, (ii) no regulated flow, but significant volume changes may occur due to seepage, evaporation and/or runoff events, and (iii) regular flow is maintained resulting in substantial volume changes. These three conditions can be addressed if it is assumed that ponds are continuously stirred tank reactors (CSTR) with unsteady flow. Based on the energy balance equation for CSTR's (e.g., Benefield and Randall, 1980; McDuffie, 1991) and previous pond temperature models (e.g., Velz, 1970; Ryan and Stolzenbach, 1971; Fritz et al. 1980; Fig. 2.1), the following expression can be used to describe heat changes in an aquaculture pond:

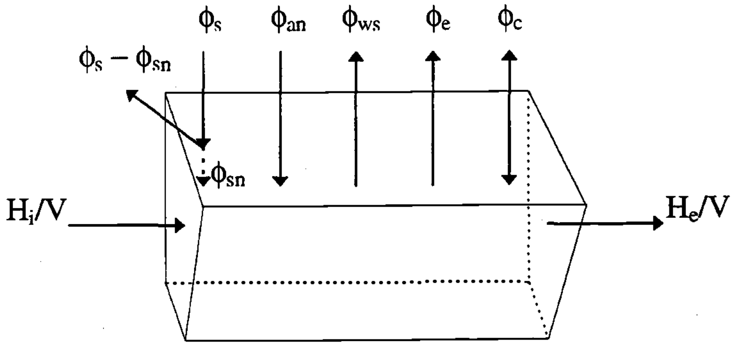

Figure 2.1. Energy transfer processes affecting water temperature profiles in a pond assumed to be a CSTR with unsteady flow. See text for explanation of the symbols.

$$\rho_w c_{pw} \frac{dT}{dt} = \frac{H_i}{V} - \frac{H_e}{V} + \frac{\phi_{net}}{d} - \phi_{vol} \qquad (1)$$

where dT/dt = rate change of pond water temperature (°C $d^{-1}$), $\rho_w$ = density of water (kg $m^{-3}$), $c_{pw}$ = heat capacity of water (kJ $kg^{-1}$ $°C^{-1}$), V = pond volume ($m^3$), $H_i$ = influent heat (kJ $d^{-1}$), $H_e$ = effluent heat (kJ $d^{-1}$), d = pond depth (m), $\phi_{net}$ = interfacial heat transfer due to various processes that occur at the pond surface (kJ $m^{-2}$ $d^{-1}$), and $\phi_{vol}$ = heat changes due to non-flow related volume variations (kJ $m^{-3}$ $d^{-1}$). Influent and effluent heat fluxes apply only when pond water is exchanged, either via source water supply or by pond water discharge, and can be computed as follows:

$$\frac{H_i}{V} = \rho_w c_{pw} Q_i T_i \qquad (2)$$

$$\frac{H_e}{V} = \rho_w c_{pw} Q_e T_e \qquad (3)$$

where $Q_i$ = influent flow rate ($m^3$ $d^{-1}$), $Q_e$ = effluent flow rate ($m^3$ $d^{-1}$), $T_i$ = influent or source water temperature (°C), and $T_e$ = effluent water temperature (°C). The change in water temperature caused by non-flow related volume variations can be calculated following McDuffie (1991). Using his expression together with Equations 2 and 3, the following ordinary differential equation can be derived from Equation 1 to obtain the rate of temperature change in a pond:

$$\frac{dT}{dt} = \frac{Q_i T_i}{V} - \frac{Q_e T_e}{V} + \frac{\phi_{net}}{\rho_w \, c_{pw} \, d} - \frac{T}{V}\left(\frac{dV}{dt}\right) \tag{4}$$

where dV/dt = rate change of pond volume ($m^3$ $d^{-1}$). Pond water temperature at any time can be obtained by integration of Equation 4.

Heat transfer processes that are typically considered in the calculation of $\phi_{net}$ for ponds include the net short-wave solar radiation penetrating the water surface ($\phi_{sn}$), net atmospheric long-wave radiation ($\phi_{an}$), long-wave water surface or back radiation ($\phi_{ws}$), evaporative heat transfer ($\phi_e$), and conductive heat transfer ($\phi_c$) (Ryan et al., 1974; Fritz et al., 1980; Henderson-Sellers, 1984; Fig. 2.1). The general expression for $\phi_{net}$ is given by:

$$\phi_{net} = \phi_{sn} + \phi_{an} - \phi_{ws} - \phi_e \pm \phi_c \tag{5}$$

Energy gained or lost via precipitation is usually considered to be negligible (Henderson-Sellers, 1984). Further, sensitivity analysis conducted by Losordo and Piedrahita (1991) suggests that pond water temperatures are only marginally sensitive to heat transfer between the water column and the underlying sediment; this process was therefore assumed to be negligible in the current work.

## Short-wave Solar Radiation

When short-wave (400-1100 nm) solar radiation ($\phi_s$) strikes the water surface, part of the energy is reflected and the remainder (i.e., $\phi_{sn}$) penetrates the water surface (Fig. 2.1), and is given by (Henderson-Sellers, 1984):

$$\phi_{sn} = \phi_s (1 - A_s) \tag{6}$$

where $A_s$ = short-wave reflectivity or albedo, which is a function of the solar altitude angle, water surface and local atmospheric characteristics, and the surrounding topography (Wetzel, 1983; Henderson-Sellers, 1984). According to the latter author, it is sufficient to assume that $A_s = 0.06$ for daily mean calculations of $\phi_{sn}$.

## Net Long-wave Atmospheric Radiation

Any material with a temperature above the absolute zero emits radiation according to the Stefan-Boltzmann fourth-power law (Henderson-Sellers, 1984). This law is used to calculate the net long-wave atmospheric radiation into the pond ($\phi_{an}$) and the water surface or back radiation losses ($\phi_{ws}$; see below) from the pond.

When solar radiation enters the atmosphere, a proportion of it is absorbed by clouds and $CO_2$, which reradiate this energy as long-wave radiation to the earth's surface. When this incident long-wave atmospheric radiation reaches the water surface, a portion of it is reflected back to the atmosphere. $\phi_{an}$ is the difference between the incident and reflected components of long-wave radiation, and can be approximated by (Henderson-Sellers, 1984):

$$\phi_{an} = (1 - r)\, \varepsilon_a\, \sigma\, T_{ak}^{\;4} \tag{7}$$

where r = water surface reflectance to long-wave radiation (decimal fraction), $\varepsilon_a$ = atmospheric emissivity (dimensionless), $\sigma$ = Stefan-Boltzmann constant ($4.896 \times 10^{-6}$ kJ $m^{-2}\ d^{-1}\ K^{-4}$), and $T_{ak}$ = absolute air temperature (°K). Water surface reflectance is typically assumed to be 0.03 (e.g., Henderson-Sellers, 1984; Losordo and Piedrahita, 1991). Several empirical formulae have been proposed for atmospheric emissivity (see Henderson-Sellers, 1984, p. 49). From this list, the formula developed by Swinbank (1963) and subsequently modified by Wunderlich (1972) provided the best results in trial simulations. This formula, which accounts for the effects of cloud cover ($C_c$) is expressed as follows:

$$\varepsilon_a = 0.937 \times 10^{-5} \times T_{ak}^{2} \left(1 + 0.17\, C_c^{2}\right) \tag{8}$$

## Water Surface Radiation

Water surface radiation is the result of heat emission from pond water, and can be estimated as follows (Henderson-Sellers, 1984):

$$\phi_{ws} = \varepsilon_w \, \sigma \, T_{wk}^{\;4} \tag{9}$$

where $\varepsilon_w$ = emissivity of water (approximately 0.97), and $T_{wk}$ = absolute water temperature (°K).

## Evaporative Heat Loss

Another component of the heat balance for pond water is the energy loss associated with the process of evaporation (i.e., via the latent heat of vaporization). As indicated by Losordo and Piedrahita (1991), evaporative heat losses from water bodies have been exhaustively studied and several expressions are available to estimate such losses. Although these authors reported that good estimates of $\phi_e$ could be obtained by the use of expressions given by Fritz et al. (1980), our experience (see also Chapter 3) suggests that more accurate evaporative heat and associated water loss estimates can be obtained using the approach of Ryan et al. (1974). This is consistent with the observations of Henderson-Sellers (1984). The formula developed by Ryan et al. (1974) is also the only one that accounts for both mechanical (forced) heat removal as a result of wind action, and convective heat removal of water vapor which is a function of the air-water temperature difference. The Ryan formula is expressed as follows:

$$\phi_e = (e_s - e_a)\left[\lambda (T_{wv} - T_{av})^{1/3} + b_0 u_2\right] \tag{10}$$

where $e_s$ = saturated vapor pressure at the current water temperature (mm Hg), $e_a$ = water vapor pressure immediately above the pond surface (mm Hg), $T_{wv}$ and $T_{av}$ are the virtual water and air temperatures respectively (°K), $\lambda$ and $b_o$ are constants with values of 311.02 kJ $m^{-2}$ $d^{-1}$ $mmHg^{-1}$ $K^{-1/3}$ and 368.61 kJ $m^{-2}$ $d^{-1}$ $mmHg^{-1}$ $(m\ s^{-1})^{-1}$ respectively, and $u_2$ = wind velocity ($m\ s^{-1}$) at a reference height of 2m above the pond water surface.

It should be noted that the convective heat removal component of Equation 10 is valid only when $T_{wv}$ is greater than $T_{av}$ (Ryan et al., 1974). Vapor pressures ($e_s$ and $e_a$ in Equation 10) can be approximated as follows (Troxler and Thrackston, 1977):

$$e_s = 25.37 \exp\left[17.62 - \frac{5271}{T_{wk}}\right] \tag{11}$$

$$e_a = R_h \times 25.37 \exp\left[17.62 - \frac{5271}{T_{ak}}\right] \tag{12}$$

where $R_h$ = relative humidity (decimal fraction), $T_{wk}$ = absolute water temperature (°K) and $T_{ak}$ = absolute air temperature (°K). The virtual water and air temperatures are given by (Ryan et al., 1974):

$$T_{wv} = \left(\frac{T_{wk}}{\left[1.0 - (0.378 \times e_s / P)\right]}\right) \tag{13}$$

$$T_{av} = \left(\frac{T_{ak}}{\left[1.0 - (0.378 \times e_a / P)\right]}\right) \tag{14}$$

where $P$ = barometric pressure (mm Hg). According to Colt (1984), $P$ can be approximated from the site altitude as follows:

$$P = \frac{760}{10^{z/19748.2}} \tag{15}$$

where z = site altitude (m).

## Conductive Heat Loss or Gain

Heat may be removed or added to pond water because of conduction between air and the water surface, a process that also depends on the air-water temperature difference. Conductive heat flux can be estimated as follows (Ryan et al., 1974):

$$\phi_c = \phi_e \times 0.61 \times 10^{-3} P \times \frac{(T_{wk} - T_{ak})}{(e_s - e_a)} \qquad (16)$$

## Model Implementation

The water temperature model has been implemented in the decision support system POND, a software that uses simulation models as the primary analysis tool for pond aquaculture facilities (see also Chapter 1). These models are solved by the use of a fourth-order Runge-Kutta integrator, which supports both daily and diurnal simulations of variables such as water temperature.

## Data Requirements

Use of the water temperature model for both daily and diurnal simulations requires a considerable number of data inputs, which can be classified into site, pond, source water and weather categories. The site data required include latitude, longitude and altitude. Pond data that are needed include dimensions and initial water temperature. Additionally, if water levels are routinely replenished in static ponds or if flow-through conditions are maintained in the ponds, use of the model requires water inflow rates and the temperature of the source water.

For seasonal-long simulations of daily pond water temperature, input weather data required for the model include mean daily air temperature, short-wave solar radiation, relative humidity, cloud cover and wind speed. When weather data are unavailable for such simulations, they can be approximated by the use of the simple weather generator described in Appendix I. Ideally, hourly measurements of weather variables are required for diurnal simulations. However, due to the non-availability of such data and because such frequent measurements of weather data are impractical under most conditions, verification of the temperature model for diurnal simulations has involved the use of reduced weather data inputs as documented below.

## MODEL VERIFICATION

Verification of the water temperature model has been accomplished for four sites (Table 2.1) maintained by the Pond Dynamics/Aquaculture Collaborative Research Support Program (PD/A CRSP). Among the selected sites, those in Thailand (Table 2.1) are located at low elevations, and are considered to be in the warm, humid tropics. The El Carao station in Honduras is located in the dry tropics, and the Rwasave station in Rwanda is a high elevation site in the tropics characterized by relatively cool air temperatures (Table 2.1). Further details regarding these sites may be obtained from Bowman and Clair (1996).

Weather data and pond information required for model verification were primarily extracted from the aquaculture database maintained by the PD/A CRSP. Two sets of model verifications namely seasonal-long simulations of mean daily pond temperature (referred to as daily simulations) and one day simulations of diurnal water temperature trends (diurnal simulations) were undertaken (Table 2.1). Diurnal trends were ignored in the former set of simulation runs. Time steps of one day and one hour were used to solve the model for daily and diurnal simulations respectively. Predicted and observed water temperatures were compared by the use of the two sample *t*-test procedure (Zar, 1984).

Table 2.1. Site and pond characteristics (including initial water temperatures) of four PD/A CRSP sites used for model verification. Dates for diurnal and daily simulations are also indicated (JD = Julian Day).

| | Bang Sai (Thailand) | AIT (Thailand) | El Carao Honduras | Rwasave Rwanda |
|---|---|---|---|---|
| Latitude | 14°45' N | 14°41' N | 14°26' N | 2°40' S |
| Longitude | 100°32' E | 100°29' E | 87°41' W | 29°45' E |
| Elevation (m) | 5 | 5 | 583 | 1700 |
| Pond size ($m^2$) | 220 | 380 | 1000 | 700 |
| Depth[a] (m) | 1 | 1 | 0.78 | 1.2 |
| Year | 1993[b], 1988[c] | 1991 | 1991-92[b], 1989[c] | 1989-90[b], 1988[c] |
| Simulation time[b] (d) | 222 | 140 | 122 | 159 |
| Temperature (°C) | | | | |
| Daily simulation | 28.7 (JD 15) | 31.0 (JD 156) | 26.1 (JD 252) | 19.9 (JD 286) |
| Diurnal simulation | 28.8 (JD 40) | 28.8 (JD 296) | 28.0 (JD 229) | 22.0 (JD 323) |

[a] Refers to the typical operating depth of the ponds. Although pond depths in all cases varied over time due to water losses and gains, they were assumed to be constant for seasonal long simulations of the mean daily water temperature.

[b] Refers to daily temperature simulations over a season.

[c] Refers to diurnal simulations that started at 0600h and lasted 24h.

Daily simulations are expected to be useful in planning or long-term farm management applications (e.g., screening of potential sites for the culture of particular fish species, use of water temperature as an input for forecasting fish yields, water chemistry calculations, estimation of fertilizer and feed requirements, and economic analysis). On the other hand, diurnal temperature simulations may be beneficial for short-term management tasks (e.g., coupled with dissolved oxygen models to assess aeration needs) or useful for research applications (e.g., analysis of short-term temperature fluctuations on fish performance or plankton dynamics).

During the physical experiments undertaken by PD/A CRSP researchers, ponds at all the sites were maintained at a more or less constant depths (Table 2.1) by periodic replenishment of water lost via evaporation and seepage. For simplicity and because source water temperatures were not routinely measured, the effects of these replenishments on the pond heat balance were assumed to be negligible (i.e., inflow was set to zero and ponds were assumed to have constant volumes).

### Daily Simulations

For each of the four sites where seasonal-long simulations were conducted, water temperature was predicted by the use of both data from actual weather records (RW), as well as generated weather (GW) data obtained from the weather model in POND. Solar radiation and air temperature values are generated in the weather model following Wunderlich (1972) and Straskraba and Gnauck (1985) respectively (see also Appendix I). For simplicity, the weather model assumes that cloud cover, relative humidity and wind speed are constant for the period simulated, and that they correspond to the mean of data recorded for the season simulated (if such data are available).

predicted values were compared to water temperature measurements reported in the PD/A CRSP database. For the Bang Sai site, observed water temperature refers to the average value of daily measurements made at three depths in the pond water column. Water samples at this site were collected during mid-morning hours. For the Rwasave site, 'observed' water temperature refers to the mean of two depth-averaged daily measurements, typically collected at 0700h and 1600h. For the AIT and El Carao sites, complete datasets were available only for diurnal measurements of water temperature recorded at three depths. These measurements were recorded at one week intervals for El Carao and two week intervals for AIT. 'Observed' daily water temperature for these two sites refers to the mean values of diurnal water temperatures recorded at the three depths, which were averaged once again to arrive at a single value for the overall pond water column.

A comprehensive weather dataset (short-wave solar radiation, cloud cover, air temperature, relative humidity, and wind speed) was available only for the AIT site, where daily measurements were made by the use of an international standard weather station located next to the ponds (C.K.Lin, Asian Institute of Technology, personal commn.). Daily mean air temperature was assumed to be the average of the daily minimum and maximum values. Cloud cover data at this site were reported in oktas, which were converted to decimal fractions following FAO guidelines (FAO, 1977).

Measured weather data for use in the seasonal-long RW simulations at the other three sites were primarily retrieved from the PD/A CRSP database. Missing points in these datasets were estimated by linear interpolation. Daily mean air temperature was again assumed to be the average of minimum and maximum air temperatures. Although measurement of $\phi_s$ is not a requirement of the PD/A CRSP data collection protocol, daily photosynthetically active radiation (PAR; E $m^{-2}$ $d^{-1}$) of wavelength 400-700 nm is measured. For the Bang Sai and Rwasave sites, PAR measurements were converted to $\phi_s$ estimates by multiplication with a factor of 505.67. This conversion factor is based on the assumption that 1 E $\approx$ 217.44 J of energy, and that only 43% of the overall radiation is photosynthetically active (Withrow and Withrow, 1956). For El Carao, PAR measurements were converted to $\phi_s$ by the use of an empirical relationship developed for this site (Piedrahita and Teichert-Coddington, 1993).

Relative humidity and cloud cover measurements are not a requirement of the PD/A CRSP data collection protocol. Because the Bang Sai site is located close to AIT and has similar weather characteristics, daily cloud cover (in oktas) and $R_h$ data collected at the latter site were used for the RW simulations. Cloud cover data were converted to decimal fractions as indicated for the AIT site above. For El Carao and Rwasave, we used mean monthly $R_h$ estimates from weather stations in the vicinity of these sites as archived in an FAO agroclimatic database (FAO, 1995). For the GW simulations, $R_h$ was set to the average value estimated from the above sources. These values corresponded to 73.7, 73.1, 74.3 and 76.3% for Bang Sai, AIT, El Carao and Rwasave respectively. Because short-wave solar radiation values were already estimated (from PAR measurements) in the RW simulations, cloud cover data were only required to estimate atmospheric emissivity (Equation 8). Calibration runs indicated that a value of 0.75 for cloud cover (indicating broken cloud cover conditions) was adequate for El Carao and Rwasave.

For the GW simulations, cloud cover data are also needed to approximate the daily incident short-wave solar radiation (see Appendix I). For both AIT and Bang Sai, the mean $C_c$ of 0.5 (indicating scattered cloud cover conditions) from the observed values was used in GW simulations. For El Carao and Rwanda, it was necessary to indirectly estimate an appropriate value of $C_c$ by comparing observed PAR values (after conversion to short-wave solar radiation estimates) to those predicted by the use of the POND weather model (Appendix I). This calibration process again suggested that setting $C_c$ = 0.75 was adequate for these two sites. Finally, RW simulations used wind speed data recorded in the PD/A CRSP database. The overall mean wind speed estimated from these data were used for the GW simulations. These means were 1.47, 1.19, 2.32 and 0.93 m $s^{-1}$ for Bang Sai, AIT, El Carao and Rwasave respectively.

## Diurnal Simulations

Sources identical to those described above for daily simulations were used to obtain data for verification of diurnal simulations at the four PD/A CRSP sites. However, model verification was accomplished by the use of recorded weather data only. It was necessary to perform additional calculations to arrive at hourly air temperature and short-wave solar radiation values. The sinusoidal function developed by Card et al. (1976) was used to estimate hourly air temperatures under the assumption that the daily minimum and maximum temperatures (recorded in the PD/A CRSP database) occurred at 0600h and 1500h respectively (Culberson and Piedrahita, 1992; see also Appendix I). Similarly, the function given by Monteith (1973; Appendix I) was used to estimate hourly radiation values from daily total short-wave insolation estimates.

## Sensitivity Analysis

It is often desirable to know model sensitivity to input data. Such sensitivity analyses are useful to assess and modify data collection protocols, and often lead to improvements in model structure and predictive capabilities. The water temperature model developed in the current study was subjected to a generalized sensitivity analysis with regard to input weather data, particularly because water temperature profiles are sensitive to these variables (e.g., Losordo and Piedrahita, 1991). This analysis was accomplished for both daily and diurnal simulations by a ±10% adjustment in the values of the recorded weather data. Simulation results from these multiple runs were compared to model output (referred to as the base runs) generated by the use of the original weather dataset. Other simulation conditions were as described above (see also Table 2.1). Sensitivity analysis was performed only for the Bang Sai and AIT sites, where more or less complete weather records were available.

For all the sensitivity analysis scenarios described above, absolute changes in model output were summarized in terms of the average shift in water temperature with respect to the change in each of the input (I) weather variables (i.e., $\Delta T/\Delta I$). Dimensions of the weather variables were chosen to enable easy interpretation of the results. Thus, instead of expressing $\Delta T$ for a 10% change in air temperature, sensitivity analysis results were summarized in terms of $\Delta T$ for a one degree change in air temperature. Finally, in order to rank the weather variables on the basis of the magnitude of their effects on model output, relative sensitivities (RS) were also calculated as follows:

$$RS = \frac{\left(\dfrac{\Delta T}{T_{mw}}\right)}{\left(\dfrac{\Delta I}{I_m}\right)} \qquad (17)$$

where: $T_{mw}$ = mean water temperature (°C) for the base run, and $I_m$ = mean value of the weather variable in the original dataset.

## RESULTS AND DISCUSSION

Simulation results for daily and diurnal simulations at the five sites are summarized in Table 2.2 and discussed in detail below.

### Daily Simulations

Temperatures predicted from RW simulations and observed water temperatures were not significantly different ($P > 0.05$) for all the four sites (Table 2.2; Figs. 2.2-2.5). Observed water and air temperatures (data not shown) tended to have similar profiles at all the sites. Water temperatures predicted by the use of the weather model were significantly different from observed values at the AIT and Rwasave sites (Table 2.2; see also Figs. 2.3 and 2.5). The discontinuities at the beginning of the simulation results for the GW runs at Bang Sai (Fig. 2.2), El Carao (Fig. 2.4) and Rwasave (Fig. 2.5) are an artifact of initial conditions (i.e., observed water temperatures) used in the simulations. The temperatures used to initiate these simulations were either higher (as in Bang Sai) or lower (as in El Carao and Rwasave) than the equilibrium water temperatures resulting from the use of data generated by the POND weather model.

For both Bang Sai and AIT, the RW predictions accurately followed patterns of the observed temperatures (Figs. 2.2 and 2.3). However, at both sites, the model appeared to slightly under-predict temperatures (see also Table 2.2). For the AIT site where diurnal measurements were used to estimate 'observed' daily mean temperatures (as indicated earlier), large discrepancies in model predictions tended to occur on the days when ponds were severely stratified, and surface water temperatures exceeded 35°C for part of the diurnal period. Presumably, similar conditions occurred in the Bang Sai ponds as well. Under such circumstances, it is debatable whether averaging temperatures over both time

Table 2.2. Summary of results obtained with the water temperature model at four PD/A CRSP sites. For daily simulations, the results are reported in terms of the means and standard deviations (SD) of the observed and predicted temperatures (obtained from both RW and GW simulation runs). For diurnal simulations, the mean and range of deviations between observed and predicted values are indicated.

| | Bang Sai (Thailand) | AIT (Thailand) | El Carao (Honduras) | Rwasave (Rwanda) |
|---|---|---|---|---|
| Daily Simulations | | | | |
| Observed mean | 28.56 | 29.96 | 25.21 | 22.37 |
| SD | 1.73 | 0.52 | 2.06 | 1.01 |
| *RW Runs* | | | | |
| Predicted mean[1] | $28.02^{ns}$ | $29.66^{ns}$ | $25.42^{ns}$ | $22.05^{ns}$ |
| SD | 1.43 | 0.66 | 2.74 | 1.13 |
| *GW Runs* | | | | |
| Predicted mean[1] | $28.18^{ns}$ | $31.57^{s}$ | $25.51^{ns}$ | $22.96^{s}$ |
| SD | 1.66 | 0.58 | 1.42 | 0.31 |
| Diurnal Simulations | | | | |
| *Deviations* | | | | |
| Mean[2] | $0.01^{ns}$ | $0.06^{ns}$ | $-0.07^{ns}$ | $-0.01^{ns}$ |
| Minimum[3] | –0.55 | –0.39 | –0.67 | –0.29 |
| Maximum[4] | 0.23 | 0.47 | 0.37 | 0.92 |

[1] Predicted mean calculated for the days when observed temperatures were available.

[2] Refers to the mean difference between predicted and observed temperatures.

[3] Refers to the lower limit of the deviation between predicted and observed temperatures.

[4] Refers to the upper limit of the deviation between predicted and observed temperatures.

[ns] Observed and predicted temperatures not significantly different at the 0.05 alpha level.

[s] Observed and predicted temperatures significantly different at the 0.05 alpha level.

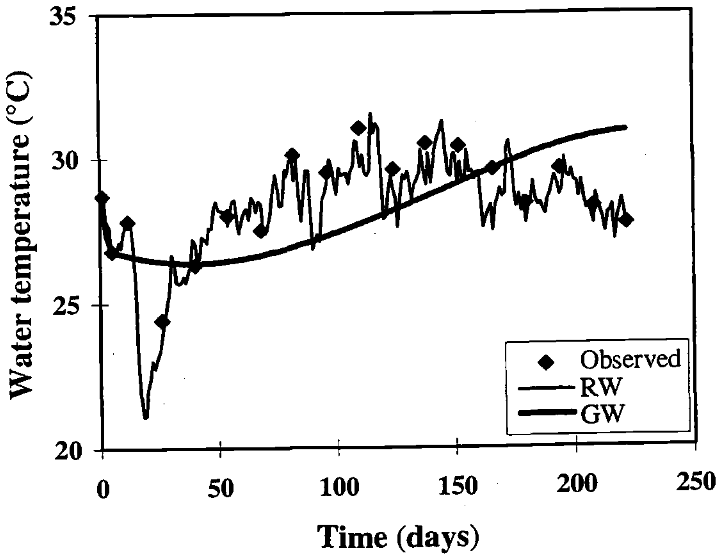

Figure 2.2. Daily pond water temperatures predicted by the use of recorded (RW) and generated (GW) weather data for Bang Sai.

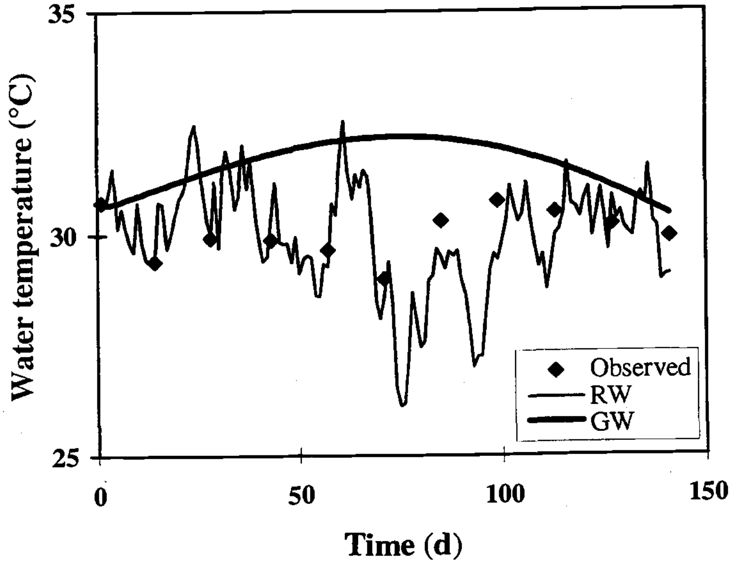

Figure 2.3. Daily pond water temperatures predicted by the use of recorded (RW) and generated (GW) weather data for AIT.

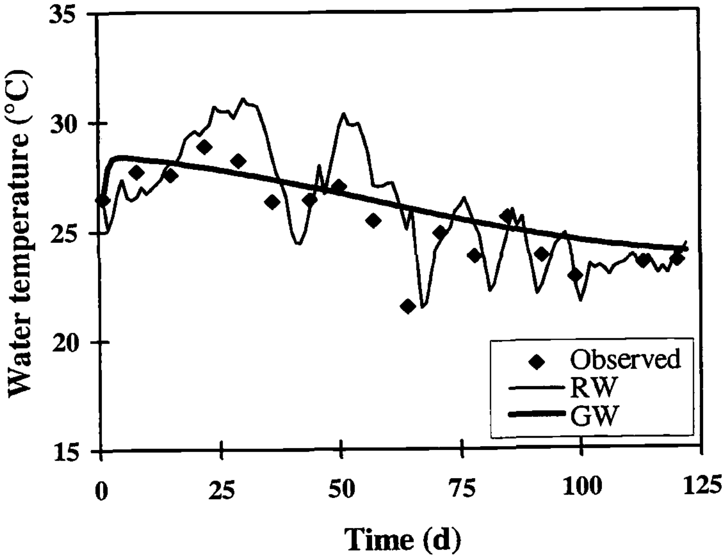

Figure 2.4. Daily pond water temperatures predicted by the use of recorded (RW) and generated (GW) weather data for El Carao.

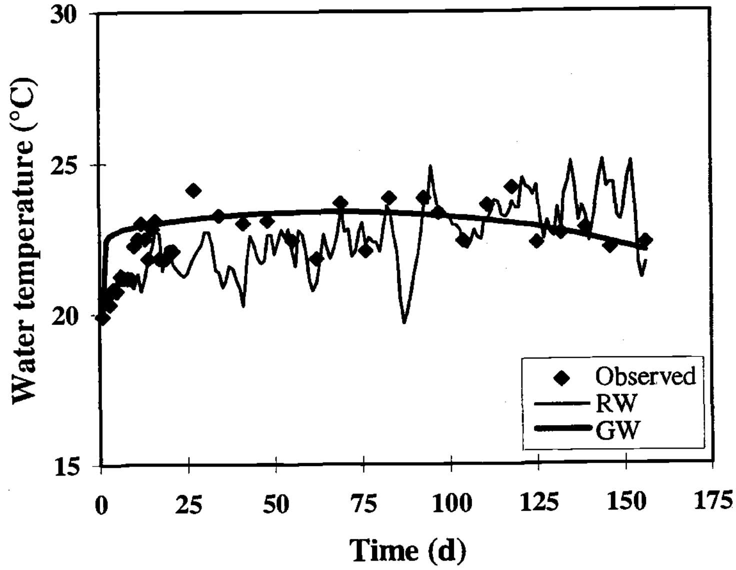

Figure 2.5. Daily pond water temperatures predicted by the use of recorded (RW) and generated (GW) weather data for Rwasave.

and pond depth as was done for AIT results in values that are representative of the daily mean temperature for the overall water column.

RW temperature predictions for El Carao (Fig. 2.4) and Rwasave (Fig. 2.5) were also relatively comparable to observed values, although the deviations over the course of the simulations were fairly high, particularly for El Carao (Table 2.2). For Rwasave, differences between RW predicted and observed water temperatures may have been caused by the lack of daily cloud cover and relative humidity data. As indicated earlier, a constant cloud cover value (0.75) and monthly relative humidity estimates were assumed. Model discrepancies at this site may also be due in part to the use of daily mean air temperatures to estimate evaporative and conductive heat fluxes. As indicated earlier, the daily simulations ignored diurnal trends in variables such as air temperature. This assumption may not have resulted in substantial errors for sites such as Bang Sai, AIT and El Carao where the average difference (i.e., amplitude) between daily minimum and maximum air temperatures was about 10-11°C. On the other hand, the high-elevation Rwasave site experienced average daily air temperature amplitudes of over 15°C with a seasonal range of 7-21°C. Thus, the use of daily mean air temperature values at such sites may not result in adequately accurate estimates of energy fluxes (e.g., evaporation) that are dependent on this variable, particularly on days when the air temperature amplitude is high. This problem may be circumvented by the use of diurnal simulations for seasonal-long periods. However, such simulations are computation-intensive, and more importantly, the benefits of diurnal simulations are unlikely to be fully realized without the additional availability of cloud cover and relative humidity measurements.

Reasons for the fairly high deviations between RW predictions and observed temperatures at El Carao may be caused by several factors. Firstly, the weather datasets for this site were the least comprehensive among all the tested sites, not only from the perspective of the lack of daily cloud cover and relative humidity data, but also because apart from short-wave solar radiation, there were several missing points for the other weather variables which were replaced by estimates obtained by interpolation. Another possible explanation for the above deviations is that the El Carao pond was shallower than the other ponds simulated (Table 2.1). The water temperature model used in this study assumes fully mixed conditions so that the various energy transfer processes are also assumed to be effective across the entire pond water column. In reality, many of these processes (e.g., radiation, evaporation) principally impact the surface water layer. Stratified pond temperature models which assume the pond water column to be composed of distinct horizontal segments (e.g., Losordo and Piedrahita, 1991; Culberson and Piedrahita, 1992) perhaps better account for the effects of such processes by performing the relevant energy transfer calculations for the surface water segment only. For shallow ponds such as those at El Carao, it is possible that the water temperature model used here may tend to cause day-to-day trends in the predicted daily temperatures to be more pronounced than the actual pond temperature profiles (Fig. 2.4).

It is interesting to note that although El Carao and the Thailand sites are located at similar latitudes (Table 2.1), water temperatures at the former location were lower than those at Thailand by an average of about 4°C (Table 2.2). Presumably, this is the result of the higher altitude of the El Carao station (Table 2.1) as well as the surrounding mountainous terrain (Bowman and Clair, 1996).

Compared to the results of the RW simulations, GW predictions were less accurate for all the four sites, particularly in terms of the general trends in seasonal water temperature profiles (Figs. 2.2-2.5). This was particularly true for AIT where GW predicted temperatures always exceeded observed values (Fig. 2.3; Table 2.2). These discrepancies appear to be related to inadequately accurate predictions of daily air temperature and/or short-wave solar radiation values by the POND weather generator at the different sites.

At Bang Sai, the GW predicted water temperatures were lower than observed values (Fig. 2.2; Table 2.2), presumably because the air temperature values generated by the POND weather generator were lower than the observed values by an average of 0.8°C over the course of the simulation period. The predicted water temperature profile also closely followed trends in the air temperature estimates generated by the POND weather model. Measured air temperatures tended to lag behind these estimates. Generated daily short-wave insolation values were, however, comparable to observed values.

At AIT, generated values for both air temperature and short-wave insolation were higher than the observed values. However, as was the case for Bang Sai, the former variable appeared to be the main reason for the poor GW predictions of water temperature (Table 2.2), because the overall mean of the predicted daily air temperatures (29.9°C) substantially exceeded the mean of the observed values (27.7°C). Further, the predicted water temperature profile (Fig. 2.3) closely matched the seasonal air temperature profile predicted by the POND weather generator.

GW predicted water temperatures tended to slightly exceed observed values at El Carao as well (Fig. 2.4; Table 2.2), apparently because predicted air temperatures exceeded observed values by an average of about 0.5°C. Mean short-wave insolation estimates from the POND weather generator at this site were, however, comparable to values obtained from PAR measurements. Finally, at Rwasave, higher short-wave insolation estimates presumably caused the GW predicted water temperatures to exceed observed values by about 0.6°C on average (Fig. 2.5; Table 2.2). Predicted short-wave insolation values exceeded those obtained from PAR measurements by about 3700 kJ $m^{-2}$ $d^{-1}$ over the course of the simulation. In contrast to the results for the other three sites, mean predicted (20.9°C) and observed (20.8°C) air temperatures were very comparable for this location.

Results of the GW simulations suggest that improvements in water temperature predictions via the use of the POND weather generator will likely require more accurate methods of estimating air temperature and short-wave solar radiation. Use of more sophisticated weather generators (e.g., Richardson and Wright, 1984; Geng et al., 1988) may enable this goal to be achieved. On the other hand, with the exception of the AIT site (Fig. 2.3), GW temperature predictions were perhaps accurate enough for most long-term planning applications. Further, the POND weather generator is easy to use, and should be beneficial in the preliminary analysis of water temperature profiles at locations for which complete weather datasets are either not available or not readily accessible. The POND weather generator has, for example, been used to generate water temperature profiles for Latin America which were in turn used to estimate potential fish yields for the inland regions of the continent (Kapetsky and Nath, in prep.).

### Diurnal Simulations

Predicted water temperature profiles over diurnal periods were consistent with observed temperatures at all the four sites where the model was tested (Figs. 2.6-2.9; Table 2.2). Differences between predicted and observed temperatures were also not significant ($P > 0.05$). For the Bang Sai and AIT sites in Thailand, deviations between predicted and observed temperatures were approximately in the range of ± 0.5°C (Figs. 2.6 and 2.7; Table 2.2). This degree of accuracy is likely to be adequate for most management and research applications where routine estimates of diurnal water temperatures are required.

Deviations between predicted and observed values at El Carao and Rwasave were higher than those for the Thailand sites (Figs. 2.8 and 2.9; Table 2.2), and were presumably caused by the same factors previously discussed in the section on daily simulations. The model also predicted a much higher water temperature for Rwasave at 0930h (Fig. 2.9), a discrepancy that may in part be due to the assumption of symmetrical diurnal distributions for air temperature and short-wave solar radiation. A tendency for the model to consistently under-predict water temperatures towards the end of the 24h simulation period is noticeable for the Bang Sai, AIT and El Carao sites (Figs. 2.6-2.8), and may also be related to the assumptions of a constant cloud cover, relative humidity

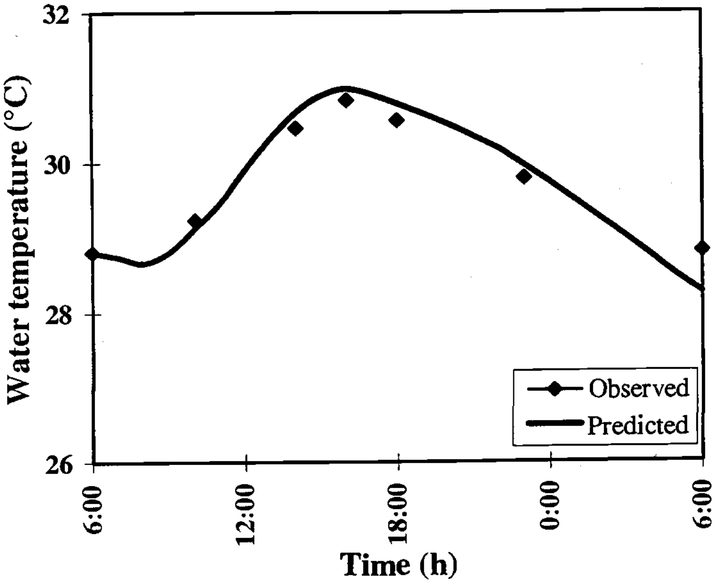

Figure 2.6. Diurnal observed and predicted pond water temperatures for Bang Sai.

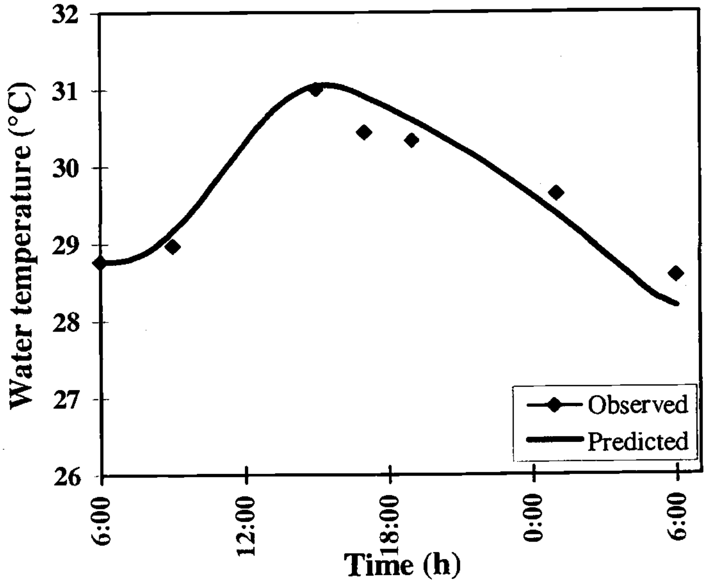

Figure 2.7. Diurnal observed and predicted pond water temperatures for AIT.

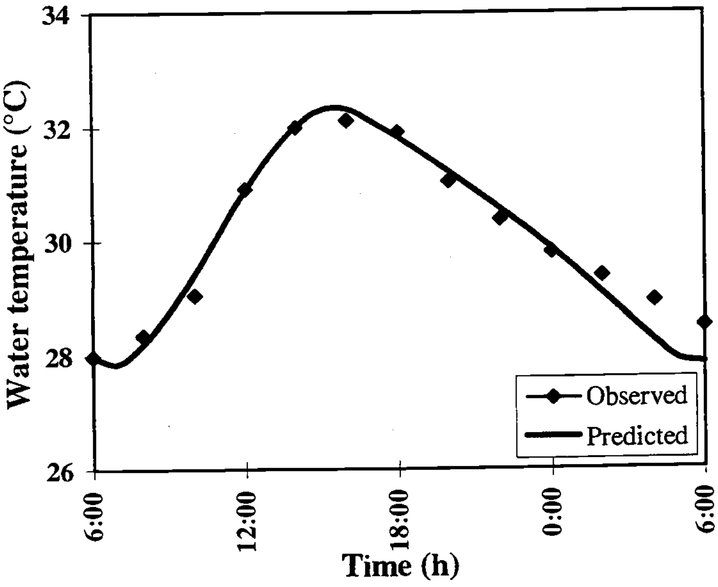

Figure 2.8. Diurnal observed and predicted pond water temperatures for El Carao.

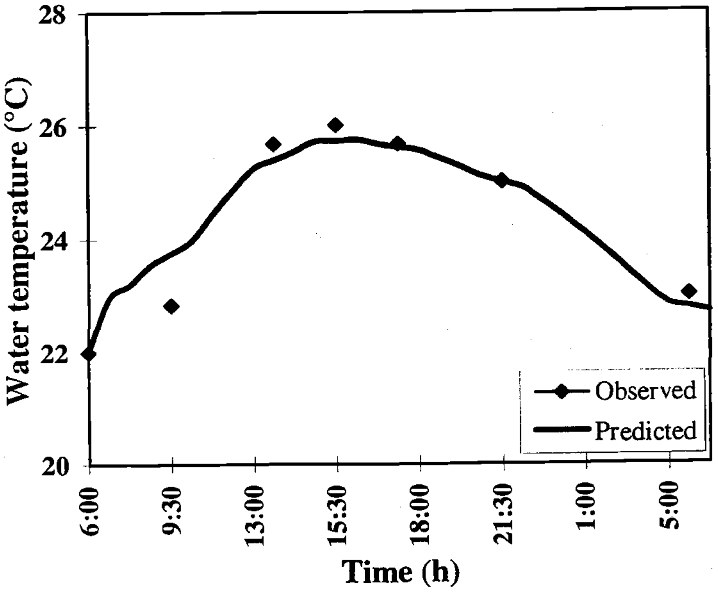

Figure 2.9. Diurnal observed and predicted pond water temperatures for Rwasave.

and wind speed over the course of a day. These variables do show pronounced diurnal trends that were ignored in the analysis. From a practical standpoint, it is unlikely that diurnal measurements of such variables can be justified in terms of the additional cost and effort. Model discrepancies may possibly be related to the assumption of fully mixed conditions in the ponds as well. For diurnal simulations lasting about one day, these discrepancies are unlikely to be a cause for concern. However, if such simulations are conducted over longer time periods (e.g., one week or more), it is possible that the cumulative errors may be fairly substantial.

## Sensitivity Analysis

Water temperatures generated from daily simulations were most sensitive to mean air temperature, followed by relative humidity, short-wave solar radiation, cloud cover, and wind speed (Table 2.3). This ranking of model sensitivity towards the weather variables for daily simulations was identical at both Bang Sai and AIT, although there were some differences in the magnitude of the sensitivities between the two sites (Table 2.3). For diurnal simulations at both sites, the ranking of model sensitivity was similar, with the exception that the sensitivity of water temperatures to wind speed was marginally higher than that for cloud cover (Table 2.3). Further, sensitivity of model output towards all the input weather variables was lower in the diurnal simulations compared to seasonal long daily simulations. Direct comparison of these two sets of simulations is, however, not strictly valid because the daily runs ignored diurnal trends and were conducted for several months (Table 2.1), whereas the diurnal simulations lasted only 24h.

The generally high sensitivity of model predictions to air temperature is not surprising because both seasonal and diurnal profiles of water and air temperatures in shallow static ponds are closely correlated (e.g., Wax et al., 1987; Losordo and Piedrahita, 1991; Kapetsky, 1994). However, the comparatively low sensitivity of model response to

Table 2.3. Relative (RS) and absolute (AS) sensitivities of water temperature model output to a ±10% change in the values of input weather variables for daily and diurnal simulations. The units for AS with regard to air temperature ($T_a$), relative humidity ($R_h$), short-wave solar radiation ($\phi_{sn}$), cloud cover ($C_c$) and wind speed ($u_2$) respectively are: °C/°C, °C/%, °C/MJ $m^{-2}$ $d^{-1}$, °C/tenth, and °C/m $s^{-1}$. Negative values indicate that water temperature decreases with an increase in the value of the input weather variable.

| | Bang Sai | | AIT | |
|---|---|---|---|---|
| | RS | AS | RS | AS |
| Daily Simulations | | | | |
| $T_a$ | 0.959 | 0.942 | 0.788 | 0.855 |
| $R_h$ | 0.210 | 0.080 | 0.204 | 0.084 |
| $\phi_{sn}$ | 0.091 | 0.308 | 0.149 | 0.295 |
| $C_c$ | 0.045 | 0.244 | 0.063 | 0.268 |
| $u_2$ | –0.038 | -0.701 | –0.053 | –1.324 |
| Diurnal Simulations | | | | |
| $T_a$ | 0.379 | 0.391 | 0.677 | 0.618 |
| $R_h$ | 0.085 | 0.036 | 0.157 | 0.061 |
| $\phi_{sn}$ | 0.083 | 0.173 | 0.115 | 0.264 |
| $u_2$ | –0.021 | –0.634 | –0.036 | –1.340 |
| $C_c$ | 0.004 | 0.050 | 0.024 | 0.142 |

changes in $\phi_{sn}$ is somewhat surprising because this variable varies substantially from day to day according to atmospheric conditions (Henderson-Sellers, 1984). Moreover, previously developed pond water temperature models (e.g., Fritz et al., 1980; Krant et al., 1982; Losordo, 1988) are apparently quite sensitive to $\phi_{sn}$. Results of the sensitivity analysis in the current study, however, indirectly suggest that both daily mean as well as diurnal water temperatures are closely related to evaporative heat flux, which is predominantly a function of ambient air temperature, relative humidity and wind speed (see Equations 10-14). These results also suggest that weather data collection protocols for aquaculture facilities such as those established by the PD/A CRSP should include routine measurements of relative humidity in addition to variables that are already measured. It may also be useful to measure daily cloud cover if more accurate predictions of water temperature are desired. Availability of comprehensive weather datasets will likely be of use in improving water temperature predictions, and enabling better estimates of water requirements for pond aquaculture (see also Chapter 3). Moreover, if such datasets are collected over long time periods (i.e., several years), they may ultimately find use in the refinement and parameterization of stochastic weather generators.

## CONCLUSIONS

The water temperature model developed in this study has been verified for geographically distinct sites. In general, the model predicts daily water temperature profiles over long-term periods with a reasonable degree of accuracy at all the sites, especially when actual weather data are used as inputs. These results suggest that the model is relatively robust, and should therefore be useful for applications such as regional-scale assessment of aquaculture potential for species with different temperature preferenda, as well as in other planning and management tasks (e.g., estimation of feed requirements and water quality management) where seasonal-long temperature predictions are needed. However, the model may exaggerate trends in daily mean water temperature for sites with shallow ponds (<0.8m in depth) or where there are large differences (>15°C) between daily maximum and minimum air temperatures. It is advisable to compare predicted and measured pond temperatures at individual locations to gauge whether the POND weather generator may be used for seasonal-long simulations in lieu of routine measurements of weather variables.

Simulations of diurnal water temperature profiles for short-term periods at different sites consistently resulted in good agreement between predicted and observed temperatures. However, a tendency for lower water temperatures towards the end of the simulation period was observed. It would be interesting to examine whether this tendency leads to larger errors over longer simulation periods (e.g., one week or more). More frequent water temperature measurements would, however, be necessary for such validation exercises. For experimental sites such as those operated by the PD/A CRSP (where routine water quality data collection occurs), this could be achieved by the use of temperature sensors attached to automatic data loggers (as in Losordo et al., 1988). Diurnal temperature projections will probably be most beneficial in systems models (designed to understand and analyze the dynamics of ponds), where temperature is likely to be one of many state variables.

Sensitivity analyses indicate that the water temperature model is most sensitive to air temperature, relative humidity and short-wave solar radiation. Therefore, increased accuracy in water temperature projections can be expected when measurements of at least these three weather variables are available as input to the model.

# CHAPTER 3

# A WATER BUDGET MODEL FOR POND AQUACULTURE

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## ABSTRACT

Previous water budget studies for aquaculture ponds have involved the identification and measurement of different water sources and sinks, but the methodology used in these studies has not been synthesized in the form of a general purpose tool for forecasting pond water requirements. The development of a water budget simulation model for aquaculture ponds is the focus of this study. Water gains considered in the model include regulated inflow, precipitation and runoff, whereas water losses include evaporation, seepage, effluent discharge, and overflow. The model has been validated for ponds located at the Asian Institute of Technology (AIT), Thailand and at El Carao, Honduras which are respectively located in the humid and dry tropics. Simulation results indicate that precipitation accounted for 69.8% of the total water gains for AIT and 43.2% for El Carao. Similarly, regulated inflow provide 27% of the gains for AIT and 52.8% for El Carao. Runoff gains were minimal at both locations, presumably a result of small watershed areas. Evaporation accounted for 54.9% and 40.1% of the overall water loss predicted for the AIT and El Carao locations, whereas seepage accounted for the remaining loss. The difference between actual and predicted amounts of regulated water inflow for the AIT pond was only 20.3 $m^3$ over a simulation period lasting five months. For El Carao, predicted water requirements were 141.3 $m^3$ lower than the amounts actually added, apparently due to poor estimates of evaporative water loss which averaged 0.32 cm $d^{-1}$ compared to pan evaporative measurements of 0.43 cm $d^{-1}$. In contrast, the predicted evaporative water loss for the AIT pond (0.47 cm $d^{-1}$) was comparable to the pan evaporation estimate of (0.45 cm $d^{-1}$) for this site. More complete weather datasets for AIT compared to El Carao appear to explain the higher accuracy in evaporative water loss estimates for the former site. If such comprehensive weather datasets are available for different locations, the water budget model shows considerable potential for the estimation of pond water requirements at individual facilities as well as over larger regions. The model can also be used as a tool to compare the benefits of water use for aquaculture relative to other agricultural practices.

## INTRODUCTION

Development of pond water budgets is important from the perspectives of estimating water requirements for ponds that rely on rainfall events and runoff as primary water sources (Boyd, 1982), and for flow-through pond facilities (which mainly use levee ponds). Such budgets are also useful in assessing whether a potential or existing source will meet the projected water demand of aquaculture facilities. Water budget analysis may also be useful in comparing the value of available water for different agricultural crops as suggested by Green and Boyd (1995), and may have implications for examining the environmental effects of pond water discharge either by intended water release or overflow.

Although various research efforts have focused on developing water budgets for different pond aquaculture systems (e.g., Szumiec, 1979a; Boyd, 1982; Teichert-Coddington et al., 1988; Green and Boyd, 1995), the general methodology used in these studies has not been synthesized in the form of a model that can be easily adapted to new locations as a general purpose tool for forecasting water budgets over long-term periods. The focus of the research presented in this paper is on the implementation and validation of a water budget model that can be used for short- and long-term assessment of pond water requirements at locations with different weather, soil and watershed characteristics.

## MODEL STRUCTURE

Sources of water into a pond include regulated inflow ($Q_i$), precipitation on the pond surface (P), and runoff from the watershed area around a pond (R) (Boyd, 1982). For many levee ponds, the latter source may be negligible. Water sinks include regulated water discharge ($Q_o$), overflow (O), and evaporation (E) (Boyd, 1982). Water seepage (S) may occasionally be a source of water (e.g., for ponds constructed in areas with a high water table), although it is typically considered as a loss term. Typical pond water sources and sinks are summarized in Figure 3.1. The differential equation that expresses the change in pond volume over time (dV/dt; $m^3$ $d^{-1}$) can be expressed as:

$$\frac{dV}{dt} = Q_i + P + R - Q_o - O - E \pm S \tag{1}$$

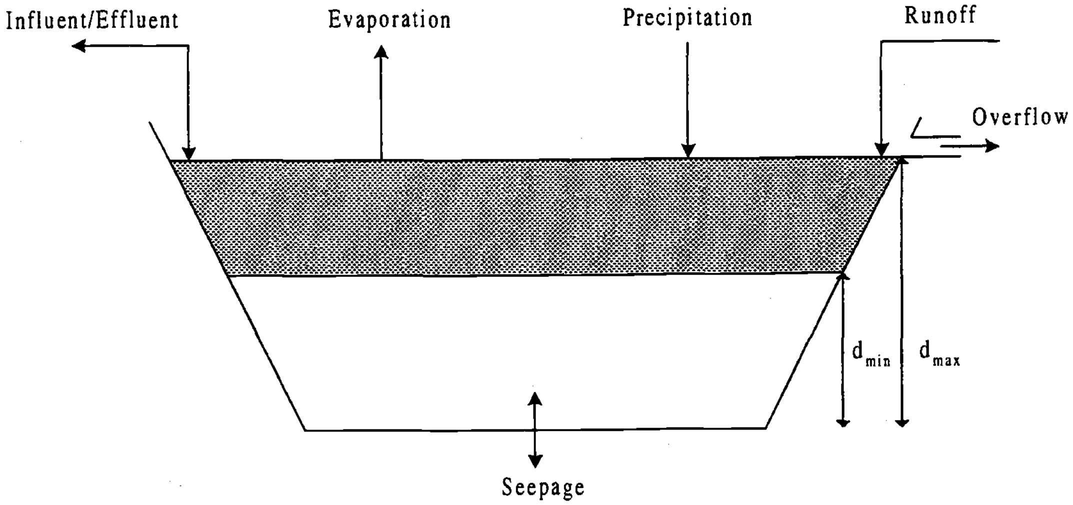

Figure 3.1. Schematic diagram showing typical water sources and sinks for an aquaculture pond. $d_{min}$ and $d_{max}$ respectively refer to the minimum desired and maximum possible pond water depth.

## Regulated Inflow

Pond water inflow may be either intermittent (e.g., when adequate water is supplied to maintain a desired pond depth) or continous (e.g., a flow-through pond). In the latter situation, the influent rate ($I_r$; % pond volume per day) is assumed to be a known factor and $Q_i$ is calculated as:

$$Q_i = \frac{I_r}{100} \times V \tag{2}$$

Estimation of the water needed to maintain a minimum pond depth ($d_{min}$; m) requires calculation of water sink and source terms other than $Q_i$ in Equation 1. Re-arrangement of this equation provides an estimate of the *net water demand* ($N_{wd}$):

$$N_{wd} = (Q_o + O + E \pm S) - (P + R) \tag{3}$$

A negative value for $N_{wd}$ indicates that the pond water sources exceed the sink terms (i.e., the water level is in the range depicted by the stippled area in Fig. 3.1), in which case water addition is not required and $Q_i$ is set to zero. However, a positive value for $N_{wd}$ indicates that it may be necessary to add sufficient water to ensure that the pond is maintained at $d_{min}$ (because the current water depth $d_{curr} < d_{min}$). For the latter situation, $Q_i$ is approximated by:

$$Q_i = \frac{A\,(d_{min} - d_{curr})}{dt} \tag{4}$$

where A = surface area of the pond at the current water level ($m^2$) and $d_{curr}$ = current pond depth (m). Equation 4 may tend to slightly over-estimate the amount of water required for ponds that have a sloped levee because it assumes that the slice of water corresponding to the difference between $d_{curr}$ and $d_{min}$ is rectangular rather than trapezoidal in shape. This is evident in Figure 3.1 if it is assumed that $d_{curr} = d_{max}$. However, this error will likely be negligible except in very small ponds that have shallow slopes and substantial flux in water levels.

## Precipitation

Water gain from rainfall falling on the pond surface can be calculated from precipitation data for a given location as follows:

$$P = \frac{A\,p_d}{1000} \tag{5}$$

where $p_d$ is the daily rainfall (mm $d^{-1}$).

## Runoff

Hydrological methods that are commonly used in aquaculture for estimating runoff have been presented by Yoo and Boyd (1994). According to these authors, the *curve number method* developed by the U.S. Soil Conservation Service (SCS) (1972) offers a simple procedure for estimating runoff from ungauged watersheds. The method involves assessment of the antecedent soil moisture, hydrologic soil group, land use and hydrologic condition for a given location. The SCS developed a series of curves that relate combinations of the above factors with the expected runoff given the amount of rainfall produced by a storm. Curve numbers (CN) for different combinations of soil, land use and hydrologic conditions have been tabulated by the SCS (see also Yoo and Boyd, 1994). The SCS equation for the maximum watershed retention ($w_r$; mm $d^{-1}$) is as follows:

$$w_r = \left(\frac{1000}{CN} - 10\right) \times 25.4 \tag{6}$$

Combining the SCS equation that relates runoff and rainfall depths with the effective watershed area (W; m$^2$) around a pond results in the following empirical equation for the amount of daily runoff (m$^3$ d$^{-1}$):

$$R = W\left(\frac{(p_d - 0.2\,w_r)^2}{p_d + 0.8\,w_r} \times \frac{1}{1000}\right) \tag{7}$$

## Regulated Water Discharge

Pond water may be discharged continually (e.g., in a flow-through pond) or intermittently (e.g., at harvest time or to alleviate poor water quality). The latter situation is difficult to assess *a priori* and is therefore not considered in the present model. However, if the rate at which effluent is released from a pond ($E_r$; % pond volume per day) is known, $Q_o$ can be calculated as:

$$Q_i = \frac{E_r}{100} \times V \tag{8}$$

## Overflow

Pond water overflow occurs when the water level exceeds the maximum depth for the pond basin (Fig. 3.1), a situation that typically depends on the depth of the drain pipe. Overflow can be calculated as follows:

$$O = \frac{A\,(d_{curr} - d_{max})}{dt} \tag{9}$$

As in the case for influent water requirements (Equation 4), the above equation may also tend to slightly over-estimate the amount of water lost by overflow, because the slice of water corresponding to the difference between $d_{curr}$ and $d_{max}$ (Fig. 3.1) is assumed to be rectangular rather than trapezoidal in shape. However, this error is probably negligible except in very small ponds that have a sudden increase in water depth. Another assumption implicit in Equation 9 is that excess water completely overflows within the time step *dt*.

## Seepage

Pond water loss or gain by seepage depends primarily on the soil porosity, methods used for pond construction, structural changes that have occurred to the pond basin over time, and pond management practices (Boyd, 1982; Teichert-Coddington et al., 1989). If the daily seepage rate ($s_r$; mm $d^{-1}$) for the soil is known, S can be simply approximated as:

$$S = \frac{A\,s_r}{1000} \tag{10}$$

Note that in Equation 10, the surface area of the pond at the current water level is used to estimate seepage losses. This is a simplified assumption to avoid estimation of the actual area (i.e., pond bottoms and sides) from which seepage may occur. The use of a constant $s_r$ value in Equation 10 for long-term simulations is somewhat questionable because pond seepage rates do vary substantially with time, particularly during rainy seasons when rainwater infiltrates ponds via the dikes resulting in lower net seepage rates (Boyd, 1982). This is also evident in the results of Green and Boyd (1995) who reported a 25% reduction in daily mean seepage rates between rainy and dry seasons for the El Carao ponds. During trial simulations, we observed higher than expected seepage losses for both the El Carao and AIT ponds. However, more consistent results were obtained when seepage losses calculated by the use of Equation 10 were reduced by 25% during rainfall events.

## Evaporation

Significant amounts of water can be lost from ponds via evaporation (Thornwaite and Holzman, 1939; Hounam, 1973; Szumiec, 1979). Evaporative water losses are primarily a function of ambient air temperature, relative humidity and wind velocity, and several empirical equations based on mass transfer concepts have been developed to estimate evaporative water losses (Hjelmfelt and Cassidy, 1975). Use of these equations results in very different evaporative water loss estimates for identical conditions (Yoo and Boyd, 1994). Gray (1970) has demonstrated the use of thermal budgets to estimate evaporative heat losses from water bodies. Although Yoo and Boyd (1994) argue that such an approach is too complicated for practical applications in aquaculture, it was decided in this study to use estimates of evaporative loss obtained from pond thermal budgets. This was because such a budget was developed in a parallel study to predict water temperature in static as well as flow-through ponds (see also Chapter 2). From this thermal budget, is convenient to estimate water loss by evaporation as follows:

$$E = \frac{A\phi_e}{\rho_w L} \tag{11}$$

where $\phi_e$= evaporative heat loss (kJ $m^{-2}$ $d^{-1}$), $\rho_w$ = water density (kg $m^{-3}$) and L = latent heat of vaporization of water (kJ $kg^{-1}$). Among aquacultural researchers, it is conventional to express evaporative water loss in terms of the daily decrease in pond depth, which can be obtained by neglecting *A* in Equation 11 and converting the resulting value (m $d^{-1}$) into appropriate units (e.g., mm $d^{-1}$).

Evaporative heat losses have been exhaustively studied in shallow water bodies and several expressions derived from the original work of Dalton (1802) are available to estimate such losses (Henderson-Sellers, 1984). Although Losordo and Piedrahita (1991) reported that good estimates of $\phi_e$ resulted from the use of expressions given by Fritz et al. (1980), our experience suggests that more accurate evaporative heat and associated water loss estimates can be obtained using the approach of Ryan et al. (1974; see model verification section below). This is consistent with the observations of Henderson-Sellers (1984). The formula developed by Ryan et al. (1974) is also the only one that accounts for both mechanical (forced) heat removal as a result of wind action, and convective heat removal which is a function of the air-water temperature difference. The Ryan formula for $\phi_e$ is as follows:

$$\phi_e = (e_s - e_a)\left[\lambda\,(T_{wv} - T_{av})^{1/3} + b_0 u_2\right] \qquad (12)$$

where $e_s$ = saturated vapor pressure at the current water temperature (mm Hg), $e_a$ = water vapor pressure immediately above the pond surface (mm Hg), $T_{wv}$ and $T_{av}$ are the virtual water and air temperatures respectively (°K), $\lambda$ and $b_o$ are constants with values of 311.02 kJ $m^{-2}$ $d^{-1}$ $mmHg^{-1}$ $K^{-1/3}$ and 368.61 kJ $m^{-2}$ $d^{-1}$ $mmHg^{-1}$ $(m\ s^{-1})^{-1}$ respectively, and $u_2$ = wind velocity (m $s^{-1}$) at a reference height of 2m.

It should be noted that the conductive heat removal component of Equation 12 is valid only when $T_{wv}$ is greater than $T_{av}$ (Ryan et al., 1974). Vapor pressures ($e_s$ and $e_a$ in Equation 12) can be approximated as follows (Troxler and Thrackston, 1977):

$$e_s = 25.37 \exp\left[17.62 - \frac{5271}{T_{wk}}\right] \tag{13}$$

$$e_a = R_h \times 25.37 \exp\left[17.62 - \frac{5271}{T_{ak}}\right] \tag{14}$$

where $R_h$ = relative humidity (decimal fraction), $T_{wk}$ = absolute water temperature (°K) and $T_{ak}$ = absolute air temperature (°K).

The virtual water and air temperatures are given by (Ryan et al., 1974):

$$T_{wv} = \left(\frac{T_{wk}}{\left[1.0 - (0.378 \times e_s / P)\right]}\right) \tag{15}$$

$$T_{av} = \left(\frac{T_{ak}}{\left[1.0 - (0.378 \times e_a / P)\right]}\right) \tag{16}$$

where $P$ = barometric pressure (mm Hg). According to Colt (1984), $P$ can be estimated from the site altitude as follows:

$$P = \frac{760}{10^{z/19748.2}} \tag{17}$$

where z = site altitude (m).

## Model Implementation and Data Requirements

The water budget model has been implemented in the decision support system POND, a software that is oriented towards the use of simulation models for management and planning applications in pond aquaculture (see also Chapter 1). Simulation models in POND are solved by the use of a fourth-order Runge-Kutta integrator.

Daily weather data required for the water budget model include air temperature, precipitation, relative humidity and wind speed. Pond-related data that are required include pond dimensions, minimum and maximum water depths, watershed area draining into the pond, average seepage rates, and water temperature. For flow-through ponds, daily influent and effluent rates are also required, whereas only regulated inflow amounts are necessary for ponds maintained at more or less steady state volumes.

# MODEL VERIFICATION

The water budget model outlined above has been tested by the use of the POND software for two shallow earthen ponds at the Asian Institute of Technology (AIT), Bangkok, Thailand (14°41' N, 100°29' E, 5 m above MSL) and the El Carao National Fish Culture Research Center, Comayagua, Honduras (14°26' N, 87°41' W, 583 m above MSL). These ponds were maintained as part of the research activities of the Pond Dynamics/Aquaculture Collaborative Research Support Program (PD/A CRSP). Model verification was accomplished from May 30 to October 31, 1991 for AIT, and from September 1, 1990 to January 2, 1991 for El Carao. Simulation trials were conducted to estimate pond water sinks and sources at both locations, and to determine net water demand required to maintain the ponds at or above the minimum water depth for the overall period of simulation. A time step of one day was used for both simulations.

## Data Sources

Sources for weather and pond data were as described below.

### Weather data

For the AIT site, daily weather data (air temperature, precipitation, relative humidity and wind speed) recorded at an international standard weather station located next to the ponds were used as inputs to the water budget model (C.K.Lin, Asian Institute of Technology, personal communication). For the El Carao site, weather data reported in the centralized database of the PD/A CRSP were used as model inputs. However, the datasets for this site did not include relative humidity measurements because this variable is not included in routine PD/A CRSP data collection protocols. Instead, we used mean monthly relative humidity estimates from a weather station in the Comayagua Valley that are reported in an FAO agroclimatic database (FAO, 1995). For both AIT and El Carao, missing data points in the weather datasets were estimated by linear interpolation.

Together with the water budget calculations. water temperature was also predicted using the simulation model described in Chapter 2. Additional weather data required for temperature predictions include short-wave solar radiation (kJ $m^{-2}$ $d^{-1}$) and cloud cover (decimal fraction). The former variable was available in the AIT weather dataset. Cloud cover data reported in oktas, and were converted to decimal fractions as suggested by FAO (1977).

For the El Carao site, only daily photosynthetically active radiation measurements (PAR; E $m^{-2}$ $d^{-1}$) were available in the PD/A CRSP database. These were converted to short-wave solar radiation estimates by the use of an empirical relationship reported for this site (Piedrahita and Teichert-Coddington, 1993). Cloud cover data were unavailable for the Comayagua Valley and a constant value of 0.5 (equivalent to scattered cloud conditions; Fritz et al., 1980) was assumed for each day of the simulation.

## Pond data

At both AIT and El Carao, the ponds were maintained at more or less steady state volumes by the intermittent addition of water to compensate for evaporative and seepage losses. Data from the PD/A CRSP database indicate that overflow did not occur at either site during the simulated periods. The AIT pond has a surface area of approximately 375 $m^2$ at the typical operating depth of 1 m, and has a very limited watershed area more or less restricted to the pond sides that approximates 60 $m^2$ (C. K. Lin, AIT, personal communication). For this pond, minimum and maximum pond depths were assumed to be 0.9 and 1.1 m respectively.

The El Carao pond has an area of about 1000 $m^2$ at a typical operating depth of 0.78 m (Egna et al., 1987). Minimum and maximum pond depths were assumed to be 0.75 and 0.9 m respectively. Green and Boyd (1995) reported that ponds at this site have an average watershed of 308 $m^2$. A runoff CN of 85 corresponding to hydrologic soil group D and pasture soil use type (see SCS, 1972) was used for both the El Carao (Green and Boyd, 1995) and AIT (assumed) sites.

Class A evaporation pans were used by PD/A CRSP researchers to estimate daily evaporative water losses. It has been shown that evaporation estimates from such pans must be adjusted downwards by the use of suitable coefficients, because pans have a smaller volume and are subjected to different weather conditions compared to water bodies such as lakes and ponds (Hounam, 1973). Pan coefficients have not been estimated at either the AIT or El Carao sites. Hounam (1973) estimated pan coefficients ranging from 0.60 to 0.81 (mean = 0.70) for several lakes. However, Boyd (1985a) found that pan coefficients for small, shallow ponds varied from 0.72 to 0.90 (mean = 0.81) over different months at one location in Alabama, USA. Green and Boyd (1995) used the mean value from the latter study to adjust Class A pan evaporative water loss measurements for El Carao. Following FAO guidelines (FAO, 1977) that take into account local weather and soil cover type conditions, we arrived at a pan coefficient estimate of 0.75 for both AIT and El Carao.

Daily seepage rates ($s_r$) for the ponds at both sites were estimated from the change in water depth between consecutive days in a rainless period corrected for evaporative water loss. However, for the El Carao site, because daily pond depth measurements were not reported in the centralized PD/A CRSP database for the simulation period (September 1, 1990 to January 2, 1991), pond data from a similar period in the preceding year were used to approximate $s_r$. The resulting estimates were 4.43 and 5.82 mm $d^{-1}$ for the AIT and El Carao ponds respectively. During rainfall events in the simulation runs, these values were reduced by 25% to adjust for rainwater that likely infiltrates the pond as discussed earlier.

## RESULTS AND DISCUSSION

There are no reported hydrological studies for the AIT ponds to compare model results. However, the water budget analysis conducted by Green and Boyd (1995) for the El Carao ponds provides a benchmark for the comparison of results generated at this site during the current study .

Total water gains and losses predicted by the water budget model for the AIT pond were 504.2 and 497.8 $m^3$ respectively. Mean predicted pond volume was 365 $m^3$, which is comparable to the typical operating volume of about 375 $m^3$ (C. K-Lin, AIT, personal communication). Mean predicted depth at 0.96 m was marginally lower than the 0.99 m calculated from depth measurements reported in the PD/A CRSP database for this pond. Data from the latter database also indicate that water was added 12 times (totaling 116 $m^3$) during the period of simulation for the AIT pond. In comparison, the net water demand projected by the water budget model was 136.3 $m^3$ (27% of the overall predicted water gain). The model predicted that precipitation was the primary source of water accounting for 69.8% of the total water gain. This is not unexpected because the simulation coincided with periods of heavy monsoon rains. Total rainfall during this period was 92.8 cm. Runoff gains amounted to only 3.2% of the water gain, again likely due to the small watershed area for this pond (about 16% of the pond area).

Evaporation and seepage contributed 54.9 and 45.1% of the overall water loss predicted by the water budget model for AIT. There was close agreement between evaporative losses predicted by the model and corrected Class A pan evaporation estimates (i.e., observed values) for the period simulated (Fig. 3.2). Overall water loss for the simulation period estimated from pan evaporation data in the PD/A CRSP database amounted to 264.5 $m^3$ compared to the amount of 273.4 $m^3$ predicted by use of the Ryan formula. Daily mean and standard deviations for observed evaporative losses were 0.45 and 0.14 cm respectively, whereas those predicted by the Ryan formula were 0.47 and 0.11 cm. Daily means were not significantly different ($P < 0.01$). Much poorer predictions of overall evaporative losses (221 $m^3$) and daily means (0.38 cm) resulted from the use of the Fritz formula (Fritz et al., 1980).

Direct comparison of seepage water loss predicted by the model to pond hydrological studies conducted elsewhere is difficult because seepage rates vary substantially from location to location (Stone and Boyd, 1989). For example, Boyd (1982) reported that seepage accounted for about 66% of the overall water loss for Auburn ponds. Mean daily seepage rates for the latter ponds varied from 4.8-7.9 mm $d^{-1}$, which is higher than the range of 2.7-6.9 mm $d^{-1}$ (mean = 4.4) estimated for the AIT pond in the current study.

The somewhat higher values of predicted water requirements for the AIT pond relative to actual additions are partly accounted by the slightly higher evaporative losses estimated

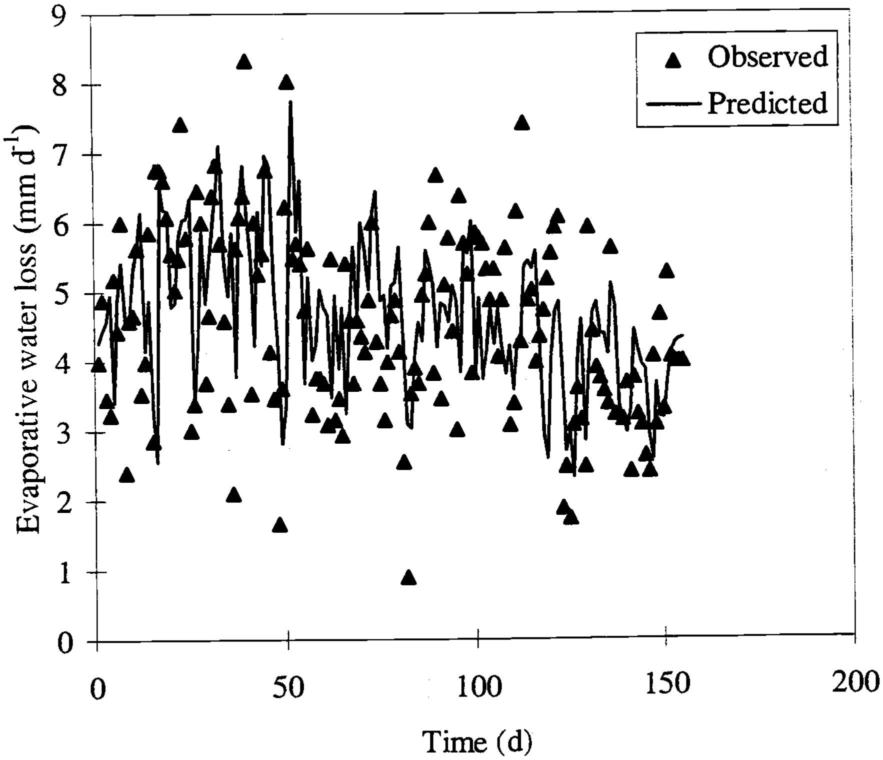

Figure 3.2. Daily observed and predicted evaporative water loss (in mm $d^{-1}$) for the AIT pond from May 30 to October 31, 1991. Observed values represent pan evaporation measurements corrected by the use of a pan coefficient as described in the text.

by the model. Differences between actual and predicted seepage losses perhaps accounted for the remaining discrepancy, although this cannot be directly verified.

The water budget model predicted total water gains and losses of 973.2 and 985.5 $m^3$ respectively for the El Carao pond. Mean predicted pond volume and depth were 756.5 $m^3$ and 0.76 m respectively; although actual volume and depth data for this pond were not available in the PD/A CRSP database for the simulation period, the predicted values are comparable to average volumes and depths of 783 $m^3$ and 0.78 m previously reported for El Carao ponds (Green and Boyd, 1995).

Data from the PD/A CRSP database indicate that water was added nine times (totalling 650 $m^3$) for the El Carao pond. In comparison, the net water demand projected by the water budget model was only 508.6 $m^3$ (52.3% of the overall predicted water gain). Precipitation was the other significant source of water for the El Carao pond, accounting for 43.2% of the total water gain predicted by the model. This proportion is similar to the value of 45.5% reported by Green and Boyd (1995) for the period June to November 1986. Precipitation gains were lower compared to those for the AIT pond because the total rainfall recorded at El Carao over the simulated period was only 41.1 cm. Runoff gains predicted by the water budget model in the current study amounted to only 4.5% of the water gain. This is consistent with the observations of Green and Boyd (1995) who reported that runoff contributed little to water budgets for El Carao presumably because of the small watershed area relative to the pond area.

Evaporative and seepage losses contributed 40.1 and 59.9% of the overall water loss predicted by the water budget model for El Carao. These proportions are very different from the values of 70 and 30% reported for this site by Green and Boyd (1995) for evaporation and seepage respectively. The discrepancy, in part, appears to be due to the lower evaporative losses predicted by the model relative to corrected Class A pan evaporation estimates (i.e., observed values) for the period simulated (Fig. 3.3). Overall water loss for the simulation period estimated from pan evaporation data amounted to 536 $m^3$ compared to the amount of 394.7 $m^3$ predicted by use of the Ryan formula. Daily mean and standard deviations for observed evaporative losses were 0.43 and 0.19 cm respectively, whereas those predicted by the Ryan formula were 0.32 and 0.13 cm respectively. Daily means were, however, not significantly different ($P < 0.01$). Once again, even poorer predictions of overall evaporative losses (370.4 $m^3$) and daily means (0.29 cm) resulted from the use of the Fritz formula.

The difference of 141.3 $m^3$ between predicted and actual amounts of regulated inflow is accounted for by the poor predictions of evaporative loss, which may have been caused by deficiencies in the weather dataset (e.g., lack of cloud cover and $R_h$ data, and several

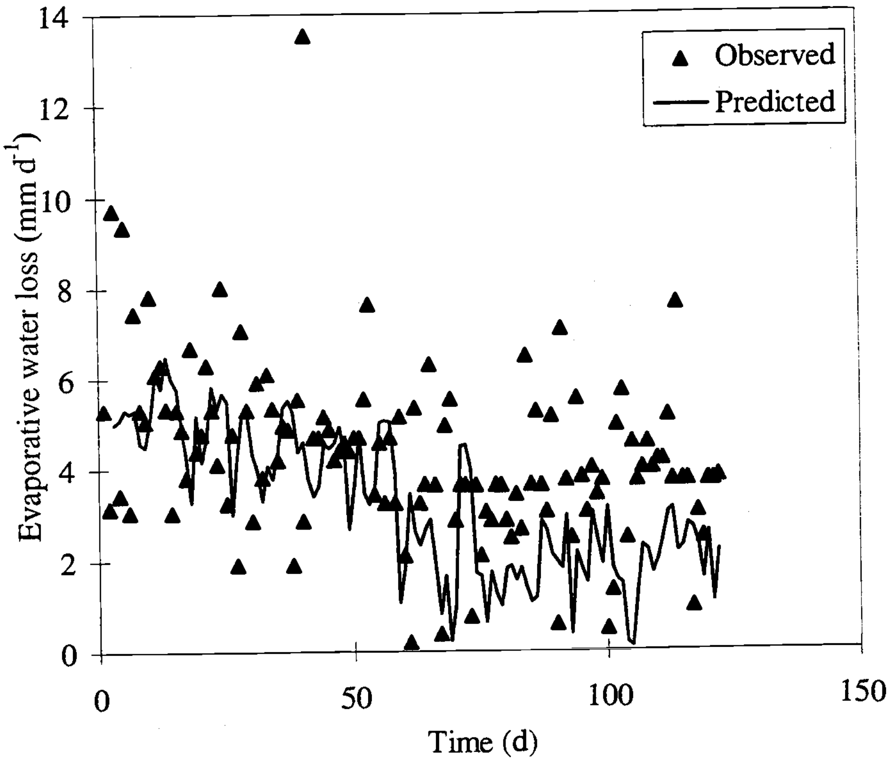

Figure 3.3. Daily observed and predicted evaporative water loss (in mm d$^{-1}$) for the El Carao pond from September 1, 1990 to January 2, 1991. Observed values represent pan evaporation measurements corrected by the use of a pan coefficient as described in the text.

missing points in other variables that were replaced by interpolated values). It is also possible that use of a constant pan coefficient may not be appropriate, a situation that merits further experimentation at individual locations along the lines of the study conducted by Boyd (1985a). The possibility that the Ryan formula for evaporation may not be appropriate at all locations should not be completely excluded. However, based on the validation work reported by Ryan et al. (1974), comparison of different formulae for evaporation (Henderson-Sellers, 1984) and the close agreement between model predictions and the AIT observations reported in the current study, the inadequacy of the weather dataset for El Carao appears to be the principal causative factor for the poor correlation between observed and predicted daily evaporative water losses.

Seepage losses predicted by the water budget model were higher compared to the results of Green and Boyd (1995) for the El Carao ponds. As indicated earlier, the daily mean seepage rate of 5.82 mm $d^{-1}$ used in the model was estimated from data reported in the PD/A CRSP database between 1 September 1989 and 2 January 1990 because daily depth measurements were not available for the period simulated in the current study. This rate is higher than the values of 3.5 mm $d^{-1}$ for the dry season of 1987 and 2.6 mm $d^{-1}$ for the rainy season of 1986 reported for the El Carao ponds (Green and Boyd, 1995). It is possible that structural changes in the pond basin (e.g., increased cracks in the dikes) may have occurred over time leading to a higher estimate of mean daily seepage loss. The proportion of water lost due to seepage is, however, comparable to the results reported by Boyd (1982) for ponds with similar daily seepage rates.

## CONCLUSIONS

In general, with the exception of the poor predicted evaporative loss estimates at El Carao which appear to be attributable to inadequate weather datasets as discussed earlier, the water budget model provided estimates of the other components of pond water budgets that are consistent with previous work (e.g., Boyd, 1982; Green and Boyd, 1995). The model can be used for flow-through facilities as well as other operations where water is routinely added to maintain desired pond depths. The model can also be adapted for different locations and/or seasons, and requires minimal measurements from ponds compared to the studies cited above. This is a particular advantage for situations where analysis of water requirements is to be done in the planning phase of aquaculture operations before physical ponds exist. The need to estimate appropriate curve numbers for use in the model can possibly be circumvented by the development of a rule-based expert system to generalize U.S. Soil Conservation Service guidelines on runoff flow from various watersheds.

Although adequate model predictions require the availability of comprehensive weather datasets (as evidenced by the difference in the accuracy of the results for AIT and El Carao), this is not a particular disadvantage because such weather datasets are increasingly becoming available from various locations world-wide (e.g., FAO, 1995), partly a manifestation of the increased demand for regional-scale studies. Indeed, one of the likely applications of the water budget model developed in this study is in regional-scale planning and analysis of water resources for aquaculture, where it can be combined with models of evapotranspiration, soil evaporation and infiltration to predict water fluxes across large regions. Green and Boyd (1995) suggested the need to compare the intensity and costs of water use for aquaculture and various terrestial agricultural activities in order to compare alternate benefits of water use - the model developed in this study provides one tool to facilitate such types of analyses.

# CHAPTER 4

# ESTIMATING FERTILIZER REQUIREMENTS OF FRESHWATER AQUACULTURE PONDS

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## ABSTRACT

Application rates of fertilizers to freshwater aquaculture ponds are typically arrived at by trial and error, or adapted from strategies that appear to be optimal at one location. The use of a fertilizer loading rate that is appropriate for a particular site can result in substantially different fish yields when applied elsewhere because of the variability among sites. Field testing of a previously developed framework that generates fertilizer recommendations on the basis of limnological principles suggests a tendency towards excess fertilizer addition when ambient nutrient concentrations are already relatively high. This appears to be primarily due to inadequate consideration of algal growth potential and nutrient cycling processes in ponds. A fertilization model was developed during the course of this study to address these limitations. The model assumes that a maximum level of gross primary productivity ($GPP_\lambda$), limited only by light availability, is possible for any pond. The effects of nutrient concentrations on algal growth rate are assessed by the use of Michaelis-Menten kinetics, whereas a skewed normal function is used to describe temperature effects. Liebig's minimum factor rule is used to approximate the combined effect of temperature and nutrient levels on algal growth, which when applied to $GPP_\lambda$ provides an estimate of the realized GPP for a given pond. The carbonate-bicarbonate alkalinity of pond water is assumed to be the main source of inorganic carbon. Simplified mass balance equations are developed to account for processes that affect nitrogen and phosphorus concentrations. The primary sink for these nutrients is assumed to be algal uptake, whereas algal respiration and fertilizer addition are the main sources. An additional term that accounts for miscellaneous processes by the use of first-order kinetics, and which may be either a nutrient source or sink, is also considered. For nitrogen, available data suggest that there is a net gain of this nutrient via these processes, whereas phosphorus is generally lost from the pond water to the underlying sediments. Model verification was undertaken by comparing fertilizer application data obtained from ponds in Honduras, Thailand and the Philippines to those generated by the fertilization model presented here. This comparative analysis indicates that the fertilization model generates nutrient application rates that are in general more

conservative compared to those actually used in the above ponds when nutrient concentrations were already fairly high. Model verification results are consistent with previous work in that responsive fertilization strategies (i.e., strategies designed to account for ambient pond water conditions) are likely to be superior in terms of fertilizer use and cost efficiency compared to the more traditional fixed input strategies.

## INTRODUCTION

The practice of fertilizing fresh water earthen ponds to increase fish yields is common in many parts of the world (Hickling, 1962; Hepher, 1978; Boyd, 1979). The addition of fertilizers stimulates primary productivity leading to an increase in food availability and therefore enhanced fish yields (Boyd, 1979; Hepher, 1978; Schroeder et al., 1990). Because of the strong correlation between fish yields and primary productivity, it should be possible to increase fish yields by management of net primary productivity (NPP) levels in ponds (McNabb et al., 1990). This can be accomplished by the use of limnological concepts that focus on the role of inorganic phosphorus (P), nitrogen (N) and carbon (C) as key nutrients which can potentially limit phytoplankton growth (Knud-Hansen et al., 1991a).

Boyd (1990, pg. 241) pointed out that evaluation of fertilizer requirements for ponds must be conducted on the basis of ecological characteristics of each individual pond because of the considerable variability among ponds. He also indicated that simplified procedures to evaluate fertilizer requirements for ponds have not been forthcoming. Lannan (1993) developed a set of guidelines that directly addresses these two issues. These guidelines were designed to provide a framework for evaluating the nutrient requirements (i.e., P, N and C) of freshwater ponds and generating fertilizer recommendations that would meet these requirements (Fig. 4.1). The guidelines were developed as part of the activities of the Pond Dynamics/Aquaculture Collaborative Research Support Program (PD/A CRSP). Use of the guidelines requires an estimate of

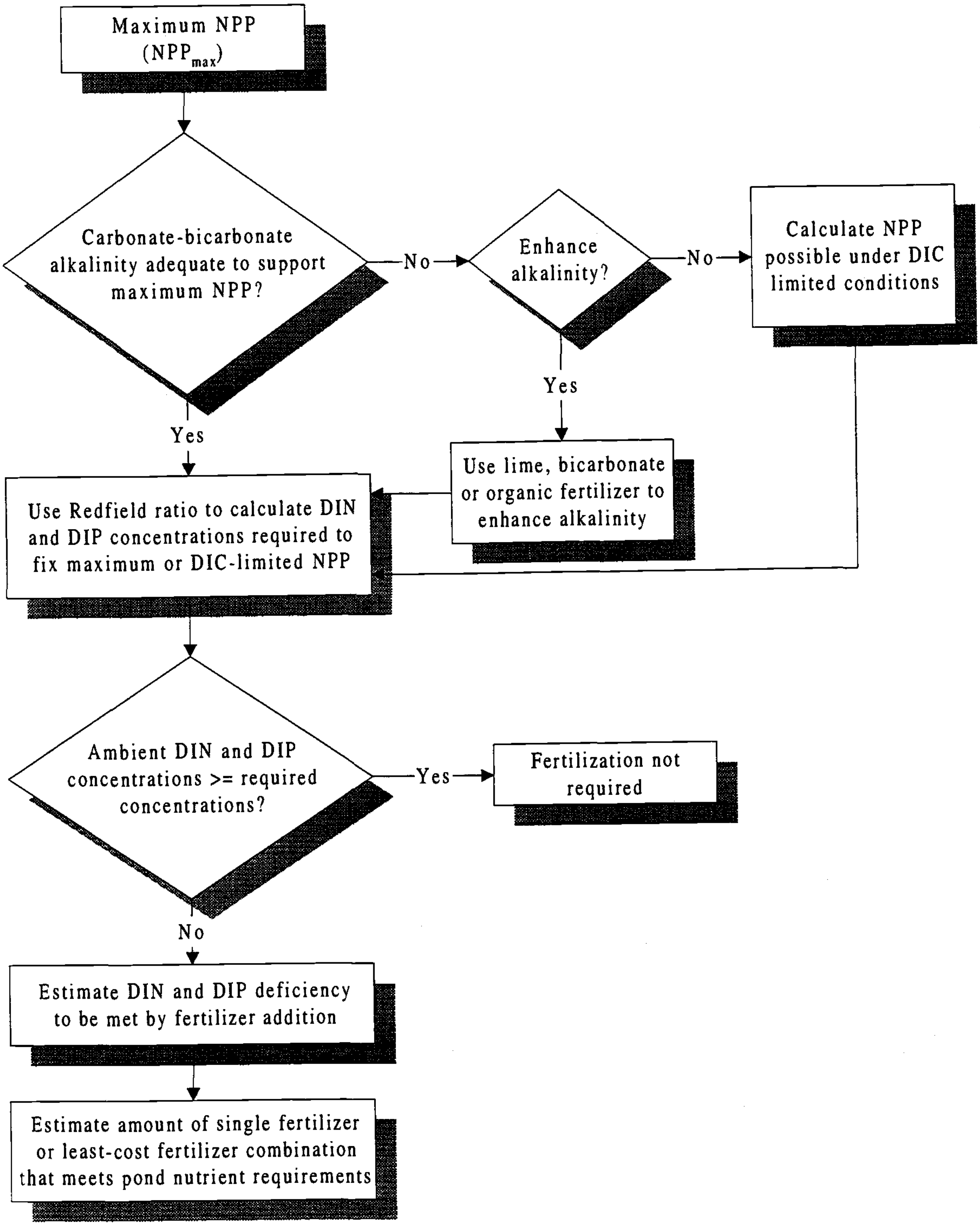

Figure 4.1. The PONDCLASS scheme for evaluating nutrient requirements of ponds, and estimating associated fertilizer needs.

the maximum level of NPP ($NPP_{max}$) possible for a given location in the absence of nutrient limitation, as well as water quality data. The latter data include measurements of carbonate-bicarbonate alkalinity, pH, temperature, dissolved inorganic nitrogen (DIN) and phosphorus (DIP). The former three variables are used to estimate the availability of dissolved inorganic carbon (DIC) for algal uptake under the assumption that the carbonate-bicarbonate alkalinity is the major source of DIC in freshwater ponds. Lannan's (1993) guidelines were implemented in the decision support system PONDCLASS[1], and represent perhaps the first attempt to synthesize information about fertilization practices in aquaculture ponds and limnological concepts into a unified framework that can be applied at different locations.

The guidelines developed by Lannan (1993) also represent a departure from traditional fertilization recommendations which typically involve the addition of fixed quantities of fertilizer materials at specific time intervals, without adequate consideration of water quality conditions in the ponds. Traditional fertilization recommendations are referred to as *fixed input fertilization strategies* in this paper. Lannan's guidelines are conceptually similar to field-based bioassay techniques that have been developed to assess pond nutrient requirements (Knud-Hansen and Guttman, in prep.). The fertilization approaches developed by Lannan (1993) and Knud-Hansen and Guttman (in prep.) can be categorized as *responsive fertilization strategies* because they account for ambient nutrient conditions in the pond water prior to generating fertilization recommendations.

Recent testing of the fertilizer recommendations generated by PONDCLASS in aquatic microcosms (Franco et al., 1993) and in PD/A CRSP ponds located in the Philippines (Hopkins et al., 1994) and Thailand (Szyper and Hopkins, 1995) has been fairly successful in that the amount of fertilizer required to produce one unit of fish

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[1] PONDCLASS is a copyright of Oregon State University.

production was typically lower compared to control treatments or prevailing practices. This is apparently because the software accounts for ambient nutrient concentrations in the pond water at the time of calculating fertilizer needs. Similar findings were also obtained for two groups of ponds that were managed on the basis of bioassay results and PONDCLASS recommendations (Hopkins and Knud-Hansen, in prep.).

However, fish growth in Honduran ponds that were managed using PONDCLASS (Teichert-Coddington and Ramos, 1995) appeared to be limited by the build-up of ammonia nitrogen ($NH_3$-N). Reasons for high $NH_3$-N concentrations at this location are unclear but may be due in part to the use of an $NPP_{max}$ value (4 gC $m^{-3}$ $d^{-1}$) that appears to be high, at least in terms of consistent primary productivity, for this location and which may result in excessive N loading. In contrast, Szyper and Hopkins (1995) typically set $NPP_{max}$ to 3 gC $m^{-3}$ $d^{-1}$ in the PONDCLASS software while estimating weekly fertilizer needs at the Thailand site where primary productivity is usually higher than at the Honduras site. Additionally, the effects of high $NH_3$-N concentrations on fish growth in Honduras were presumably amplified because of relatively high pH's in the range of 8-10 (Teichert-Coddington and Ramos, 1995). At these pH's, the fraction of $NH_3$-N that exists in the toxic, unionized form would be quite high (Emerson et al., 1975). Finally, the poor results obtained with PONDCLASS at Honduras may also have been due to inadequate consideration of nutrient cycling within the software. Water quality data for the PONDCLASS experiment in the Philippines (Hopkins et al., 1994) that are recorded in the aquaculture database maintained by the PD/A CRSP also indicate frequent occurrence of high total ammonia concentrations.

In general, these results suggest that revisions to the guidelines developed by Lannan (1993) are perhaps advisable so as to avoid similar problems of nutrient build-up which is both economically and ecologically inefficient. The objectives of the research presented in this paper are (i) to critically examine the assumptions and rationale of the fertilization guidelines developed by Lannan (1993), (ii) to modify the guidelines in the form of a simplified model that can be used to estimate nutrient requirements for freshwater ponds, and (iii) to assess results obtained from the above model at different geographical locations.

## Gross or Net Primary Productivity

As indicated in Figure 4.1, the starting point in the PONDCLASS fertilization guidelines is an estimate of $NPP_{max}$. Based on work by Bowman (1992), Lannan (1993) provided a table that lists suggested ranges of $NPP_{max}$ for different geographical locations that could serve as initial estimates for use in the PONDCLASS software. However, the rationale for using $NPP_{max}$ instead of the maximum gross primary productivity ($GPP_{max}$) in arriving at fertilizer recommendations is unclear because most models developed to predict phytoplankton productivity involve estimation of GPP and respiration, with NPP obtained as the difference between these two rates (e.g., Di Toro et al., 1971; Straskraba and Gnauck, 1985). This is because the overall or gross productivity is a function of light ($\lambda$), temperature ($\tau$) and nutrient ($\nu$) limitations as follows (e.g., Straskraba and Gnauck, 1985):

$$GPP = \mu_{max} B f(\lambda, \tau, \nu) \tag{1}$$

where $\mu_{max}$ = maximum specific phytoplankton growth rate ($d^{-1}$), and B = phytoplankton biomass ($gC\ m^{-3}$). If none of the environmental variables limit growth, Equation 1 provides an estimate of $GPP_{max}$.

Although there are models that provide estimates for $\mu_{max}$ (e.g., Eppley, 1972; Bannister, 1974; Smith, 1980), use of Equation 1 also requires phytoplankton biomass estimates, in addition to an evaluation of the effects of light, temperature and nutrients on phytoplankton growth. Under most pond aquaculture operating conditions, it is difficult to estimate plankton biomass and evaluate ambient light conditions. Other water quality parameters (temperature and nutrient concentrations) are, however, routinely measured especially on commercial farms. If we assume that there is an upper limit to the gross productivity which is set by the light conditions in a given pond, Equation 1 can be simplified as:

$$GPP = GPP_{\lambda} \ f(\tau, \nu) \qquad (2)$$

where $GPP_{\lambda}$ is the gross productivity for the phytoplankton biomass in the pond under its particular light regime. We propose that $GPP_{\lambda}$ should be the starting point for evaluating nutrient requirements of a pond rather than $NPP_{max}$ because it is theoretically a more appropriate rate in terms of the growth response of phytoplankton to environmental conditions. In other words, it is the realized GPP for a pond that is a measure of the combined effects of environmental variables on algal productivity, rather than NPP because the latter rate depends on algal respiration which is highly variable (Reynolds, 1984). Equation 2 assumes that the effects of light on phytoplankton growth are independent of other environmental parameters. This is not strictly valid because both light and temperature are known to affect photosynthetic rates; further, relationships between ambient light levels and nutrient concentrations have also been observed under both natural and experimental conditions (see discussions in Reynolds, 1984 and Kirk, 1994). However, because $\lambda$ is difficult to estimate under typical production conditions, it is assumed that ambient light conditions in a given pond will determine its $GPP_{\lambda}$.

## Nutrient and Temperature Limitations

Fertilization guidelines developed by Lannan (1993) assume that pond managers are interested in estimating the amounts of N and P required to ensure that phytoplankton growth is not limited by these nutrients. It was also noted that C limitation may occur in ponds that have low alkalinity (e.g., McNabb et al., 1990), and that such limitation could be alleviated by increasing the alkalinity (see detailed discussion in the section on *Nutrient Cycling* below). However, it may occasionally be desirable to examine the effects of limiting phytoplankton growth by manipulating nutrient levels either to reduce algal biomass, alter phytoplankton species composition, or for reasons associated with the cost and availability of fertilizer resources. This suggests that retaining the $\nu$ term in Equation 2 is desirable.

Nutrient limitation of phytoplankton growth can be approximated by the use of the Monod equation to describe Michaelis-Menten enzyme kinetics (Dugdale, 1967). Droop (1973) used a slight modification of the Monod equation to account for nutrients that are actually available for algal uptake. Because such threshold concentrations may exist for N, P and C in ponds as well, the Droop equation is used to describe growth limitation by each of the three primary nutrients ($\nu_S$) as follows:

$$\nu_S = \frac{(S - S_0)}{k_S + (S - S_0)} \tag{3}$$

where S, $S_0$ and $k_S$ are respectively the ambient concentrations, threshold concentrations and half-saturation constants for inorganic N, P and C. The abbreviations of the terms in Equation 3 for nitrogen are $\nu_n$, DIN, $k_N$, and $N_0$. Similarly, the terms for phosphorus are $\nu_p$, DIP, $k_P$, and $P_0$. Finally, those for carbon are $\nu_c$, DIC, $k_C$, and $C_0$. Equation 3 is similar to the one given by King and Garling (1986) for uptake kinetics of inorganic C, where it was assumed that a minimum threshold concentration of this nutrient is required to initiate photosynthesis.

There appear to have been very few attempts to analyze nutrient limitation in aquaculture ponds by the use of Michaelis-Menten kinetics. One example involved the demonstration of carbon limitation of net primary productivity by McNabb et al. (1990) in ponds from Indonesia and Thailand. However, the same methodology has not been used to examine N and P limitation. Instead, most researchers (e.g., Knud-Hansen et al., 1990) have preferred to demonstrate algal growth versus nutrient relationships by the use of linear regression fits between primary productivity and nutrient concentrations. Such regressions cannot be used to identify when a given nutrient (N, P or C) adversely impacts algal growth, or to assess minimum threshold concentrations for nutrient uptake by algae. Moreover, such relationships do not indicate when a given nutrient is present at a concentration that is non-limiting.

We examined water quality data from experiments conducted by PD/A CRSP researchers at Bang Sai, Thailand to assess nutrient limitations of algal productivity. Data were extracted from the aquaculture database maintained by the PD/A CRSP. NPP was estimated for these ponds from losses of DIC between dawn and dusk (Vollenwieder, 1974), and averaged over the duration of the experiment. Average GPP was assumed to be equal to NPP × 1.5 to account for algal respiration. The adjustment factor of 1.5 is more conservative than the value of 3.3 obtained by Colman and Edwards (1987). However, because tanks in the latter study were loaded with high amounts of septage and had a high algal biomass, respiration rates were presumably much higher than typical rates in earthen ponds. Early morning DIC calculated from alkalinity, pH and temperature measurements (Harvey, 1955; Park, 1969) was assumed to be the reservoir of carbon for algal uptake during the day. Average GPP was plotted against DIN, DIP and DIC concentrations (Figs. 4.2-4.4) to examine nutrient limitation. In all the cases, temperature was assumed to be non-limiting (i.e., $\tau = 1$) because pond temperatures were typically in the range of 25-30°C, which is likely to be near optimal for algal growth at the Bang Sai site.

Several ponds in treatment set I appear to be DIN limited (Fig. 4.2). However, at least five ponds in this treatment set do not show a kinetic relationship between GPP and DIN (Fig. 4.2). These ponds were presumably limited by some other factor, most likely very low DIP concentrations (Fig. 4.3). Compared to treatment set I, ponds in set II were more productive (Fig. 4.2) and in general also showed a lower tendency towards nitrogen limitation. Data presented in Figure 4.4 clearly show that ponds in treatment set I were not limited by DIC. Some tendency towards DIC limitation can be seen in the ponds comprising treatment set II (Fig. 4.4) where DIN and DIP concentrations were relatively high (Figs. 4.2 and 4.3). Figure 4.4 also includes data from McNabb et al. (1990). NPP

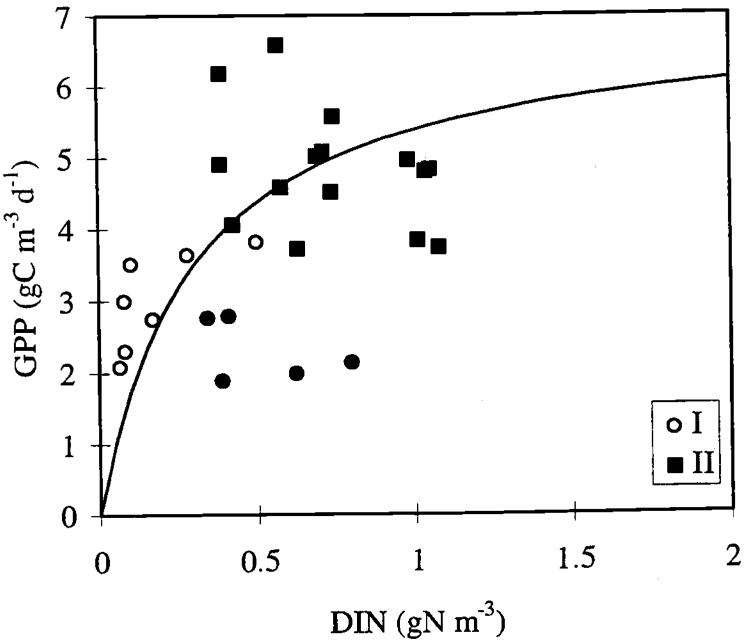

Figure 4.2. Gross primary productivity (GPP) in relation to dissolved inorganic nitrogen (DIN) concentrations in two sets of ponds (I and II) at Bang Sai, Thailand. Dark circles represent the ponds in set I that were severely phosphorus limited (see also Fig. 4.3). The Michaelis-Menten curve was fitted using the following parameters: $GPP_{\lambda} = 7.0$, $k_N = 0.3$, and $N_o = 0$.

reported by these authors for DIC limited ponds were also converted to GPP values using the adjustment factor of 1.5.

In general, the data presented suggest that although minimum threshold concentrations for N and P appear to be close to zero (Figs. 4.2 and 4.3), the value of $C_o$ seems to be about 4-5 gC $m^{-3}$ (Fig. 4.4). Data presented in these figures also indicate that GPP may be limited at any given time by DIN, DIP or DIC. Such plots are a valuable tool to assess which of these three nutrients most limits algal growth, and to develop site-specific Michaelis-Menten curves that can be used as a guide for fertilizer management. Further, the lack of a kinetic relationship between algal productivity and one of these nutrients

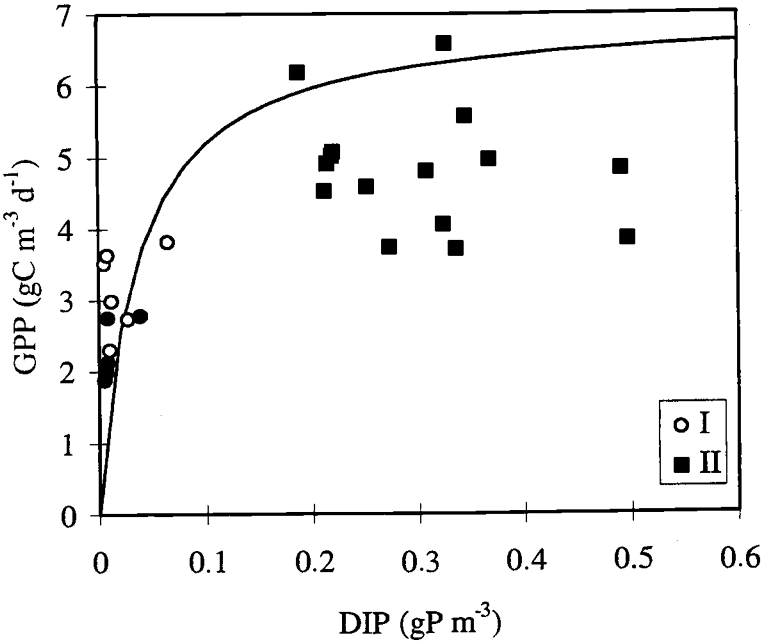

Figure 4.3. Gross primary productivity (GPP) in relation to dissolved inorganic phosphorus (DIP) concentrations in two sets of ponds (I and II) at Bang Sai, Thailand. Dark circles represent the ponds in set I that did not show a kinetic response to DIN (see also Fig. 4.2). The Michaelis-Menten curve was fitted using the following parameters: $GPP_\lambda = 7.0$, $k_P = 0.035$ and $P_o = 0$.

suggests that further addition of this nutrient by fertilization is not warranted unless growth limitation by another nutrient is alleviated.

Lannan (1993) did not consider the effects of temperature on primary productivity. Input temperature data were only used to calculate dissociation constants for the carbonate-bicarbonate alkalinity system, which in turn affect the availability of inorganic C. However, phytoplankton growth rates do vary with temperature (e.g., Clendenning et al., 1956; Eppley, 1972; see also Reynolds, 1984), typically reaching a maximum within some optimal temperature range, with reduction in growth rates on either side of this

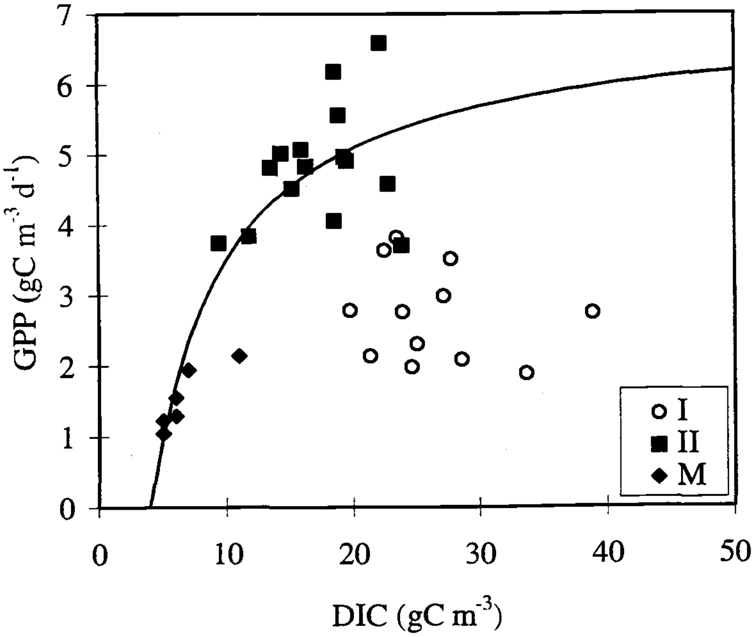

Figure 4.4. Gross primary productivity (GPP) in relation to dissolved inorganic carbon (DIC) concentrations in three sets of ponds at Bang Sai, Thailand. GPP and DIC for set I and II were estimated from data reported in the PD/A CRSP database, whereas the set of ponds labelled M represent data from McNabb et al. (1990). The Michaelis-Menten curve was fitted using the following parameters: $GPP_\lambda = 7.0$, $k_C = 6$, and $C_o = 4$.

plateau. Effects of temperature are likely to be more important at locations where pronounced changes in seasonal water temperatures occur. The following "skewed normal" function can be used to approximate temperature dependence of algal growth rates (Lehman et al., 1975; Svirezhev at al., 1984):

$$\tau = \begin{cases} \exp\left\{-4.6\left[(T_{opt} - T)/(T_{opt} - T_{min})\right]^4\right\}, & \text{if } T < T_{opt} \\ \exp\left\{-4.6\left[(T - T_{opt})/(T_{max} - T_{opt})\right]^4\right\}, & \text{if } T \geq T_{opt} \end{cases} \qquad (4)$$

where $T_{min}$, $T_{opt}$ and $T_{max}$ are the minimum, optimum and maximum temperatures for algal growth.

## Multiple Resource Limitations

It is generally accepted among aquaculture researchers (e.g., Boyd, 1990; Lannan, 1993: Knud-Hansen and Guttman, in prep.) that algal response to growth factors (i.e., temperature and nutrient concentration in the current context) follows Liebig's minimum factor rule. However, such a response does not appear to have been verified on the basis of data from experimental ponds. Algal physiologists have developed a variety of empirical relationships to describe the combined effects of multiple limiting factors on phytoplankton growth (Straskraba and Knauck, 1985). The most commonly used expressions include Liebig's minimum factor rule and the multiplicative effect function (de Groot, 1983). Additional relationships, derived from experiments with bacterial cultures, that could also be considered based on their simplicity include the mean effect approach and the inverse sum function (Benefield and Randall, 1980). These four functions in order can be expressed as follows:

$$\begin{aligned}
\nu &= \min(\tau,\ \nu_n,\ \nu_p,\ \nu_c), && \text{(Liebig's minimum factor)} && (5.1)\\
&= (\tau \times \nu_n \times \nu_p \times \nu_c), && \text{(Multiplicative effect)} && (5.2)\\
&= (\tau + \nu_n + \nu_p + \nu_c)/4, \text{ or} && \text{(Mean effect)} && (5.3)\\
&= 4/(\tau + \nu_n + \nu_p + \nu_c) && \text{(Inverse sum)} && (5.4)
\end{aligned}$$

The functions given in Equations 5.1-5.4 were used together with Equation 2 (in which $GPP_\lambda$ was set to 7 gC $m^{-3}$ $d^{-1}$) to predict GPP for the Thailand site. As before, temperature was assumed to be non-limiting (i.e., $\tau = 1$). DIN, DIP and DIC data for use in Equation 3 were extracted from the PD/A CRSP database (as discussed above; see also Figs. 4.2-4.4). GPP values predicted in this manner for all four functions were compared with 'observed' GPP data by the use of Student's *t*-test with a significance level of 0.05. This analysis indicated that GPP values predicted by the use of the inverse sum function and Liebig's minimum factor rule were not significantly different from observed values

($P > 0.05$), whereas those predicted by the use of the mean and multiplicative functions were significantly different ($P < 0.05$).

Predicted GPP values were also regressed against observed GPP data for comparative analyses. Regression results are consistent with previous work (de Groot, 1983) in that the multiplicative function (Equation 5.2) is the poorest predictor of algal response to multiple nutrient limitation (Table 4.1) and represents perhaps the worst-case scenario of algal growth. The mean effects function (Equation 5.3) is the most optimistic among all the four functions in that it will over-predict GPP, as is evident from the high value for the intercept term in the regression relationship between predicted and observed values (Table 4.1). The inverse sum function (Equation 5.4) resulted in the lowest residuals between predicted and observed GPP (Table 4.1). However, because this function also shows some tendency towards over-prediction of GPP, a more conservative approach would be to use Liebig's law of the minimum (Equation 5.1), at least until more evidence accumulates to support the use of Equation 5.4. Model users should be aware that GPP values predicted on the basis of Liebig's law may underestimate actual production rates in their ponds (Table 4.1).

Table 4.1. Linear regression relationships between GPP predicted by the use of Equations 2 and 5.1-5.4, and observed GPP for Bang Sai, Thailand. Mean values of the residuals between predicted and observed GPP's are also indicated.

| | Intercept | Slope | $r^2$ | Mean Residual |
|---|---|---|---|---|
| Liebig's law (Eq. 5.1) | -0.388 | 0.935 | 0.69 | -0.641 |
| Multplicative model (Eq. 5.2) | -0.972 | 0.744 | 0.64 | -1.967 |
| Mean effect model (Eq. 5.3) | 2.247 | 0.576 | 0.57 | 0.599 |
| Inverse sum model (Eq. 5.4) | 0.666 | 0.866 | 0.63 | 0.146 |

## Nutrient Cycling

The main allochthonous sources of C, N and P in pond aquaculture are fertilizers and feeds. For simplicity, the present discussion assumes that ponds do not receive supplemental feeds. In aquaculture ponds, the primary source of inorganic C for algal uptake is the carbonate-bicarbonate alkalinity of the pond water (Arce and Boyd, 1975). Fertilizer materials that add C to a pond include lime and manures (Schroeder, 1987). The former material increases alkalinity, unless pond soil are acidic enough to neutralize some of the pond water alkalinity in which case additional lime must be added to compensate for this loss (Boyd, 1979; Bowman and Lannan, 1995). Decomposition of allochthonous organic matter such as manures as well as autochthonous material (e.g., precipitated algae) is an important source of $CO_2$ for algal uptake (Schroeder, 1974; Schroeder and Buck, 1987). Respiratory activities of pond biota including fish also add C to the pond water (Schroeder, 1987). Losses of C include assimilation by algae and heterotrophs, as well as accumulation in fish flesh (Zur, 1981). $CO_2$ may also be lost or gained via diffusion at the air-water interface (Schindler et al., 1972).

In the case of N, apart from fertilizer addition, other sources include algal respiration, excretion from pond biota (including fish), and recovery from sediments (Schroeder, 1987). Algal growth is the predominant sink for pond water N. Further, some N is lost via denitrification and diffusion (Bouldin et al., 1974), via seepage and to the fish biomass in the pond (Boyd, 1985a). Schroeder et al. (1991) indicate that the expected accumulation of N in the water column does not occur presumably because rates of N turnover in the pond sediments are fairly rapid.

As noted by Delince (1992), there is limited information on P cycling in ponds. In general, the interactions of pond water and sediment P are typically more complex compared to those relevant to N, and vary substantially according to soil type and chemical composition (Boyd, 1995). According to this author, the predominant sources of P include fertilization, algal respiration, and excretion by pond biota. The main sinks for P include accumulation in the pond sediments and assimilation into fish biomass.

It is evident from the preceding discussion that a variety of processes are involved in the cycling of C, N and P within the pond water-sediment system. The rates of these processes are also likely to vary substantially with environmental conditions (e.g., temperature, substrate availability, etc) and are very difficult to quantify. In terms of practical guidelines, the most important issues relevant to nutrient cycling are to assess whether C, N and P supplementation is required, and to estimate the amount of fertilizer material(s) that would meet this requirement.

With regard to the inorganic C balance, the carbonate-bicarbonate alkalinity system typically acts as a battery in which carbon is removed during the day primarily by photosynthesis and replenished by respiratory activities at night (King, 1970). Thus, management of this system indirectly controls DIC supply. Carbon supplementation may be necessary for ponds with low alkalinity or when initially high alkalinities drop drastically in chemically fertilized ponds which have high rates of primary production (Knud-Hansen et al., 1993; Szyper and Hopkins, 1995). The potential for such changes in the alkalinity of freshwater systems induced by intense photosynthesis has been discussed by King (1970). Research by various PD/A CRSP researchers (e.g., Green et al., 1989; McNabb et al., 1990; Knud-Hansen et al., 1991b, 1993; Diana et al., 1991a; Hopkins et al., 1994) indicates that routine pond manuring in the range of 250-500 kg ha$^{-1}$ wk$^{-1}$ chicken manure (CM) on a dry matter basis or the addition of soluble carbonates tends to stabilize pond water alkalinities at levels where DIC is unlikely to limit algal growth. Recent field experiments (Hopkins and Knud-Hansen, in prep.; J. Szyper, University of Hawaii, personal communication) also suggest that maintaining carbonate-bicarbonate alkalinities in excess of 50 mg L$^{-1}$ will ensure that adequate DIC is available to maintain high algal production rates. Finally, data presented in the current study (Fig. 4.4) indicate that early morning DIC concentrations in the range of 15-20 gC m$^{-3}$ would preclude carbon limitation from occurring. The mid-value of this range (17.5 gC m$^{-3}$)

corresponds to a carbonate-bicarbonate alkalinity of 60 mg $L^{-1}$ for a pond with a temperature of 30°C and pH 7.

It is difficult to assess the amounts of manure that may be required to increase pond water alkalinity both due to the variability in their composition and because the actual mechanisms by which manure addition helps to regulate alkalinity changes are not clear. On the other hand, the increase in alkalinity that follows the addition of lime, or other chemical compounds such as $Na_2CO_3$ or $NaHCO_3$ can be calculated stoichiometrically. For example, C limitation is likely to occur at a carbonate-bicarbonate alkalinity of 20 mg $L^{-1}$, assuming other nutrients required by algae are non-limiting and the water temperature is in the optimal range for growth. The amounts of $CaCO_3$, $Na_2CO_3$, or $NaHCO_3$ required to increase alkalinity to 50 mg $L^{-1}$ (i.e., a change of 0.6 meq $L^{-1}$) are about 300, 500 and 320 kg $ha^{-1}$ respectively. Local production economics will determine whether such alkalinity enhancement is appropriate, and will dictate the types of materials that are suitable for the purpose.

For inorganic pond water N and P, there is no analogy to the carbonate-bicarbonate alkalinity system. Therefore, it is necessary to estimate the amounts of these nutrients that are recyled within the pond. Lannan (1993) suggested that the amounts of these nutrients required from fertilizer addition should be calculated as the difference between the theoretical quantities required to achieve $NPP_{max}$ and ambient concentrations in the pond water (Fig. 4.1). Similarly, other researchers (e.g., Batterson et al., 1988; Yusoff and McNabb, 1989; McNabb et al., 1990) used DIN and DIP concentrations to assess the supply of inorganic N and P for algal uptake. However, use of ambient concentrations does not reflect the *rates* at which N and P become available from their respective pools in the pond within the duration between fertilizer applications. Data extracted from the PD/A CRSP database for the Honduras experiment where PONDCLASS was tested (Teichert-Coddington and Ramos, 1995) illustrates the drawbacks of using concentrations as a measure of nutrient supply.

For one pond where ambient DIN (all in the form of total ammonia nitrogen) was 1.97 mg $L^{-1}$, PONDCLASS recommended a weekly addition of 206 kg $ha^{-1}$ CM and 51.5 kg $ha^{-1}$ of urea. Based on the $NPP_{max}$ value of 4 gC $m^{-3}$ $d^{-1}$, the weekly N requirement for algal growth is about 4.9 g $m^{-3}$. Because this requirement was greater than the existing DIN pool, the PONDCLASS software recommended addition of a nitrogen source. However, a good portion of the DIN pool is likely to be recycled within the pond via the processes identified earlier. Thus, the pool of 1.97 mg $L^{-1}$ may have been adequate to meet algal N requirements for several days and the addition of fertilizer N may not have been warranted at the time.

The generally high quantities of N added to Honduran ponds managed by the use of PONDCLASS over the entire experiment were economically wasteful and presumably the result of inadequate consideration of N cycling in the pond. Based on water temperature and pH data for the sampling date discussed above, the unionized ammonia concentration was about 0.12 mg $L^{-1}$, which is in the range where tilapia growth is adversely affected (Abdalla, 1989). It is also likely that the deleterious effects of high $NH_3$-N concentrations were increased by the addition of urea, prolonged use of which may cause an increase in water pH (e.g., Vlek and Craswell, 1979; Knud-Hansen and Pautong, 1993). We observed a similar situation in Philippine ponds managed using PONDCLASS (Hopkins et al., 1994) where addition of nitrogenous fertilizers (16-20-0 and/or urea) was recommended even though total ammonia concentrations exceeded 2.0 mg $L^{-1}$. Based on the typical pH and water temperature conditions reported in the PD/A CRSP database for this location, such concentrations correspond to unionized ammonia levels of 0.25-0.5 mg $L^{-1}$, which again are in the range where Nile tilapia growth is likely to be severely limited (Abdalla, 1989). Hopkins and Knud-Hansen (in prep.) also reported the occurrence of unionized ammonia concentrations in excess of 0.5 mg $L^{-1}$ in ponds managed by the use of PONDCLASS in Thailand.

Work by Schroeder (1987) suggests that 30% of the DIN required for daily gross photosynthesis in the ponds studied originated from fertilizer N and that about 50% was the result of algal respiration. Miscellaneous processes in the pond presumably met the remaining needs. Because daily GPP varies with geographical locations, it is likely that the N required for algal growth ($N_{ag}$) and the proportion of fertilizer N that supplements the overall DIN pool will vary accordingly. Based on the above observations, a simplified differential equation can be developed for the rate change of DIN (gN $m^{-3}$ $d^{-1}$) as follows:

$$\frac{dDIN}{dt} = N_{fert} + N_{ar} - N_{ag} \pm N_{misc} \qquad (6.1)$$

where $N_{fert}$ and $N_{ar}$ are the rates of daily N supply from fertilizer addition and algal respiration respectively. $N_{ag}$ can be estimated as the product of GPP (from Equation 2) and the N:C Redfield ratio (0.175 on a weight basis; Redfield et al., 1963) in a manner similar to previous authors (Yusoff and McNabb, 1989; McNabb et al., 1990; Lannan, 1993), with the exception that they used daily values of NPP. If it is assumed that algal respiration ($N_{ar}$) returns half of the N assimilated to the DIN pool (Schroeder, 1987), then $N_{ar} = 0.5 \times N_{ag}$.

$N_{misc}$ is a lumped variable that reflects the net result of miscellaneous processes (i.e., that are not related to algal growth and respiration or fertilizer addition) affecting DIN in the pond. Unfortunately, these processes have not been adequately studied in fish ponds (Boyd, 1990). Depending on the specific culture conditions (e.g., water quality, soil characteristics and fish biomass), it is possible that the variable $N_{misc}$ may reflect a net source or sink for N. Based on the nitrogen budget and steady-state total ammonia concentrations (0.5 mg $L^{-1}$) reported by Schroeder (1987), it would appear that there is a net daily gain of about 15% of the DIN pool from processes not associated with fertilizer addition and algal dynamics. For the current study, we assumed a more conservative estimate (10%) for the DIN pool that is recycled on a daily basis as a result of miscellaneous processes (i.e., $N_{misc} = 0.1 \times DIN$). Integration of Equation 6.1 over the time period between fertilizer additions (e.g., one week) will result in the expected DIN concentration in the pond.

If we assume that the fertilization regime is such that nitrogen limitation does not occur (i.e., $\nu_n = 1$), the difference between $N_{ag}$ and the sum of $N_{ar}$ and $N_{misc}$ reflects the *net nitrogen demand* ($N_{req}$) for the pond. A negative $N_{req}$ value indicates that the nitrogen sources exceed the sink term ($N_{ag}$), in which case fertilizer addition is not required and $N_{fert}$ is set to zero. Conversely, a positive $N_{req}$ value indicates that fertilizer addition may be warranted. Sometimes, however, surplus nitrogen or $N_s$ (defined as the amount of N in excess of the minimum threshold concentration $N_o$ required for algal uptake) may be available in the pond. This occurs when DIN concentrations greatly exceed daily algal N needs as discussed in the earlier example from Honduras. To estimate $N_s$, it is necessary to approximate the expected DIN concentration within the current time step used in the integration. If the time step is one day, this concentration ($DIN^*$) is the sum of the present DIN and the result of Equation 6.1 with $N_{fert} = 0$. The difference between $DIN^*$ and $N_o$ is an estimate of $N_s$. $N_{fert}$ can then be calculated by applying the following rules:

$$N_{fert} = \begin{cases} N_{req} + (N_o - DIN^*), & \text{if } DIN^* < N_o \\ N_{req} - N_s, & \text{if } 0 \leq N_s \leq N_{req} \\ 0 & \text{if } N_s > N_{req} \end{cases} \qquad (6.2)$$

Finally, Equation 6.1 is re-evaluated by inserting the value of $N_{fert}$ from Equation 6.2 so as to obtain the rate change of DIN. The sum of $N_{fert}$ calculated at each time step over the entire integration period is a rough estimate of the overall fertilizer N requirements for that period.

A set of calculations similar to those for nitrogen can be developed for phosphorus. Thus, the rate change for DIP (gP $m^{-3}$ $d^{-1}$) is given by:

$$\frac{dDIP}{dt} = P_{fert} + P_{ar} - P_{ag} \pm P_{misc} \qquad (7.1)$$

where $P_{fert}$ and $P_{ar}$ are the rates of daily P supply from fertilizer addition and algal respiration respectively. $P_{ag}$ is estimated as the product of GPP (from Equation 2) and the P:C Redfield ratio (0.025 on a weight basis; Redfield et al., 1963). Presumably the quantity of P returned to the pond water via algal respiration is comparable to that for N, in which case $P_{ar} = 0.5 \times P_{ag}$. Because pond sediments typically act as a large sink for phosphorus (Hepher, 1958; see also Boyd, 1995), the $P_{misc}$ term (i.e., P loss/gain due to miscellaneous processes) likely reflects a net loss from the DIP pool. Over a one month period, 70-90% of the DIP was lost from the overlying water due to uptake by sediments in laboratory mud-water systems (Boyd and Musig, 1981). These data suggest that P loss to sediments follows more or less first order kinetics with a daily magnitude of about 6%. A daily P loss of 10% was used in the current study to account for accumulation in fish biomass as well as sediments (i.e., the lumped variable $P_{misc}$ is a negative term with a magnitude of $0.1 \times$ DIP. Using a rationale identical to that for N above, the amount of fertilizer P ($P_{fert}$) that is required can be calculated by applying the rules below:

$$\begin{aligned} P_{fert} = {} & P_{req} + (P_o - DIP^*), && \text{if } DIP^* < P_o \\ & P_{req} - P_s, && \text{if } 0 \le P_s \le P_{req} \\ & 0 && \text{if } P_s > P_{req} \end{aligned} \qquad (7.2)$$

where $P_{req}$ = net phosphorus demand, $DIP^*$ = intermediate DIP concentration obtained from Equation 7.1 by setting $P_{fert} = 0$, and $P_s$ = surplus P in the pond. The sum of $P_{fert}$ calculated at each time step using Equation 7.2 over the integration period is an estimate of the overall amount of phosphorus required from fertilizer addition.

## Fertilization Guidelines

The fertilization model developed in the current study comprises Equations 1-7 and has been implemented in the decision support system POND[2]. The steps involved in evaluating nutrient requirements and generating fertilizer application rates by the use of this model are summarized in Figure 4.5.

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[2] POND is a copyright of Oregon State University.

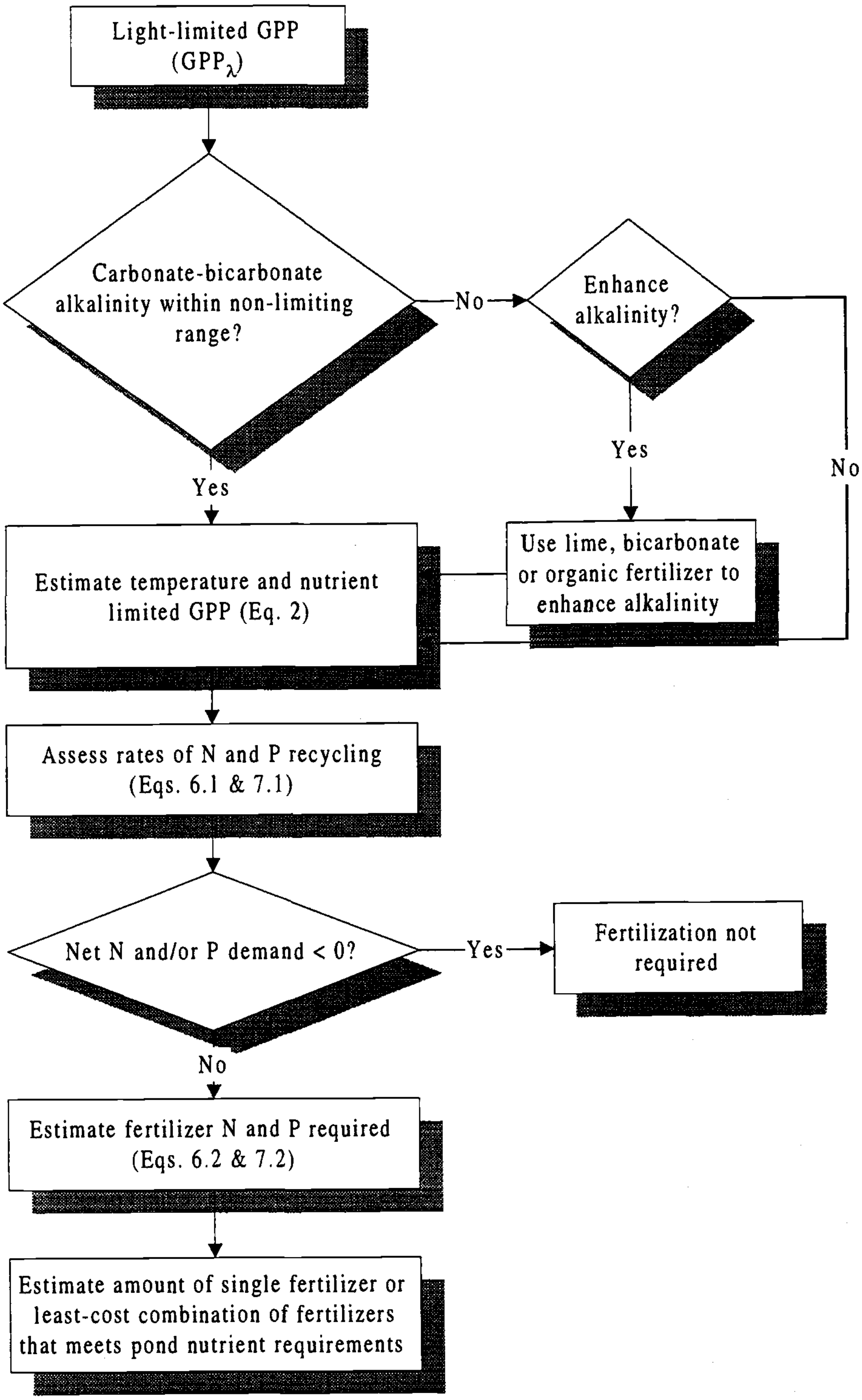

Figure 4.5. A refined scheme based on the fertilization model developed in this study that can be used to assess nutrient requirements of ponds, and estimate associated fertilizer needs.

## MODEL VERIFICATION

It is difficult to accomplish rigid validation of the fertilization model developed in this study without actually conducting physical experiments that are designed to test the performance of the model and its assumptions. Such experiments would ideally involve the management of a set of ponds on the basis of recommendations obtained from the fertilization model together with routine measurement of nutrient fluxes, light conditions, and algal productivity in ponds. In the absence of such experiments, an alternate approach that involved the comparison of fertilizer recommendations generated by PONDCLASS to those obtained from the fertilization model for identical water quality conditions was used for model verification.

Water quality and fertilizer composition data for PONDCLASS experiments conducted at the Asian Institute of Technology (AIT) in Thailand (Szyper and Hopkins, 1995), at the El Carao research station in Honduras (Teichert-Coddington and Ramos, 1995) and at the Freshwater Aquaculture Center (FAC) in the Philippines (Hopkins et al., 1994) were extracted from the PD/A CRSP database. These data were then used in POND to generate weekly fertilization rates for four sampling dates per site. It was assumed that the fertilization protocol was such that adequate N and P would be added to prevent algal growth limitation by these nutrients (i.e., $v_n$ and $v_p$ were set to 1). This was done to ensure as much similarity between the PONDCLASS and POND fertilization approaches as possible. The following parameters for carbon uptake (assumed from PD/A CRSP experiments at Bang Sai, Thailand; see also Fig. 4.4) were used in the fertilization model: $k_C = 6$ and $C_o = 4$. The nutrient threshold parameters $N_o$ and $P_o$ were set to zero. Phytoplankton temperature parameters $T_{min}$, $T_{opt}$ and $T_{max}$ were assumed to be 20, 30 and 35°C respectively.

$GPP_\lambda$ was assumed to be 5, 6 and 7 gC $m^{-3}$ $d^{-1}$ for El Carao, FAC, and AIT respectively. A lower value was used for El Carao because algae are typically less productive for this site compared to AIT, as previously indicated. The highest value of GPP given by Green (1992) for ponds at El Carao was 16.80 $gO_2\ m^{-3}\ d^{-1}$, which is equivalent to 4.84 $gC\ m^{-3}\ d^{-1}$ assuming that 1 gC is fixed for each 3.47 $gO_2$ produced (Stumm and Morgan, 1981). Because $GPP_\lambda$ is to be interpreted as an upper limit to primary productivity, the value of 5 $gC\ m^{-3}\ d^{-1}$ assumed for El Carao appears to be reasonable. The AIT and Bang Sai sites are located in the same geographical region of Thailand, and therefore the $GPP_\lambda$ value obtained from an examination of the data for the latter site (Figs. 4.2-4.4) was used for the AIT analysis. PD/A CRSP data also suggest that the FAC ponds are somewhat less productive compared to Bang Sai and AIT; therefore, $GPP_\lambda$ was set to a lower value (i.e., 6 $gC\ m^{-3}\ d^{-1}$) for this location.

Fertilizer application rates recommended by POND were compared to the amounts actually used at El Carao, AIT and FAC (i.e., the least cost fertilizer combinations generated by PONDCLASS that were reported in the PD/A CRSP database). The POND software also includes an optimization routine that generates least-cost fertilizer mixes that are expected to satisfy the predicted nutrient requirements for a pond. Cost data were included in the comparative analysis to ensure that differences in fertilizer application rates between PONDCLASS and POND, if any, were not caused by assumptions of different costs. Fertilizers that were used in the PONDCLASS experiments at El Carao included chicken manure (CM), urea and diammonium phosphate (DAP), respective costs of which were 0.016, 0.28 and 0.33 US $/kg (Molnar et al., 1996). For AIT, available fertilizers were CM, urea and triple superphosphate (TSP), with respective costs of 0.01, 0.27 and 0.47 US $/kg (Molnar et al., 1996). For FAC, urea and an N:P:K (16-20-0) mixture were the two fertilizers used in the PONDCLASS experiments with respective costs of 0.29 and 0.30 $/kg (K. Hopkins, University of Hawaii, personal communication). An additional assumption in fertilizer calculations for El Carao and AIT was that only 50% of the total N and 75% of the total P in chicken manure (CM) becomes available for algal uptake following fertilizer application (Nath, 1992).

GPP rates predicted by the fertilization model for El Carao (Table 4.2) are within the range of 2.01-4.84 gC $m^{-3}$ $d^{-1}$ previously reported for this site (Green, 1992). For the PONDCLASS experiment conducted at this site (Teichert-Coddington and Ramos, 1995), an organic matter requirement for the pond was always specified. This requirement resulted in the addition of CM for each sampling date. However, because such a requirement is not imposed in the POND fertilization model, CM addition was not recommended (Table 4.2) apparently because it is a more expensive N source compared to urea or diammonium phosphate.

Application rates of urea recommended by POND at El Carao are much lower than those generated by PONDCLASS for all the four sampling dates (Table 4.2). This is particularly noticeable on June 29th, 1993 when DIN levels were already very high. These results suggest that the likelihood of high $NH_3$-N levels limiting fish growth is reduced, whereas the application rates of urea recommended by PONDCLASS (Table 4.2) apparently led to ammonia toxicity (Teichert-Coddington and Ramos, 1995). Moreover, the lower application rates of urea suggested by POND will likely minimize upward changes in pH, which in turn should reduce the effects of $NH_3$-N on fish growth. Diammonium phosphate (DAP) additions were recommended at El Carao for the last two sampling dates (Table 4.2) so as to meet P requirements. Until then, DIP concentrations appeared to be high enough to meet algal growth requirements. Reduction in N and P requirements as predicted by the POND fertilization model were presumably due to a more complete consideration of nutrient cycling processes in ponds. Results similar to those obtained for El Carao are possible only when responsive fertilization strategies are adopted, as opposed to fixed input approaches, which involve the addition of a certain amount of fertilizer N, P and/or C to aquaculture ponds irrespective of their water quality.

In general, DIC levels at El Carao appear to be adequate to preclude the occurrence of C limitation of algal growth (Table 4.2). However, it is possible that DIC losses and therefore reduced alkalinities (similar to those reported for PD/A CRSP ponds in Thailand) may occur over time if the fertilizer recommendations from POND (Table 4.2)

Table 4.2. Weekly fertilizer recommendations generated by PONDCLASS on four occasions at El Carao, AIT and FAC compared to those obtained from the model (in italics) developed in this study. PONDCLASS fertilizer application rates and water quality data were extracted from the PD/A CRSP database. Mean GPP predicted by the use of the POND fertilization model is also shown.

| Date[a] | Mean GPP ($gC\ m^{-3}\ d^{-1}$) | Ambient nutrient concentrations ($g\ m^{-3}$) | | | Nutrient requirements ($g\ m^{-3}\ wk^{-1}$)[d] | | Weekly fertilizer recommendations ($kg\ ha^{-1}\ wk^{-1}$) | | |
|---|---|---|---|---|---|---|---|---|---|
| | | DIN | DIP[b] | DIC[c] | N | P | CM[e] | Urea | Other[f] |
| *El Carao* | | | | | | | | | |
| May 25 | 3.50 | 0.04 | 1.50 | 11.0 | 2.21 (15.75) | 0 | 230 (*0*) | 81.3 (*35.0*) | 0 (*0*) |
| June 29 | 4.33 | 1.97 | 0.95 | 23.4 | 0.07 (0.53) | 0 | 230 (*0*) | 81.4 (*1.1*) | 0 (*0*) |
| Aug 10 | 3.98 | 0.31 | 0.49 | 15.7 | 2.22 (15.82) | 0.07 (0.52) | 206 (*0*) | 77.6 (*34.2*) | 0 (2.2) |
| Sept 18 | 4.26 | 0.89 | 0.25 | 21.3 | 1.74 (12.43) | 0.25 (1.75) | 240 (*0*) | 61.7 (*24.0*) | 0 (*7.7*) |
| *AIT* | | | | | | | | | |
| Jan 24 | 6.38 | 0.06 | 0 | 34.8 | 4.04 (29.74) | 0.68 (4.99) | 437.7 (*582.7*) | 56.9 (*51.6*) | 0 (*0*) |
| Feb 04 | 4.87 | 0.31 | 0 | 35.4 | 2.79 (20.58) | 0.52 (3.81) | 242.5 (*210.2*) | 38.0 (*40.4*) | 0 (*0*) |
| Feb 11 | 6.20 | 0.92 | 0 | 27.3 | 2.98 (21.98) | 0.66 (4.85) | 242.5 (*266.7*) | 47.6 (*42.1*) | 14.1 (*0*) |
| Apr 08 | 6.10 | 1.13 | 0.02 | 24.4 | 2.67 (19.64) | 0.63 (4.64) | 242.5 (*254.6*) | 15.5 (*37.3*) | 11.7 (*0*) |
| *FAC* | | | | | | | | | |
| Jan 15 | 5.58 | 0.66 | 0.45 | 43.6 | 2.87 (21.90) | 0.24 (1.82) | | 72.0 (*41.2*) | 14.8 (*21.1*) |
| Jan 29 | 5.61 | 2.41 | 0.79 | 47.4 | 0.40 (3.07) | 0.06 (0.42) | | 46.0 (*4.9*) | 0 (*5.3*) |
| Feb 12 | 5.14 | 0.19 | 0.15 | 22.0 | 3.10 (23.67) | 0.40 (3.15) | | 68.2 (*39.8*) | 52.8 (*36.0*) |
| Feb 26 | 5.42 | 2.52 | 0.93 | 32.0 | 0 | 0 | | 44.0 (*0*) | 0 (*0*) |

[a] Dates of fertilizer application. PONDCLASS experiments were conducted in 1993 at El Carao and FAC, and in 1994 at AIT.

[b] Zero DIP values in the PD/A CRSP database for AIT presumably indicate negligible concentrations of soluble ortho-phosphate.

[c] Calculated from pH, alkalinity and water temperature data.

[d] Weekly nutrient requirements predicted by the use of POND. Data in parentheses are requirements expressed in $kg\ ha^{-1}\ wk^{-1}$.

[e] CM = chicken manure on a wet weight or as-is basis. This fertilizer was used only at El Carao and AIT.

[f] Refers to other synthetic fertilizers that were used principally for P supplementation. These included DAP (diammonium phosphate) at El Carao, TSP (triple superphosphate) at AIT, and a 16-20-0 mix at FAC.

are adopted because CM addition was not suggested by the software. If such trends are noted in real ponds, the ameliorative strategies discussed earlier may be warranted.

GPP values predicted by POND for the AIT site (Table 4.2) were higher than those for El Carao, an outcome that was expected because of the higher $GPP_\lambda$ value used in Equation 2. Compared to El Carao, fertilizer application rates (particularly of urea) obtained by the use of POND at this site are fairly similar to those recommended by PONDCLASS (Table 4.2), with the exception that triple superphosphate (TSP) addition was not suggested. The initial application of CM in the PONDCLASS-treated pond at the AIT site was much higher than subsequent rates (Table 4.2), and may have been related to changes in fertilizer costs over time. The latter rates (242.5 kg $ha^{-1}$ $wk^{-1}$ on a wet weight basis; see Table 4.2) roughly correspond to the minimum amounts of CM that would be recommended by PONDCLASS if an organic matter requirement for the pond is specified (Lannan, 1993). Even though such a requirement was not forced in the POND fertilization model, CM addition was recommended by this model (Table 4.2). This was due to the need for P amendments at this site as is evident from the low DIP concentrations, and because the least-cost optimizer presumably found CM to be a cheaper source for this nutrient compared to TSP.

Except for the last date on which comparisons were undertaken at AIT (April 8, 1994), the amounts of urea recommended by POND and PONDCLASS were very comparable (Table 4.2). A tendency towards lower additions of this fertilizer with time can also be observed in recommendations obtained by both software applications at AIT, and were likely due to the increase in DIN concentrations (Table 4.2). This tendency was more pronounced in the recommendations obtained using POND. As was the case for El Carao, DIC levels at this site appear to be adequate to prevent C limitation; nevertheless, a tendency towards decreased concentration over time can be observed (Table 4.2). Under actual management conditions, ponds that show such tendencies may benefit from increased manure addition or other ameliorative strategies (as previously discussed), especially if the carbonate-bicarbonate alkalinity drops below about 50-60 mg $L^{-1}$ of $CaCO_3$ equivalents.

For the FAC site, POND predicted much lower nitrogen requirements compared to PONDCLASS as evidenced by urea application rates shown in Table 4.2. In particular, the requirements for this nutrient were much lower on two sampling dates (January 29th and February 26th, when DIN concentrations were high). Addition of limited quantities of phosphorus in the form of an N:P:K mixture (16-20-0) was also recommended by the POND (Table 4.2). On the last sampling date, relatively high DIP concentrations presumably resulted in the software not recommending addition of a phosphorus fertilizer.

## DISCUSSION

The comparative analyses of fertilizer recommendations generated by PONDCLASS and POND for El Carao, AIT and FAC presented above indicate that both software programs adjust fertilizer quantities in response to ambient nutrient concentrations in the pond water. However, such adjustments are more pronounced in the fertilizer application rates recommended by the latter software on occasions when ambient nutrient concentrations are already relatively high. On such occasions, fertilizer application rates obtained using POND are in general more conservative than those obtained from PONDCLASS. This is likely due to a more comprehensive consideration of nutrient cycling processes in POND, which should translate into lower fertilization costs. Further, the probability of unionized ammonia reaching levels that impede fish growth is also likely to be reduced when real ponds are managed using the POND fertilization protocol. On the other hand, recommendations obtained from both software programs are comparable when ponds require high dosages of nitrogen and/or phosphorus to ensure rapid algal productivity rates.

Schelske (1984) noted that application rates of fertilizers to fish ponds are often very high relative to algal requirements, rarely take into consideration which nutrients limit primary production, and how much of the limiting nutrients need to be added to ponds. This situation is primarily the result of the prevalence of fixed fertilization strategies. Model verification results presented herein contribute to mounting evidence (e.g., Hopkins et al., 1994; Szyper and Hopkins, 1995; Knud-Hansen and Guttman, in prep.; Hopkins and Knud-Hansen, in prep.) that responsive fertilization strategies are likely to result in improved economic efficiency of fertilized pond aquaculture systems compared to fixed input strategies. Further, because nutrient concentrations in pond water vary substantially over time, it is highly unlikely that fixed application rates of nitrogen, phosphorus and/or carbon fertilizers which are expected to be economically optimal can be determined. The term 'economically optimal' is used in the current context to indicate fertilizer application rates which result in the highest economic efficiency measured in terms of fertilizer costs required to produce one unit of fish, and does not address alternate uses of the fertilizers in terrestial crop production. Arguments in support of responsive management strategies are further strengthened by the fact that in addition to the variability of nutrient concentrations in a given pond with time, there is also variability among ponds at a given location, as well as among geographical locations due to differences in pond water, soil and climatic characteristics.

As with any computer-assisted management tool, users of the POND fertilization guidelines should observe certain precautions when the software is used. For instance, although the effects of nutrient cycling are considered in the fertilization model, fairly high application rates of N can still be suggested particularly for locations where algal productivity is likely to be high (e.g., results for AIT in Table 4.2). If urea is chosen to meet this demand and its use is prolonged, fairly high pH's and total ammonia levels may occur simultaneously in ponds. Because the toxicity of unionized ammonia varies among fish species (Colt and Armstrong, 1981), tables such as those given by Emerson et al. (1975; see also Boyd, 1990) should be used to determine the proportion of total $NH_3$-N that exists in the unionized form for the ambient water pH and temperature. If the potential for growth limiting concentrations of unionized $NH_3$-N for the cultured fish species exists, alternate N sources should be used or fertilization with synthetic nitrogenous fertilizers should be suspended for a few days so that $NH_3$-N concentrations can drop to levels that are safe for fish. As a general rule, available data seem to suggest that fertilization with synthetic N sources should be deferred if total ammonia levels exceed about 1.0 mg $L^{-1}$ and water pH's are routinely higher than about 8.0. N fertilization rates should also be adjusted downwards when local weather conditions (e.g., prolonged cloudy periods) are likely to impede phytoplankton growth or when plankton blooms crash because uptake of nitrogen will drop under such circumstances possibly leading to accumulation of ammonia N in the pond water.

Despite the encouraging results obtained with the fertilization model, field verification of its recommendations should be undertaken in the form of pond experiments designed to enable estimation of various parameters used in the fertilization model. In particular, it would be beneficial to develop nutrient budgets for locations with diverse pond water and soil conditions, and to estimate the rates of nutrient fluxes. This is particularly important for nitrogen because very little is known about the fate of this nutrient in aquaculture ponds. For phosphorus, there is much evidence to suggest that it may in fact be returned to the water column at relatively high rates once equilibrium has been established between the pond water and the underlying sediments after long periods of heavy phosphorus fertilization (e.g., Eren et al., 1977; Boyd, 1995; Shrestha and Lin, 1996). Under such conditions, the $P_{misc}$ term in Equation 7.1 will be positive, with a rate constant that is likely to vary depending on the soil type and its phosphorus adsorption capacity.

Experiments should also be conducted at different locations to examine ranges of nutrient addition, to develop associated GPP-nutrient relationships, and to evaluate economic consequences of forcing ponds to be nutrient limited. For instance, it may be advisable to reduce nitrogen loading rates in order to minimize the possibility of unionized ammonia accumulation. Further, it may also be useful to vary N:P ratios in ponds either for cost concerns, or to manage the composition of algal species in ponds.

It is also important to note that there is currently no upper limit to the amounts of manure that may be recommended by POND because the maximum amount of manure that can be applied to ponds likely varies according to several factors including dissolved oxygen levels in the pond, manure source, and fish biomass. Model users should therefore be somewhat cognizant of the maximum manure loading rates that their ponds can withstand on a routine basis. For example, application rates of CM that were generated by POND for the AIT site are less than the highest amount of this fertilizer (1000 kg $ha^{-1}$ $wk^{-1}$ on a dry matter basis) that has been used without any apparent problems at a similar site in Thailand (Diana et al., 1991b).

## CONCLUSIONS

Substantial refinements of the fertilization guidelines developed by Lannan (1993) have been accomplished in the form of a model that has been implemented in the decision support system POND. This model is conceptually similar to Lannan's (1993) approach in that it is based on limnological principles and is a responsive management strategy, but differs in the following ways:

a) An estimate of the light-limited gross primary productivity ($GPP_\lambda$) is used as the starting point for fertilizer calculations instead of the maximum net productivity ($NPP_{max}$),

b) The fertilization model accounts for the effects of temperature and nutrient limitations on algal productivity (and therefore fertilizer needs), and

c) Recycling of N and P in ponds is more fully considered in estimating nutrient requirements.

Verification of the POND fertilization model on the basis of PD/A CRSP data from Honduras, Thailand and the Philippines suggests that fertilizer application rates generated by the model are likely to be more conservative than those obtained by the use of PONDCLASS. It is also expected that improved consideration of nutrient cycling will reduce the probability of unionized ammonia accumulation in ponds. Experimental verification of the fertilization model for different locations should be undertaken to assess its performance under field conditions. Nevertheless, model verification results support previous work which indicate that responsive fertilization strategies such as the model developed in this study are likely to result in better nutrient utilization in ponds compared to fixed input approaches, and should result in improved cost efficiency of fertilization practices.

# CHAPTER 5

# A MANAGEMENT-ORIENTED FISH BIOENERGETICS MODEL FOR POND AQUACULTURE SYSTEMS

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# ABSTRACT

Bioenergetic models are potentially useful tools for analyzing fish growth in relation to different pond management practices. However, existing models have provided limited opportunity for practical use either because of their complexity and high data requirements, or because they do not adequately estimate endogenous food consumption by fish in ponds. Therefore, a study was undertaken to develop a simplified bioenergetics (BE) model for fish growth in ponds. This model predicts growth as a function of fish size, food consumption, photoperiod, temperature, dissolved oxygen and unionized ammonia concentrations. A new approach which involves the use of the pond's critical standing crop is used in the BE model to predict the proportion of endogenous food in the diet of pond fish. The BE model also allows for the estimation of supplemental feed requirements (as well as wasted feed) for single or multiple fish populations in a pond by the use of either a specified satiation feeding level or on a percent body weight (%BW) basis.

In contrast to previous fish growth models which have typically been applied to only one fish species, the BE model has been successfully calibrated for Nile tilapia (*Oreochromis niloticus*), tambaqui (*Colossoma macropomum*), pacu (*Piaractus mesopotamicus*), common carp (*Cyprinus carpio*), and channel catfish (*Ictalurus punctatus*). Further, model validation has also been accomplished for these species across various production scenarios such as fertilization regimes, feeding levels, and stocking densities. Sensitivity analysis indicates that among the ten parameters in the BE model, output is very sensitive to three anabolic, one catabolic and two temperature parameters.

Numerical experiments conducted with the BE model indicated that fertilized tilapia ponds with higher fish stocking rates will require supplemental feeding to be initiated earlier compared to those stocked at lower rates, and that the amount of supplemental

feed required to maintain a target feeding level increases rapidly with increasing fish biomass. A second set of model experiments indicated that traditional fixed feeding rates (in terms of %BW $fish^{-1}$ $d^{-1}$) results in higher feed requirements, increased waste feed, and higher food conversion ratios compared to satiation feeding rates predicted by the BE model for locations with different water temperature profiles. For fed ponds, feeding curves obtained from the BE model decrease monotonously with increasing fish weight in a manner similar to published feeding tables, but are likely to be more useful compared to such tables because they are automatically adjusted for the effects of various variables such as fish size, water temperature and photoperiod on fish appetite. For fertilized and fed ponds, BE model feeding curves are characterized by an initial increase followed by a gradual reduction or leveling-off in the feeding rates, apparently because the model accounts for the contribution of natural food to the diet of pond fish. The BE model appears to be a robust and flexible tool for describing fish growth in aquaculture ponds, and can be of use both in routine pond aquaculture management and planning applications, and to explore production scenarios that have not previously been studied in physical experiments.

## INTRODUCTION

Bioenergetic models are useful both for analyzing factors that affect fish performance, and as management tools for fish production (Cuenco et al., 1985a). In the present context, the term *performance* refers to growth, feeding, and metabolism of fish in a particular environment. Management tasks relevant to pond aquaculture that may be addressed by the use of such models include prediction of fish yields under conditions where endogenous (natural) food is the only source of nutrition to fish (e.g., Liu and Chang, 1992), generation of supplementary feed schedules based on endogenous food resource production and fish biomass, analysis of observed fish yields relative to production targets, management of fish densities and harvest schedules, and assessment of water quality management as a potential tool for increased production. Some of these tasks require consideration of water quality processes, oxygen consumption and metabolite excretion by fish, as well as production economics which are beyond the scope of this study.

Key variables that significantly influence fish growth are size (or weight), food availability, photoperiod, temperature, dissolved oxygen and unionized ammonia concentrations (Pütter, 1920; Fry, 1947; Winberg, 1960; Ursin, 1967; Warren and Davis, 1967; Brett et al., 1969; Stauffer, 1973; Huisman, 1976; Corey et al., 1983; Cuenco et al. 1985a). These variables appear to affect fish growth via their impacts on food intake (Brett 1979). Further, activities associated with the development and maturation of reproductive structures reduce growth because energy that might otherwise have been used for tissue build-up is diverted to these structures (Brody, 1945; Brett and Groves, 1979).

Consumed food is used to meet energy losses associated with bioenergetic processes such as fecal and metabolite excretion, standard (maintenance) metabolism, stress response, heat increment (specific dynamic action), active metabolism (swimming), and gametogenesis (Winberg, 1960; Brett and Groves, 1979). Energy in excess of these losses is reflected in fish growth. The fate of consumed food has been modeled for different fish species by the use of comprehensive bioenergetic models (e.g., Machiels and Henken, 1986; Cacho, 1991; van Dam and Penning De Vries, 1995). Following the observations of earlier workers (e.g., Pütter, 1920; Winberg, 1960; Paloheimo and Dickie, 1965; Warren and Davis, 1967), these bioenergetic models assume that growth is manifested as a result of the difference between food intake and metabolism.

Comprehensive bioenergetic models provide a fundamentally sound basis for modeling fish performance, but they tend to be extremely detailed and data intensive. Therefore, such models perhaps best serve as a theoretical framework for understanding fish performance rather than as practical models for pond management. Simplified versions of bioenergetic models that can be used in a management context to analyze factors that affect fish growth have been developed. For example, Stauffer (1973) and Corey et al. (1983) developed models which account for the effects of fish size, varying ration size and temperature on fish growth. However, their models were only calibrated for salmon, and do not address the effects of low dissolved oxygen and/or high unionized ammonia concentrations on fish growth. More importantly, these two models are not necessarily applicable to pond aquaculture systems because they assume that exogenous feed is the sole source of fish nutrition, whereas many species of pond fish grow quite effectively on the natural food resources available in such systems. Cuenco et al. (1985a) developed a useful and flexible bioenergetics model applicable to various aquaculture systems. This model was parameterized for different fish species (e.g., trout, catfish and tilapia). In the Cuenco model, bioenergetic processes associated with energy consumption (i.e., excretion, standard metabolism, stress response, heat increment and active metabolism) were grouped into a generic pool of metabolic losses, and fish growth expressed as the difference between food intake and losses within this pool. The Cuenco model accounts for all the key variables that influence fish growth, with the exception of photoperiod and reproductive losses. The model also does not adequately quantify endogenous food consumption, a principal source of nutrition to pond fish (Hepher, 1978).

An alternate bioenergetic model for modeling Nile tilapia (*Oreochromis niloticus*) growth in warmwater ponds has been developed by Liu and Chang (1992) on the basis of principles previously outlined by Ursin (1967). Conceptually, this model is similar to the Cuenco model in that bioenergetic processes are grouped into tissue synthesis or anabolism (which includes food intake) and tissue breakdown or catabolism, with the difference between them being realized as fish growth. Variables considered by Liu and Chang (1992) include body weight, gametogenetic activities and endogenous food consumption. The amount of endogenous food consumed was assumed to be a function of the stocking density of fish in the pond (rather than standing crop as demonstrated by Hepher, 1978) and the amount of fertilizers added.

In general, currently available bioenergetic models that can be used for pond aquaculture management have either not adequately addressed the effects of key variables on fish growth and or have not been parameterized for many species of pond fish. Moreover, these models have been subjected only to limited validation and have rarely been used in an experimental manner to explore different pond production scenarios. The development of a management-oriented bioenergetics (BE) model, together with relevant calibration and validation results for different species is presented herein. Results from a generalized sensitivity analysis exercise and from various model experiments are also presented.

## MODEL STRUCTURE

From an energetic standpoint, the Ursin model views fish growth as the difference between food consumed (anabolism), and the sum of energy required to process food (feeding catabolism) as well as maintenance requirements (fasting catabolism). In the BE model (as described in detail below), the amount of food consumed is assumed to be a function of fish size, photoperiod, temperature, dissolved oxygen (DO) and unionized ammonia (UIA) concentrations following Ursin (1967), Brett (1979) and Cuenco et al. (1985a). These five variables also affect feeding catabolism because its rate is proportional to the amount of food consumed. Fasting catabolism, however, depends primarily on fish size and temperature (Ursin, 1967). Because it is difficult to predict the onset of maturity and the proportion of intake energy that may be diverted for gametogenetic activities (Brett, 1979), the BE model assumes that energy losses due to these physiological changes are negligible (e.g., as might be the case in intensive carp ponds or in a monosex culture of Nile tilapia). Another fundamental assumption of the BE model is that the composition of fish and their diet is identical (Ursin, 1967).

## Size effects

It is generally accepted that the growth rate of fish increases at a declining rate with size or weight (W) (Pütter, 1920; von Bertalanffy, 1938). In its simplest form, this relationship is often expressed as a power function (e.g., Winberg, 1960; Hepher, 1978). However, von Bertalanffy (1938) and Ursin (1967) indicated that anabolism and catabolism may be paced at different rates in relation to fish weight, with subsequent effects on fish growth. This is captured in the following equation for fish growth rate which has separate exponents for anabolism and catabolism (*m* and *n* respectively) (Ursin, 1967):

$$\frac{dW}{dt} = HW^{m} - kW^{n} \tag{1}$$

where H = coefficient of anabolism ($d^{1-m}$) and k = coefficient of catabolism ($d^{1-n}$).

## Food Consumption

The parameter *H* in Equation 1 can be expanded to consider daily ration, feeding catabolism and digestibility of the food consumed as follows (Ursin, 1967):

$$\frac{dW}{dt} = b(1-a)R - kW^{n} \tag{2}$$

where *a* = fraction of the food assimilated that is used for feeding catabolism (0-1), *b* = the efficiency of food assimilation (0-1), and R = daily ration (g $d^{-1}$), which is the sum of the endogenous or natural food ($R_n$) and supplemental feed ($R_s$) consumed. The term *b(1 - a)* in Equation 2 represents energy that is available for growth and fasting catabolism.

Based upon previous work (e.g., Winberg, 1960; Ursin, 1967; Warren and Davis, 1967), daily ration can be calculated as a function of fish size, food consumption ($f$) and environmental conditions (E):

$$R = h\,f\,E\,W^{m} \tag{3}$$

where $h$ = coefficient of food consumption.

The parameter $f$ (0-1) as defined by Ursin (1967) is the ratio of the actual food intake rate (R) to the intake rate at complete satiation ($R_{max}$). In ponds that receive supplemental feed, $f$ is the sum of the proportion of natural food resources ($f_n$) and feed ($f_s$) in the diet, with associated intake rates given by the product of each of these proportions and $R_{max}$ (e.g., $R_n = f_n R_{max}$). When the BE model is used to simulate fish growth in fertilized ponds, $f_s = 0$ and $f = f_n$. Similarly, for ponds that receive only feed inputs, $f_n = 0$ and $f = f_s$. Because one of the potential applications of the BE model is to estimate the amount of feed required for a given pond, it is convenient to also define a satiation or target feeding level parameter $f_t$ ($0 \leq f_t \leq 1$). This is essentially a management parameter that controls the degree of satiation to which stocked fish should be fed. The daily ration at $f_t$ is denoted as $R_t$.

Cuenco et al. (1985c) modeled natural food consumption as a function of feed added to the pond under the assumption that waste feed has a fertilizing effect on the pond environment. This function is, however, not useful for ponds that are not fed. The parameter $f_n$ was modeled by Liu and Chang (1992) on the basis of a function developed by Ivlev (1961), who observed that food intake by fish tends to increase asymptotically towards a maximum intake level. The Ivlev function depends on the quantity of food resources available and the number of fish present in the pond. Liu and Chang (1992) used a fertilizer richness parameter (equivalent to the loading rate of chicken manure in the experiments simulated) to estimate endogenous food consumption. However, the approach used by Liu and Chang (1992) cannot be easily extended for use in ponds that receive various levels of fertilizer inputs or a mixture of organic and synthetic fertilizers because some estimate of the fertilizer richness parameter would be required. Moreover, Liu and Chang (1992) assumed endogenous food consumption to be function of the number of fish, instead of fish standing crop as demonstrated by Hepher (1978). This assumption implies that the amount of food consumed by pond fish is constant for a particular fertilization regime and culture period, unless the number of fish is substantially altered either due to mortality or partial harvest.

In reality, endogenous food consumption by fish in fertilized ponds that are treated identically typically varies over time (Hickling, 1962; Hepher, 1978). During the initial phase of fish production, adequate endogenous food appears to be produced in properly fertilized ponds thus sustaining fish at satiation feeding levels (i.e., $f = 1$), but once the fish biomass (FB) or standing crop in the pond exceeds the "critical standing crop" (CFB), the proportion of endogenous food relative to the amount required to satiate fish declines until the carrying capacity of the pond is reached (Hepher, 1978). Although the parameter $f$ can potentially decline to zero, this situation does not appear to occur in fertilized ponds perhaps because there is adequate food to meet maintenance requirements of fish even at relatively high biomass levels as a result of adaptation to conditions of limited food availability (Hepher et al., 1983; Hepher, 1988).

There have been very few efforts to determine the quantity of supplemental feed that is to be added to fertilized ponds so as to ensure that a desired target satiation level is met. The task is especially difficult for fish species such as Nile tilapia and common carp which may derive a substantial portion of their nutritional requirements from natural food resources. The parameter $f_s$ in the BE model is intended to enable estimation of supplemental feed requirements. Functions developed for $f_n$ and $f_s$ in the model depend on fertilization and feeding practices, and are described below.

## Natural Food Only

A simple expression to approximate the relationship between endogenous food consumption and fish biomass is as follows:

$$f_n = \begin{cases} 1.0, & \text{if } FB < CFB \\ CFB/FB, & \text{if } FB \geq CFB \end{cases} \qquad (4)$$

This expression appears to capture the pattern of decreasing proportions of natural food in fish diet when fish biomass exceeds CFB, and approaches the carrying capacity of a pond (Hepher, 1978; see also Fig. 5.1A). Fish biomass in the BE model is expressed on a volumetric (kg $m^{-3}$) rather than the traditional areal basis (kg $ha^{-1}$) to account for differences in pond volumes.

Use of Equation 4 requires estimates of the CFB, which can be obtained from fish growth data because the short-interval growth rate of individual fish in fertilized ponds tends to increase initially, reaches a maximum at the CFB and then decreases thereafter (Hepher, 1978). Nile tilapia growth rates estimated from data reported in the aquaculture database maintained by the Pond Dynamics/Aquaculture Collaborative Research Support Program (PD/A CRSP) indicate similar patterns (Fig. 5.2). These data originated from fertilized ponds located at Bang Sai, Thailand. The ponds labeled SD1, SD2 and SD3 (Fig. 5.2) were stocked with 33g fish at 1, 2 and 3 fish $m^{-2}$ respectively, whereas the remaining pond was stocked with 1g fish at 2 fish $m^{-2}$. If we assume that CFB corresponds to the fish biomass at the point when growth rates reach a maximum, Figure 5.2 suggests that CFB appears to have been reached by day 30 for the SD2 and SD3 ponds, by day 60 for the SD1 pond, and only by day 90 for the remaining pond (presumably because of the smaller stocking weight). For the SD2 and SD3 ponds, it is possible that the CFB actually occurred prior to the first sampling interval (30 days after stocking), but this is difficult to ascertain from the available data.

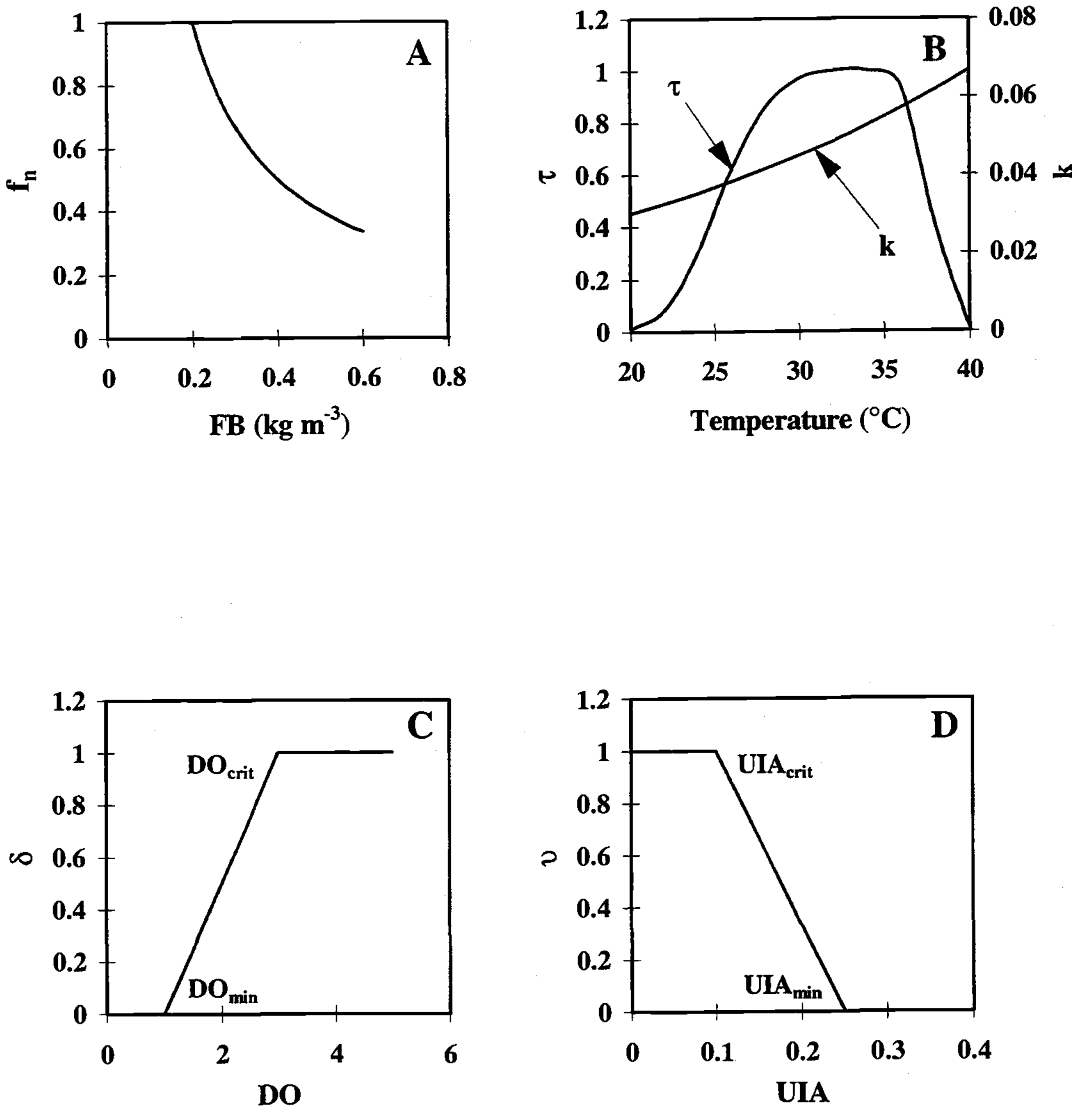

Figure 5.1. Functions used in the BE model. (A) natural food consumption ($f_n$; 0-1) as a function of fish biomass (FB); (B) temperature effects on anabolism (τ; 0-1) and catabolism (k); (C) dissolved oxygen effects (δ; 0-1) on growth; (D) unionized ammonia effects (υ; 0-1) on growth.

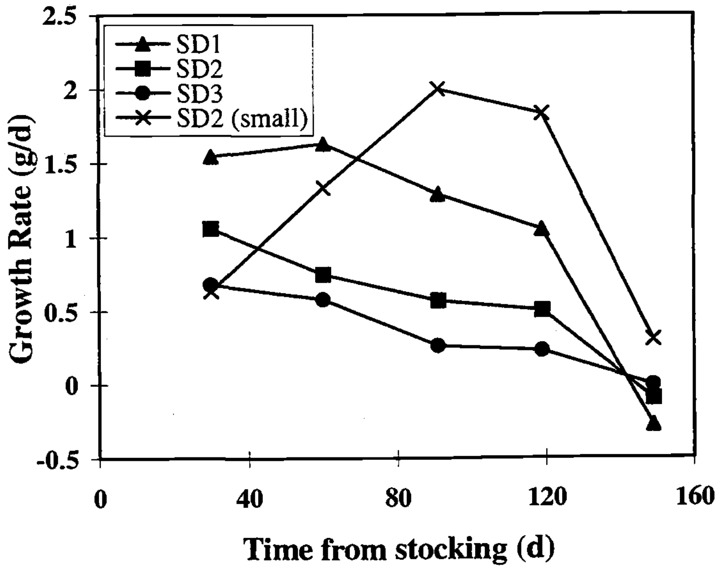

Figure 5.2. Mean short-interval growth rates for Nile tilapia in fertilized ponds located at Bang Sai, Thailand. The pond labeled SD2 (small) was stocked with 1g fish, whereas the others were stocked with 33g fish.

## Natural Food Plus Supplementary Feed

The BE model assumes that supplemental feed is not required in ponds if fish biomass is less than CFB. Another implicit assumption is that fish attempt to satisfy their nutritional requirements from endogenous food resources before supplemental feed is consumed. If the model is used to predict supplemental feed requirements, it is necessary to specify $f_t$, which replaces $f$ in Equation 3. The parameter $f_s$ is set to zero unless two conditions are satisfied: (i) the CFB is exceeded, and (ii) $f_n < f_t$. The difference between the latter two parameters represents $f_s$. The daily supplemental feed amount ($R_a$; g $d^{-1}$) can then be calculated as follows:

$$R_a = \frac{f_s}{q} R_{max} \tag{5}$$

where $q$ = feed quality coefficient (0-1). This coefficient is to be interpreted as a measure of both the quality of the supplemental feed as well as feeding practices. Feeds like rice bran that are widely used in tropical pond aquaculture may not be particularly palatable to some fish species and consequently a large proportion is not directly consumed. A lower value for $q$ should be used in such cases. Conversely, a high quality feed together with good feeding practices warrants the use of a higher value for $q$.

The supplemental feed actually consumed by fish and the amount of feed wasted ($R_w$) in g $d^{-1}$ are calculated as follows:

$$R_s = q\ R_a \tag{6}$$
$$R_w = (1 - q)\ R_a \tag{7}$$

In practice, fish ponds may occasionally contain one or more fish lots or populations (of either the same or different species). For such scenarios, the total amount of feed supplied and wasted are assumed to be the sum of the rates calculated by the use of Equations 5 and 7 respectively for each of the fish lots.

In situations where the feeding rate is specified as a percentage of the body weight per day (%BW $d^{-1}$), $R_a$ is calculated directly and Equation 5 is not evaluated. It is difficult to estimate the amount of feed reaching fish that belong to different lots in a single pond even if identical feeding rates are specified. For instance, a pond may contain two populations (e.g., tilapia and catfish), each being fed at the same rate on a %BW basis. However, the actual feed consumed by fish within each lot is likely to differ because of differences in fish size and appetite. In such situations, the total amount of feed added to the pond is calculated and then averaged over the number of lots in it to arrive at a single rate ($R_a$) for each lot.

When feeding rates are specified on a %BW $d^{-1}$ basis, and complete satiation is not reached (i.e., $f < 1$), Equations 6 and 7 are used to estimate $R_s$ and $R_w$ respectively. However, if feed is supplied in excess of satiation levels, a situation that can occur in ponds with an abundance of natural food, $R_s$ and $R_w$ are given by:

$$R_s = (1 - f_n)\, R_{max} \tag{8}$$

$$R_w = (1 - q)\, R_a + \left[(f_n R_{max} + q R_a) - R_{max}\right] \tag{9}$$

Note that $R_w$ under conditions of excess feeding comprises two components: (i) a fraction of the applied feed that is unavailable for consumption, and (ii) an estimate of feed supplied in excess of satiation.

## Supplementary Feed Only

Sometimes, it may be desirable to analyze feed requirements when the cultured fish species does not to any large extent exploit endogenous food resources in ponds or the production of such resources is negligible. Examples of cultured species that do not harvest natural food resources to any appreciable level include channel catfish (Wiang, 1977, cited in Lovell, 1988) and tambaqui (Merola and Pagan-Font, 1988). From a modeling context, the above scenarios are equivalent to setting $f_n = 0$ and $f_s = f_t$. Equations 5-9 can then be used to estimate feed requirements or evaluate growth responses to pre-specified feeding rates as discussed above. It should be noted that the effects of SD are not accounted for when the BE model is used to simulate growth in fed ponds. Possible repercussions of this assumption are discussed in a later section of this paper.

## Effects of Environmental Variables

Expressions used to evaluate the effects of each of the four environmental variables (photoperiod, temperature, DO and UIA) on fish growth are described below.

*Photoperiod*: Many cultured fish including tilapias tend to feed only during daylight hours (Caulton 1982). The daily photoperiod (h) at different sites can be obtained from sunrise and sunset hour angle calculations (Hsieh, 1986), and the photoperiod or daylight scaler ($\pi$) then estimated as photoperiod/24. A photoperiod of 12h for instance would result in $\pi = 0.5$. This linear scaler is used to adjust daily food intake in the BE model.

*Temperature*: Food consumption tends to increase with temperature ($T$) from a lower limit below which fish will not feed ($T_{min}$) until the optimum temperature ($T_{opt}$) for the given fish species is reached; beyond $T_{opt}$, consumption decreases rapidly to zero until an upper limit ($T_{max}$) is reached above which fish will not feed (Brett et al., 1969; Brett 1979). Cuenco et al. (1985a) used a triangular function to describe this relationship. However, many fish species such as tilapias (Caulton, 1978) tend to have a maximum food consumption rate within a temperature range rather than at a single optimum temperature. Therefore, the "skewed normal" function used by Svirezhev et al. (1984; see also Fig. 5.1B) which is more or less flat around a known optimal temperature appears to be more appropriate to describe the effects of temperature on food consumption, and therefore anabolism. This function ($\tau$) is dimensionless, and is given by:

$$\tau = \begin{cases} \exp\left\{-4.6\left[(T_{opt} - T)/(T_{opt} - T_{min})\right]^4\right\}, & \text{if } T < T_{opt} \\ \exp\left\{-4.6\left[(T - T_{opt})/(T_{max} - T_{opt})\right]^4\right\}, & \text{if } T \geq T_{opt} \end{cases} \quad (10)$$

However, catabolism increases exponentially with temperature within the tolerance limits for a given species (Ursin, 1967; see also Cuenco et al., 1985a). In the BE model, the exponential function of the Ursin model has been modified to include the lower temperature tolerance limit for the given species (assumed to be equivalent to $T_{min}$) as follows (Fig. 5.1B):

$$k = k_{min} \exp\left[s\,(T - T_{min})\right] \tag{11}$$

where k = coefficient of fasting catabolism ($g^{1-n}$/day), $k_{min}$ = coefficient of fasting catabolism at $T_{min}$ ($g^{1-n}$/day), and $s$ = a constant to describe temperature effects on catabolism ($°C^{-1}$).

*Dissolved Oxygen*: DO typically does not affect food consumption if its concentration is above a critical limit ($DO_{crit}$) that is species dependent, but further decrease in DO levels reduces food consumption more or less linearly until concentrations of DO below which fish will not feed are reached ($DO_{min}$) (Cuenco et al. 1985a). Following this group of authors, such effects can be expressed by the use of the function δ (0-1; Fig. 5.1C):

$$\delta = \begin{cases} 1.0, & \text{if } DO > DO_{crit} \\ (DO - DO_{min})/(DO_{crit} - DO_{min}), & \text{if } DO_{min} \leq DO \leq DO_{crit} \\ 0.0, & \text{if } DO < DO_{min} \end{cases} \tag{12}$$

*Unionized Ammonia*: The effects of UIA are similar to those of DO with the exception that food consumption is affected only if UIA *exceeds* a certain critical concentration ($UIA_{crit}$). Beyond $UIA_{crit}$, food consumption decreases with increasing UIA until the latter reaches a certain maximum value ($UIA_{max}$), beyond which food is not consumed (Colt and Armstrong, 1981; Cuenco et al. 1985a). The function υ (0-1; Fig. 5.1D) developed by these authors is as follows:

$$\upsilon = \begin{cases} 1.0, & \text{if } UIA < UIA_{crit} \\ (UIA_{max} - UIA)/(UIA_{max} - UIA_{crit}), & \text{if } UIA_{crit} \leq UIA \leq UIA_{max} \\ 0.0, & \text{if } UIA > UIA_{max} \end{cases} \tag{13}$$

*Combined Effects of Environmental Variables*: The parameter *E* in Equation 3 reflects the combined effects of photoperiod, temperature, DO and UIA on food consumption. Brett (1979) synthesized available literature documenting the effects of these factors on fish growth, and observed that the extent to which each factor limits growth is dependent on the other factors. Empirical relationships that can be used to describe the combined effects of limiting factors on growth include Liebig's minimum factor rule, the multiplicative effect function, the mean effect approach and the inverse sum function (Benefield and Randall, 1980; Straskraba and Gnauck, 1985; O'Neill et al., 1989). These functions have been developed primarily on the basis of experimental results obtained with bacterial cultures and plant growth. They have not been extensively used for fish growth modeling. However, Cuenco et al. (1985a) applied the minimum factor function to examine the effects of DO and UIA on food consumption. Further model experimentation by these authors (Cuenco et al., 1985b) suggested that the effects of DO and UIA on growth were probably better described by use of the multiplicative function.

The latter approach is more consistent with experimental observations which indicate that the effects of high UIA concentrations on fish growth are more pronounced when DO is low (Merkens and Downing 1957, Thurston et al. 1981). Further, Cuenco et al. (1985b) also found that the combined effects of temperature with DO or UIA were also better described by the use of the multiplicative function. In the absence of further information on the combined effects of photoperiod, temperature, DO and UIA on fish growth, the BE model assumes that their combined effects are adequately represented by the multiplicative function (i.e., $E = \pi \times \tau \times \delta \times \upsilon$).

## Effects of Mortality

Losses of stocked fish as a result of mortality are a major concern in aquaculture operations. However, such losses are difficult to predict because they may occur either due to prolonged or sudden exposure to poor water quality and/or pathogenic organisms. The BE model does, however, enable consideration of this factor by the use of a daily mortality or loss rate ($\lambda$; $d^{-1}$) as follows:

$$\frac{dP}{dt} = - \lambda P \tag{14}$$

where P = population size of the fish in the particular lot (P; fish $ha^{-1}$), the initial condition of which is the stocking density (SD).

### Model Implementation

The BE model is one among a family of simulation models that have been implemented in the decision support system POND (see also Chapter 1). These models have been formulated as sets of ordinary differential equations that are solved by the use of a fourth-order Runge-Kutta integrator. Equations 1 and 14 are the differential equations relevant to the BE model. For the current study, a time step of one day was used for all the simulations.

## MODEL PARAMETERIZATION

Calibration of the BE model requires time-series data pertaining to fish growth, water temperature, DO, UIA and feed application. Such data are either not routinely collected in experimental and field trials or not often reported in the published literature. Nevertheless, the BE model has been calibrated for Nile tilapia, common carp (*Cyprinus carpio*), tambaqui (*Colossoma macropomum*), pacu (*Piaractus mesopotamicus*) and channel catfish (*Ictalurus punctatus*) by the use of an automatic parameter estimation technique (Chapter 7). Model parameters estimated for the five fish species are indicated in Table 5.1.

Table 5.1. Best-fit model parameters estimated for five fish species. Parameter estimation procedures are described in Chapter 7.

| Bioenergetic Parameter | Nile tilapia | Tambaqui | Pacu | Common carp | Channel catfish |
|---|---|---|---|---|---|
| *Anabolism Parameters* | | | | | |
| Efficiency of assimilation ($b$) | 0.7108 | 0.6695 | 0.7719 | 0.7129 | 0.7865 |
| Anabolism exponent ($m$) | 0.6277 | 0.6855 | 0.7154 | 0.6722 | 0.6327 |
| Food consumption coefficient ($h$) | 0.4768 | 0.2863 | 0.2415 | 0.3282 | 0.2885 |
| *Catabolism Parameters* | | | | | |
| Feeding catabolism coefficient ($a$) | 0.0559 | 0.1057 | 0.0529 | 0.0786 | 0.1133 |
| Catabolism exponent ($n$) | 0.8373 | 0.5336 | 0.5332 | 0.5166 | 0.5118 |
| Minimum catabolism coefficient ($k_{min}$) | 0.0104 | 0.0146 | 0.0094 | 0.0104 | 0.0227 |
| Temperature parameter ($s$) | 0.0288 | 0.0110 | 0.0290 | 0.0027 | 0.0119 |
| *Temperature Scalers* | | | | | |
| Minimum ($T_{min}$) | 18.7 | 14.4 | 17.5 | 10.1 | 13.3 |
| Maximum ($T_{max}$) | 39.7 | 38.6 | 31.4 | 36.2 | 36.0 |
| Optimum ($T_{opt}$) | 32.4 | 29.0 | 28.1 | 30.6 | 30.8 |

For each species, data sources used in model calibration and parameter estimation results are discussed in the relevant section below . Because DO and UIA information were not available in the data sources, it was assumed that these variables were within the ranges where fish growth was independent of their concentrations. Further, in the absence of detailed information on feed quality and feeding practices, a value of one was assumed for the parameter $q$. Feeding rates in the data sources were typically reported in terms of %BW $d^{-1}$, and were used to estimate the amount of feed added to the ponds. The daily mortality rate was estimated from survival data reported in the various sources.

## Nile tilapia

Data from an experiment conducted at the El Carao research station in Honduras (Teichert-Coddington et al., 1991) were used for model calibration. Experimental details reported by these authors are briefly summarized here. The experiment involved the following four treatments (replicated three times in 0.1 ha earthen ponds): (a) chicken litter only (CL), (b) chicken litter for the first month, followed by feed (CL1), (c) chicken litter for the first two months, followed by feed (CL2), and (d) chicken litter for the first three months, followed by feed (CL3). For all treatments, chicken litter and feed were supplied at 1000 kg $ha^{-1}$ $wk^{-1}$ (DM basis) and 3% of the estimated fish biomass respectively. Sex-reversed Nile tilapia (mean weight of 28.5g) were stocked at 1 fish $m^{-2}$ and harvested after 147d. Growth and survival data for the above experiment were extracted from the PD/A CRSP aquaculture database. Daily water temperature for use in growth simulations of this species was predicted by use of the model described in Chapter 2; weather data required as input to the latter model were also extracted from the PD/A CRSP database. Only growth data from the CL1 and CL3 treatments were used for model calibration. Data from the other two treatments were used for validation purposes (see *Model Validation* section below). Mean CFB's for the CL1 and CL3 treatments were estimated from observed growth data to be 0.156 and 0.143 kg $m^{-3}$ respectively.

The simulation runs assumed that feed consumption would commence only once the CFB was exceeded.

Parameters estimated from this experiment (Table 5.1) resulted in good predictions of Nile tilapia growth (Fig. 5.3; Table 5.2). Reduced growth rates for the CL3 treatment presumably resulted from food limitation because supplemental feeding commenced well after the CFB was reached. Periods of slow growth predicted by the model for both treatments (Fig. 5.3) were apparently the result of low water temperatures (in the range of 19-22°C). It is difficult to observe such effects in actual growth data because of the relatively long sampling intervals (about four weeks).

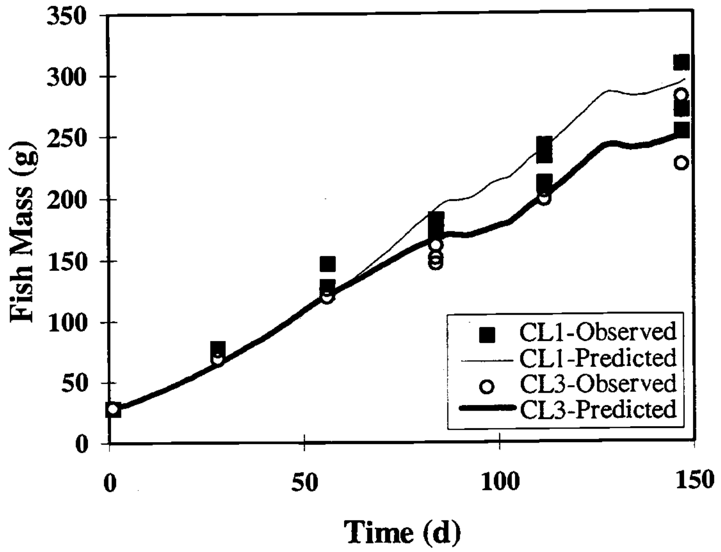

Figure 5.3. BE model calibration results for Nile tilapia ponds at El Carao, Honduras.

## Tambaqui

Data from a 255d experiment conducted at the Centro de Pesquisa e Treinamento em Aquicultura (CEPTA) in Itiquira, Brazil (Merola and Pagan-Font, 1988) were used to

Table 5.2. Summary model calibration and validation results for the five species chosen for analysis.

| Fish Species | Site | Data Source | Period Simulated | Treatment[a] | Final Fish Weights (g) | | Percent Relative Error[b] |
|---|---|---|---|---|---|---|---|
| | | | | | Observed | Predicted | |
| *Calibration* | | | | | | | |
| Nile tilapia | El Carao, Honduras | 1 | 27/7/89 to 21/12/89 | Feed + Fert (CL1) | 276.4 | 294.2 | +6.4 |
| | | 1 | 27/7/89 to 21/12/89 | Feed + Fert (CL3) | 258.4 | 251.4 | -2.7 |
| Tambaqui | Pirassununga, Brazil | 2 | 1/10/84 to 13/6/85 | Feed[c] | 298.0 | 304.6 | +2.2 |
| Pacu | Itiquira, Brazil | 3 | 26/4/86 to 11/03/87 | Feed[d] | 699.6 | 727.9 | +4.0 |
| Common carp | Golysz, Poland | 4-6 | 10/6/72 to 10/10/72[e] | Feed | 400.0 | 401.8 | +0.5 |
| Channel catfish | Stoneville, MS, USA | 7 | 1/5/94 to 1/10/94 | Feed | 463.0 | 454.6 | -1.8 |
| *Validation* | | | | | | | |
| Nile tilapia | El Carao, Honduras | 1 | 27/7/89 to 21/12/89 | Fertilizer only (CL) | 206.4 | 197.8 | -4.2 |
| | | 1 | 27/7/89 to 21/12/89 | Feed + Fertilizer (CL2) | 256.5 | 275.3 | +7.3 |
| | El Carao, Honduras | 8 | 11/8/88 to 20/12/88 | Fertilizer | 131.3 | 124.7 | -5.0 |
| | Bang Sai, Thailand | 9 | 2/2/87 to 1/7/87 | Fertilizer, SD 1 fish $m^{-2}$ | 189.7 | 204.9 | +8.0 |
| | | | | Fertilizer, SD 2 fish $m^{-2}$ | 116.7 | 126.1 | +8.0 |
| | | | | Fertilizer, SD 3 fish $m^{-2}$ | 86.0 | 101.9 | +18.5 |
| | Bang Sai, Thailand | 10 | 9/10/91 to 19/3/92 | Feed | 325.7 | 369.6 | +13.5[h] |
| Tambaqui | Gualaca, Panama[f] | 11 | | Feed | 426.0 | 375.7 | -11.8[h] |
| | Colombia[f] | 12 | | Feed | 1240.0 | 1068.1 | -13.9[h] |

Table 5.2, Continued.

| Fish Species | Site | Data Source | Period Simulated | Treatment[a] | Final Fish Weights (g) | | Percent Relative Error[b] |
|---|---|---|---|---|---|---|---|
| | | | | | Observed | Predicted | |
| Pacu | Pirassununga, Brazil | 13 | 25/2/82 to 25/2/83 | Feed | 624.0 | 649.2 | +4.0 |
| | Pirassununga, Brazil[g] | | 22/2/82 to 22/2/83 | Feed | 567.0 | 589.7 | +4.0 |
| Common carp | | | | | | | |
| | Golysz, Poland | 4-6 | 10/6/72 to 10/10/72[e] | Feed | 920.0 | 889.4 | -3.3 |
| | Haifa, Israel | 14 | 9/5/78 to 30/6/78 | Feed | 482.0 | 503.3 | +4.4 |
| | Haifa, Israel | 14 | 7/7/78 to 28/8/78 | Feed | 533.0 | 540.6 | +1.4 |
| | Haifa, Israel | 14 | 5/9/78 to 23/10/78 | Feed | 335.0 | 347.9 | +3.9 |
| Channel catfish | Auburn, Alabama | 15 | 15/4 to 15/10[i] | Feed | 500.0 | 449.9 | -10.0 |

*Notes*:

[a] Refer to text for explanation of treatment codes, if any.

[b] Calculated as [(P - O)/O] * 100, where P and O are the final predicted and observed weights (g) respectively.

[c] Organic fertilizers (cattle or poultry manure) were added during the initial phase of the study, but suspended thereafter because a parallel study suggested that its contribution to fish growth was minimal.

[d] Cattle manure was added for the first eight months of the study, but its effects on growth were difficult to assess and therefore not considered in the current analysis.

[e] Stocking and harvest dates are approximate estimates because growth data were read off a graph.

[f] See text for additional assumptions that were made to accomplish model validation.

[g] Data for this experiment were obtained from Dr. Newton Castagnolli (personal commn.).

[h] Possible reasons for these relatively high error values are discussed in the text.

[i] The year of the experiment was not mentioned by Lovell (1977).

*Data Sources*:

1. Teichert-Coddington et al., (1991); 2. Merola and Pagan-Font (1988); 3. Lima et al. (1988); 4. Szumiec (1979a); 5. Szumiec (1979b); 6. Szumiec and Szumiec (1985); 7. Robinson and Li (1995); 8. Teichert-Coddington et al. (1990); 9. Diana et al. (1990); 10. Diana et al. (1993); 11. Peralta and Teichert-Coddington (1989); 12. Gomez et al. (1995); 13. Bernardino and Ferrari (1989); 14. Rappaport and Sarig (1979); 15. Lovell (1977).

calibrate the BE model for tambaqui. Fish of mean weight 11.7g were stocked at a density of 1.7 fish $m^{-2}$ in a 0.71 ha earthen pond. Feed was applied at rates varying from 3.5% to 2% BW $d^{-1}$ depending on fish size. Time-series water temperature data reported by Merola and Pagan-Font (1988) were used as input to the BE model. Parameter estimation for this species assumed that feed was the only source of nutrition.

Model parameters for tambaqui (Table 5.1) result in the growth profile shown in Fig. 5.4 (see also Table 5.2). Predicted fish weights tended to be slightly lower than observed weights during the entire simulation except towards the end. It is possible that the estimated model parameters are not adequate to accurately predict growth of this species when temperatures are within its optimum range. The availability of additional replicates for the experiment conducted by Merola and Pagan-Font (1988) would have been beneficial in generating a parameter set more representative of tambaqui growth.

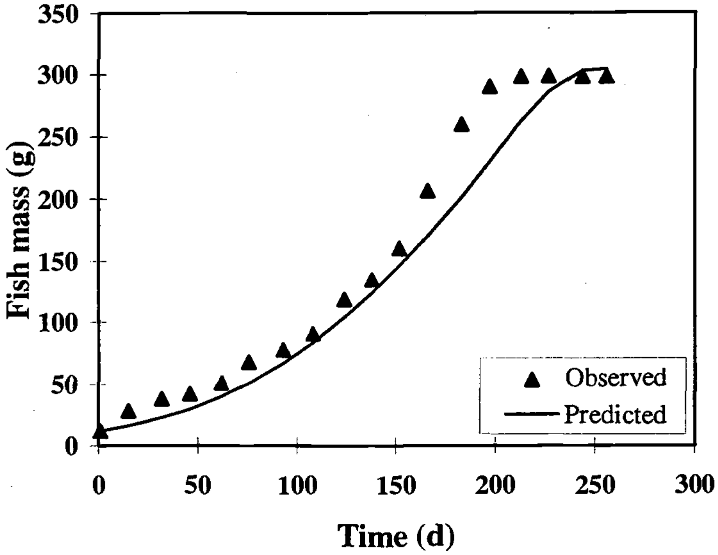

Figure 5.4. BE model calibration results for tambaqui at Pirassununga, Brazil.

## Pacu

Data for this species were obtained from Lima et al. (1988), a study which involved two phases in 0.1 ha ponds, namely fingerling culture for 230d (two replicates) followed by a grow-out phase that lasted 89d (three replicates). Stocking rates were 2 and 0.6-0.8 fish $m^{-2}$ respectively for the two phases. Because the BE model does not account for the effects of SD in fed ponds, data from both phases were combined for model calibration. This enabled analysis of growth over a longer culture period. Feeding rates ranged from 1.5-3% BW $d^{-1}$. Lima et al. (1988) do not provide details regarding adjustment of feeding rates; therefore, it was assumed that these rates decreased with increasing biomass. Time-series water temperature data reported by the above authors were used as input to the BE model. Estimated parameters are indicated in Table 5.1. Simulations with the calibrated model result in good correspondence between observed and predicted growth (Fig. 5.5; Table 5.2). The model also accurately predicted periods of poor growth associated with low water temperatures during the initial phase of culture.

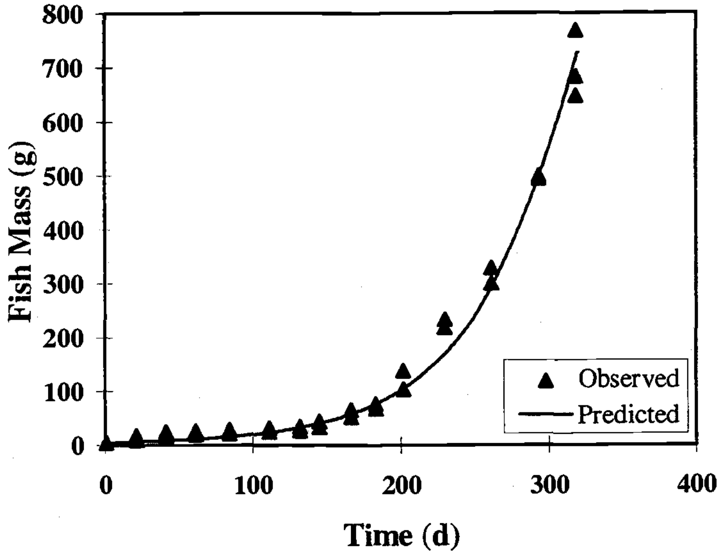

Figure 5.5. BE model calibration results for pacu at Itiquira, Brazil.

## Common Carp

Data from experiments conducted during 1969-1974 at the Golysz experimental station in Poland were used to calibrate the BE model for common carp. These data have been published in a variety of reports; thus, mean monthly water temperatures for the Golysz station were obtained from Szumiec (1979a), feeding rates from Szumiec (1979b) and growth data from Szumiec and Szumiec (1985). For parameter estimation, growth data for 1-2 year old fish ($C_{1-2}$) were used. Excellent correspondence between fish weights predicted by the use of the calibrated model and observed weights was obtained for this species throughout the simulation period (Fig. 5.6), and the relative error was the lowest among the five fish species tested (Table 5.2). Slower growth rates towards the end of the simulation period were presumably due to low water temperatures, a trend that was accurately predicted by the set of growth parameters for the common carp.

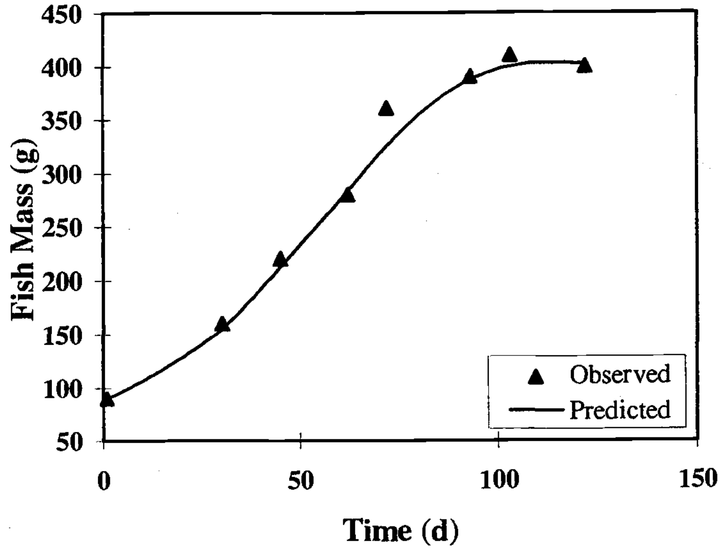

Figure 5.6. BE model calibration results for common carp at Golysz, Poland.

## Channel Catfish

Model calibration for catfish was accomplished using growth, feeding and water temperature data for experiments conducted at the Stoneville Research Station, Mississippi (Robinson and Li, 1995). Biweekly fish weights reported by these authors were apparently only estimates and not obtained by regular sampling since this practice increases stress and mortality (Dr. Menghi Li, Mississippi State University, personal commn.). 50g fish were stocked in the ponds on May 1 at a density of 2.47 fish $m^{-2}$, fed to satiation, and harvested after 153d. Model predictions with the best-fit parameter set (Table 5.1) compared very favorably to observed weights for this species (Fig. 5.7). The final harvest weight predicted by the growth model was only marginally lower than the actual weight reported by Robinson and Li (1995; Table 5.2).

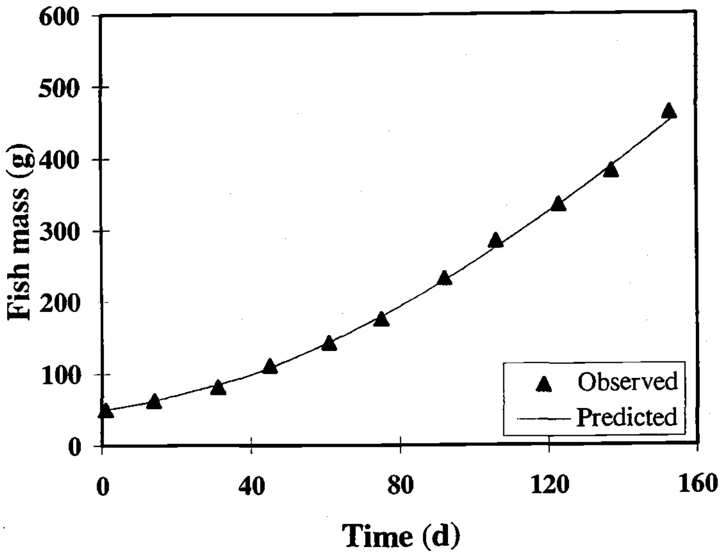

Figure 5.7. BE model calibration results for channel catfish at Stoneville, Mississippi, USA.

## MODEL VALIDATION

The BE model was validated for each of the five fish species as described below. Unless otherwise noted, model validations used the same assumptions listed in the *Model Parameterization* section.

### Nile tilapia

As indicated earlier, data from two of the treatments (CL and CL2) in the experiment conducted by Teichert-Coddington et al. (1991) were used for model validation. Mean CFB's for these two treatments were estimated from growth data in the PD/A CRSP database to be 0.144 and 0.204 kg $m^{-3}$ respectively. Growth predictions were in general quite good (Fig. 5.8; Table 5.2), although predicted weights tended to exceed observed weights for CL2 treatment. This discrepancy may have resulted from the higher CFB value estimated for the CL2 ponds compared to the range of 0.143-0.156 kg $m^{-3}$ for the other treatments in this experiment. We assume CFB to be the fish biomass at the point where individual growth rates calculated from routine samplings are the highest. In reality, this point may occur in between sampling intervals and can result in errors in CFB estimates. Although more frequent sampling intervals (e.g., two weeks instead of one month) would perhaps provides opportunity for increased accuracy in the estimation of CFB's, increased stress to stocked fish may result from such practices.

As was the case with the calibration trials for tilapia, low growth phases in the simulated growth profiles (Fig. 5.8) were apparently the result of sub-optimal water temperatures. It is also interesting to note that fish weights up to day 60 in all the four experimental treatments (Figs. 5.3 and 5.8) were not substantially different. This lends further support to Hepher's (1978) argument that supplemental feed addition may not be warranted in well-fertilized ponds until the CFB is reached.

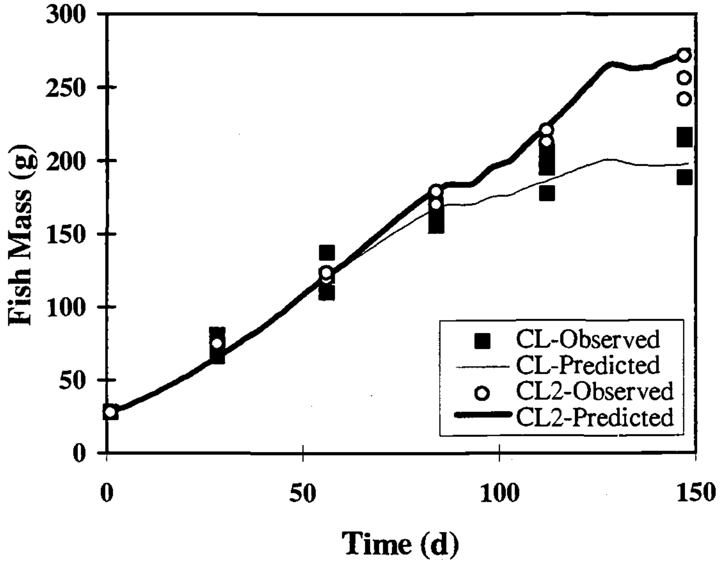

Figure 5.8. BE model validation results for Nile tilapia growth in fertilized (CL) and both fertilized and fed (CL2) ponds at El Carao, Honduras.

Additional validations were conducted to evaluate model predictions at CRSP sites in Honduras (El Carao) and Thailand (Bang Sai). The relevant experiments are described in Teichert-Coddington et al. (1990) and Diana et al. (1990, 1993) respectively.
Fish growth information and weather data (used to predict water temperature by the use of the model described in Chapter 2) from these experiments were extracted from the PD/A CRSP database.

The BE model provided good predictions of fish weights for the fertilization trial at El Carao (Teichert-Coddington et al., 1990), except towards the end of the experiment when the predicted weight was somewhat lower than the mean of the observed weights (Fig. 5.9; Table 5.2). The above authors reported large fluctuations in natural food resources during the last phase of the experiment, effects of which are not captured in the simplified

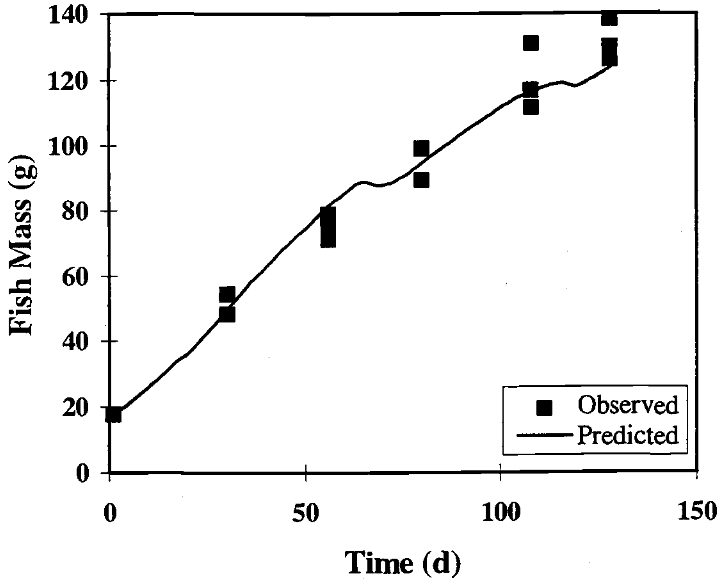

Figure 5.9. BE model validation results for Nile tilapia growth in ponds fertilized with chicken litter (500 kg $ha^{-1}$ $wk^{-1}$) at El Carao, Honduras.

expression (Equation 4) used to account for natural food consumption in the BE model. It is worthwhile pointing out that the mean estimated CFB of 0.066 kg $m^{-3}$ in these ponds fertilized with chicken litter at 500 kg $ha^{-1}$ $wk^{-1}$ on a DM basis was much lower than the values of 0.144-0.204 kg $m^{-3}$ that we estimated for the same set of ponds fertilized with twice the amount of litter (Teichert-Coddington et al., 1990). Clearly, in addition to SD, fertilizer loading rates influence the CFB for a given location. CFB's are also likely to vary according to climatic, soil and water quality characteristics among other factors. This variation has implications for feeding practices because ponds that have lower CFB's likely require supplemental feeding to commence earlier compared to fertilized ponds that can support a higher biomass of rapidly growing fish.

The first Bang Sai experiment (Diana et al., 1990) examined the effects of three stocking densities (1, 2 and 3 fish $m^{-2}$) on tilapia growth in ponds fertilized with chicken manure at 500 kg $ha^{-1}$ $wk^{-1}$. Mean CFB's were estimated to be 0.077, 0.078 and 0.11 kg

$m^{-3}$ for ponds stocked at 1, 2 and 3 fish $m^{-2}$ respectively. Predicted fish weights tended to be somewhat lower than observed growth profiles for the 1 and 2 fish $m^{-2}$ treatment (Fig. 5.10). Final predicted fish weights were, however, comparable to harvest weights for these treatments, but somewhat higher for the 3 fish $m^{-2}$ treatment (Fig. 5.10; Table 5.2). The latter result may be due to errors in the CFB estimate for this treatment (i.e., a higher CFB compared to the lower SD treatments) or because the CFB-based function (Equation 4) may not adequately represent sharp decreases in the proportion of natural food in fish diet caused by a combination of inadequate fertilizer addition and high fish biomass. In this context, it is important to point out that Hepher (1978) developed the critical standing crop concept based primarily on observations of common carp growth in Israeli ponds. The stocking density in his fertilized ponds was only about 0.12 fish $m^{-2}$ and the critical standing crop estimated to be about 140 kg $ha^{-1}$. Unfortunately, Hepher did not report the time period that had elapsed prior to fish standing crops reaching the critical standing crop. Nevertheless, his estimate is much lower than that calculated for Nile tilapia ponds in the current study (e.g., 790 kg $ha^{-1}$ for the Bang Sai ponds stocked at 2 fish $m^{-2}$).

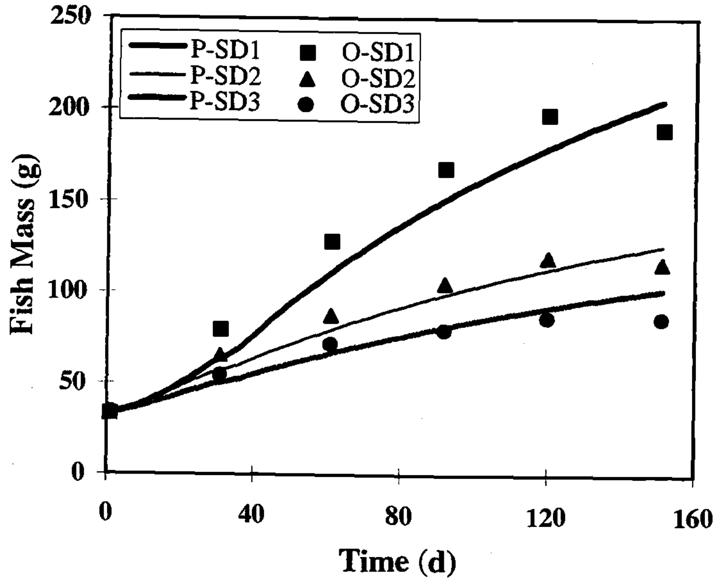

Figure 5.10. Predicted (P) and observed (O) weights for validation trials of Nile tilapia in ponds stocked at 1 (SD1), 2 (SD2), and 3 (SD3) fish $m^{-2}$ at Bang Sai, Thailand.

Validation results for the above experiment do, however, indicate that the CFB approach provides capabilities for examining fish growth at different stocking densities in ponds where fish depend on natural food resources. This also implies that the CFB function provides a means of estimating when supplemental feeding should commence in ponds that are stocked at different densities, as well as the quantity of feed that should be added.

For the second experiment at Bang Sai, fish were stocked at 2 fish $m^{-2}$ and fed to complete satiation (Diana et al., 1993). Because a high quality feed was used throughout this experiment, the digestibility coefficient (i.e., the parameter $b$ in Equation 4) was assumed to be 10% higher than the calibrated value given in Table 5.1. Validation results suggest that the model tends to under-predict growth at this site (Fig. 5.11; Table 5.2). The discrepancy between final simulated and mean observed weights (Table 5.2) may be due to the fact that the simulations assumed that DO is in the range where growth is unaffected, whereas Diana et al. (1993) reported a correlation between fish growth and periods of low DO concentrations for the above experiment.

For both of the Bang Sai experiments, the BE model tended to under-predict Nile tilapia weights (Figs. 5.10 and 5.11) except towards the end of the simulation runs. This may be a function of differences in growth potential and temperature sensitivities of the tilapia strains cultured at the Honduras and Thailand locations. The latter strain appears to grow much more rapidly during the initial culture phase. If improved accuracy is required at a new location, it may be advisable to re-calibrate the model (e.g., by use of the methodology outlined in Chapter 7) using locally available growth, feeding, temperature and SD data.

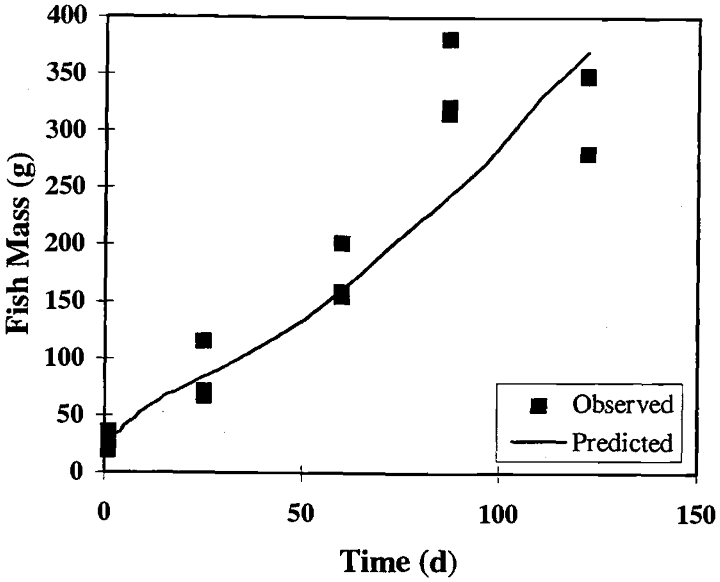

Figure 5.11. BE model validation results for Nile tilapia growth in fed ponds at Bang Sai, Thailand.

## Tambaqui

Published reports on tambaqui growth that include fish growth, water temperature and feeding data as well as stocking and harvest details are limited. The only report that provided complete details (Merola and Pagan-Font, 1988) was used for model calibration. For the purpose of validation, two other reports that provided some experimental details of tambaqui culture were used. The first of these reports pertains to a 129d experiment at Gualaca, Panama (Peralta and Teichert-Coddington, 1989). Fish were stocked at densities of 0.25 and 1 fish m$^{-2}$; data from the latter treatment were used for model validation. Feeding rates reported by the authors were used as input to the BE model. Because stocking and harvest dates were not reported, we assumed a culture period from April to August. Only monthly fish weights and feeding rates for a 11 month culture period were available in the second report (Gomez et al., 1995). Fish were stocked at a density of 1 fish $m^{-2}$. A culture period of January 1 to November 30 was assumed. For both experiments, water temperature data were not available and the weather model in POND (see Appendix 1) was used to predict pond water temperatures.

Final fish weights predicted by the BE model for both of these experiments (Table 5.2) were about 12-14% lower than reported weights. These discrepancies may be the result of poor predictions of water temperatures resulting from use of the POND weather model (which assumed constant wind, cloud cover and relative humidity conditions) or different culture periods in the actual experiment compared to the ones that we assumed. The discrepancies may also be due to less than ideal model parameters because tambaqui in both of the reports used for validation were grown to a larger size compared to the experiment that was used for model calibration (Merola and Pagan-Font, 1988; Table 5.2). Peralta and Teichert-Coddington (1989) reported that the growth rate of tambaqui increases after it has reached several hundred grams, a tendency that may not be adequately reflected in the current parameter set for this species. However, in the absence of additional fish growth data and other grow-out culture details for tambaqui, the presently calibrated model can be used to obtain initial growth estimates of this species under different culture conditions.

## Pacu

Model validation for pacu was accomplished by the use of data from experimental trials conducted at another CEPTA station in Pirassununga, Brazil. The first set of growth, water temperature and feeding data were obtained from an experiment conducted during 1982-83 (Bernardino and Ferrari, 1989). The second set of data were obtained from unpublished data collected by a CEPTA researcher (Dr. Newton Castagnolli, personal commn.) during 1983-84.

Validation results for this site (Fig. 5.12; Table 5.2) suggest that the estimated growth parameters will result in very good predictions of pacu growth. The discrepancy between predicted and observed fish weights during the intermediate phase of culture for the 1983-84 experiment (Fig. 5.12) may have been caused by the use of inaccurate feeding rates during model validation. The original reports indicated that feed was supplied at 5% BW $d^{-1}$ for the first month of culture followed by feed at the rate of 1-3% BW $d^{-1}$. However, it was unclear as to how and when feeding rates were adjusted. Model validations assumed a decrease in feeding rate with increasing fish biomass, which may not have been the case in the actual experiment.

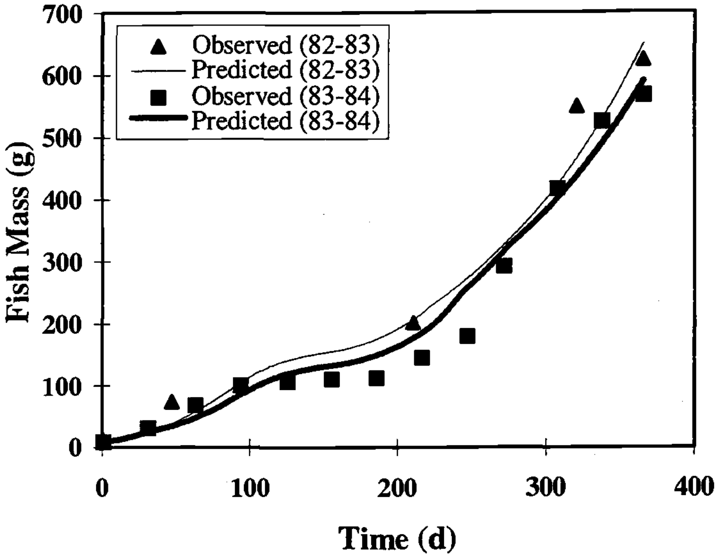

Figure 5.12. BE model validation results for pacu during 1982-83 and 1983-84 at Pirassununga, Brazil.

## Common Carp

For model validation, growth data from the Golysz research station in Poland (Szumiec and Szumiec, 1985) for 2-3 year old fish ($C_{2\text{-}3}$) were used. Temperature and feeding data were obtained from the sources listed in the *Model Parameterization* section. Growth predictions (Fig. 5.13; Table 5.2) were somewhat lower than observed values, and may be due to different temperature sensitivities of the two age classes (e.g., Hepher, 1988). It is also possible that water temperatures for the time period from which the growth data were obtained (see Table 5.2) were different from the average temperature data for the Golysz station (Szumiec, 1979a) that were used as input to the model. Further, feeding rates used as model input are also only typical ones that are followed at the station (Szumiec, 1979b), and may have been different for the actual time period that was simulated.

Additional validations were conducted to compare model output to carp growth results reported from Israeli ponds (Rappaport and Sarig, 1979). Water temperature data were also obtained from this report. Only stocking and harvest fish weights were reported by the above authors. For carp stocked at 1 fish $m^{-2}$, predicted weights were comparable to harvest weights obtained for three experiments (Table 5.2). In general, the validation results obtained for Polish and Israeli ponds suggest that predictions using the parameter set for common carp are likely to be adequate for most management and planning applications of the BE model.

## Channel Catfish

Lovell (1977) summarized growth, feed allowance and water temperature data from pond feeding studies on the channel catfish. These data were used for model validation (Fig. 5.14). Final predicted fish weights were lower than the values reported by Lovell

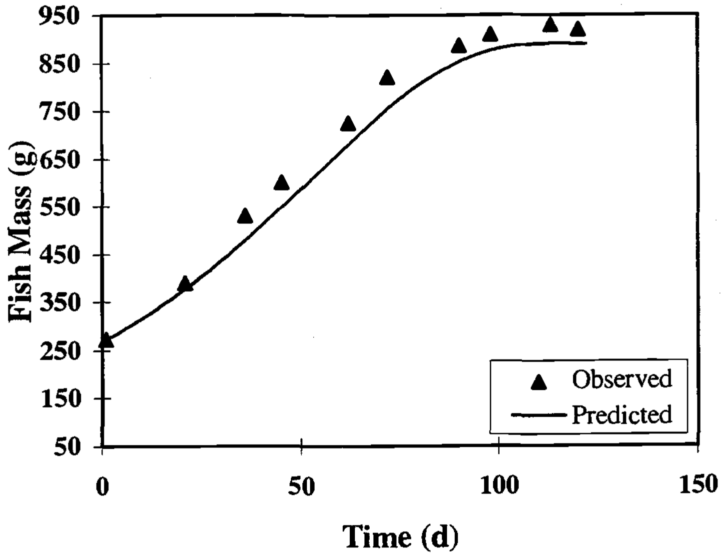

Figure 5.13. BE model validation results for common carp ponds at Golysz, Poland.

(1977; Table 5.2). SD's for the experiments from which Lovell (1977) derived his feeding tables ranged from 0.59 to 0.74 fish $m^{-2}$. These densities are about three to four times as high as the SD used in the experiment (Robinson and Li, 1995) from which growth data was extracted for model calibration. It is possible that discrepancy between predicted and observed fish weights for Lovell's dataset is a result of the BE model not accounting for the effects of higher SD's on growth in fed ponds, particularly because the model predicts fish weights upto about 200g quite accurately (Fig. 5.14).

Another explanation for the discrepancy between model predictions and observed data relates to the type of diet used. A diet with 36% protein was used in the studies summarized by Lovell (1977), whereas diets with lower protein content (28-32%) were used by Robinson and Li (1995). The former diet may enable more rapid growth in catfish, but its effects are not directly captured by the BE model because of the assumption of identical composition of fish and their diet (following Ursin, 1967). The

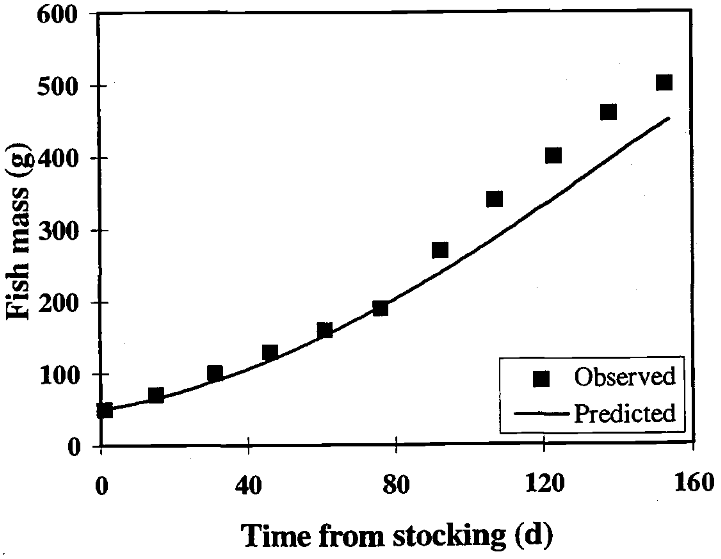

Figure 5.14. BE model calibration results for channel catfish ponds at Auburn, Alabama, USA.

parameter *q* does allow adjustment of feed quality and provides one avenue of increased model accuracy. Alternately, model re-calibration using culture conditions that are typical of the relevant locality can be accomplished using a parameter estimation method such as the one described in Chapter 7.

## SENSITIVITY ANALYSIS

The BE model was subjected to a generalized sensitivity analysis with regard to the 10 model parameters (M) listed in Table 5.1. Sensitivity analysis was conducted only for Nile tilapia at the El Carao research station. Other model experimental conditions were as described for the CL1 treatment in the *Model Parameterization* section above (see also

Table 5.2). Sensitivity analysis was accomplished by a ±10% adjustment in the values of the model parameters for tilapia (Table 5.1). Simulation results from these multiple runs were compared to model output (referred to as the base runs) generated by the use of the original parameter set.

For all the sensitivity analysis scenarios, absolute sensitivity (AS) was summarized in terms of the average change in fish weight over the simulation period of about five months with respect to the change in each of the model parameters (i.e., $\Delta W/\Delta M$). Further, in order to rank the sensitivity of the model parameters on the basis of the magnitude of their effects on fish weights, relative sensitivities (RS) were also calculated as follows:

$$\mathrm{RS} = \frac{\left(\dfrac{\Delta W}{W_m}\right)}{\left(\dfrac{\Delta M}{M_i}\right)} \tag{15}$$

where $W_m$ = average fish weight (g) for the base run, and $M_i$ = original value of the i$^{th}$ parameter (from Table 5.1).

Results of the sensitivity analysis (Table 5.3) indicate that the model is extremely sensitive to the the anabolism exponent ($m$), followed in order by the optimum temperature scaler ($T_{opt}$), the food consumption coefficient ($h$), the catabolism exponent ($n$), the efficiency of assimilation ($b$), and the minimum temperature scaler ($T_{min}$). The model is, however, only marginally sensitive to the other parameters (Table 5.3). Further, there was no response to the changes in $T_{max}$ because the effects of this parameter occur only when ambient water temperatures exceed $T_{opt}$ (see also Equation 12), a situation that was not encountered at El Carao where model output was somewhat sensitive to $T_{min}$. This situation will likely be reversed if $T_{opt} \leq T \leq T_{max}$. Thus, the effects of parameter changes on model output are in part a function of site characteristics. Model sensitivity to these three temperature parameters will, of course, change if any one of them is varied because the parameters are related (Equation 10). Parameters to which the model is very sensitive should be estimated as accurately as possible, via a combination of careful field experimentation (e.g., frequent sampling, estimation of food consumed, etc) and appropriate use of available parameter estimation techniques (e.g., as in Chapter 7).

Table 5.3. Relative (RS) and absolute (AS) sensitivities of Nile tilapia weight predicted by the bioenergetics model to a ±10% change in the values of parameters given in Table 5.1 that were obtained from model calibration. Parameters are ranked according to the magnitude of the sensitivity of the model output. Negative values indicate that fish weight decreases with an increase in the parameter value.

| Bioenergetic Parameter | RS | AS |
|---|---|---|
| Anabolism exponent (*m*) | 5.3461 | 87.5213 |
| Optimum temperature scaler ($T_{opt}$) | -1.9374 | -31.7167 |
| Food consumption coefficient (*h*) | 1.6916 | 27.6932 |
| Catabolism exponent (*n*) | -1.6696 | -27.3342 |
| Efficiency of assimilation (*b*) | 1.6617 | 27.2034 |
| Minimum temperature scaler ($T_{min}$) | -0.8272 | -13.5413 |
| Minimum catabolism coefficient ($k_{min}$) | -0.4292 | -7.0258 |
| Temperature parameter (*s*) | -0.1080 | -1.7674 |
| Feeding catabolism coefficient (*a*) | -0.0992 | -1.6247 |
| Maximum temperature scaler ($T_{max}$) | 0 | 0 |

Although the BE model is substantially different from the model developed by Liu and Chang (1992) due to the higher number of variables considered in the former, there are some similarities in these models because they are extensions of Ursin's (1967) work. Comparison of the results of the sensitivity analyses for parameters that are common to the two models is therefore of interest. Thus, Liu and Chang (1992) reported that model output was extremely sensitive to the parameter *n*, with an RS of 8.80 (i.e., about five times as sensitive as the BE model's response to a change in the same parameter). It is not clear whether this is due to the additional parameters that are included in the catabolic component of the BE model or related to the different parameter values in the two models. On the other hand, the sensitivities of both models to the parameters *m*, *h* and *b* are fairly comparable.

## MODEL APPLICATIONS

Simulation models are useful tools for predicting the response of ecosystems such as aquaculture ponds to conditions that are too complex or too expensive to explore experimentally, or have not previously been tested in physical experiments (Grant, 1986; Cuenco, 1989; Haefner, 1996). Model-based experiments can also provide useful insights into ecosystem behavior, which increases our understanding of the principles governing different systems, enables improved designs for physical experiments, and provides opportunity to identify management strategies that lead to increased biological and economic efficiency. The use of the BE model for these purposes is discussed below. Unless otherwise indicated, these model experiments used the same assumptions listed in the *Model Parameterization* section.

### Supplemental Feeding in Fertilized Ponds

Two key elements of any supplemental feeding strategy for pond aquaculture systems include: (i) initiation of feed addition, and (ii) quantity of feed to be added (Hepher, 1978; 1988). For species such as tilapia and carp that efficiently use natural food resources in fertilized ponds, the arguments of Hepher (1978) as well as evidence presented in this paper and other reports (e.g., Teichert-Coddington et al., 1990; Green, 1992; Diana, 1996) suggest that supplemental feed addition is not required until the CFB for a pond is reached.

Although it is necessary to specify the CFB for a pond prior to a simulation run, the BE model can be used to determine when feed addition should commence at various locations. This is because the model accounts for differences in fish growth rates caused by variations in environmental conditions among geographical regions. Consequently, the time period required to reach CFB (as predicted by the model) also varies from region to region, and can be used to determine when supplemental feeding should be initiated.

### Effects of temperature

Consider, for instance, the problem of estimating supplemental feed requirements for Nile tilapia culture at three sites with altitudes 0, 500 and 1000m above MSL respectively. For convenience, it is assumed that all the sites are located at the same latitude and longitude as El Carao. Ponds at these sites are expected to show decreasing water temperatures with increasing elevation; therefore, fish growth rates and appetite levels are also likely to decline with elevation. Model experimental conditions were assumed to be identical to those reported by Teichert-Coddington et al. (1991; see also Table 5.2).

Two sets of simulations were conducted to predict fish growth at the three sites using the weather model in POND to provide inputs for generating water temperature profiles. For the first set of simulations, a fixed feeding rate (FFR) of 3% BW $d^{-1}$ was provided after the first month of culture. For the second set, the fish were allowed satiation feeding rates (SFR). CFB's at MSL, 500m and 1000m were assumed to be 0.20, 0.15 and 0.10 kg $m^{-3}$. The value of 0.15 kg $m^{-3}$ assumed for the 500m site is similar to that estimated for the El Carao ponds (see *Model Parameterization* and *Validation* sections above). A higher value was assumed for the site located at MSL, which is consistent with previous estimates from heavily fertilized ponds at a warm water site in Thailand (Bolte et al., 1995). The lower value assumed for the 1000m site reflects the likelihood of slower rates of natural food production in cooler waters.

Mean predicted water temperatures (°C) at MSL, 500m and 1000m were 29.6, 26.8, and 24.1 respectively. Final predicted fish weights at these elevations for both the FFR and SFR simulations were 431.7, 340.4, and 144.2g respectively. Total feed requirements for the FFR simulations at MSL, 500m, and 1000m were 7410, 6579 and 3773 kg $ha^{-1}$ respectively. Corresponding food conversion ratios (FCR) were 2.15, 2.52, and 4.01 respectively. For the SFR simulations, feed requirements at the three elevations were 1913, 1742, and 455 kg $ha^{-1}$ respectively. Similarly, FCR's were 0.55, 0.67, and 0.48.

Results of the FFR simulations suggest this practice is likely to be economically inefficient presumably because it does not take into account the proportion of natural food in the diet of pond fish, and changes in fish appetite caused by increasing size and varying temperature conditions. Apart from economic considerations, wasted feed also contributes to poor water quality in ponds which can depress fish growth, and may adversely the surrounding environment if water is routinely discharged from the pond facility. On the other hand, feeding curves predicted for the SFR simulations (Fig. 5.15) take into consideration factors affecting fish appetite as well as contributions to the diet from endogenous food resources. These curves also provide some indication as to when feeding should commence at the different elevations (Fig. 5.15). In a similar manner, the BE model should also be of use in generating supplemental feeding guidelines for locations that show seasonal differences in water temperature and photoperiod.

The above results are pertinent to supplemental feeding practices in real ponds because currently available feeding tables for fish such as tilapia (e.g., Marek, 1975; Hepher, 1988; Lim, 1989) and carp (e.g., Hepher, 1988) only suggest that feeding rates (as %BW) in ponds should decline with increasing fish weight. This is certainly true for situations where the artificial feed is the primary source of nutrition (because the relative

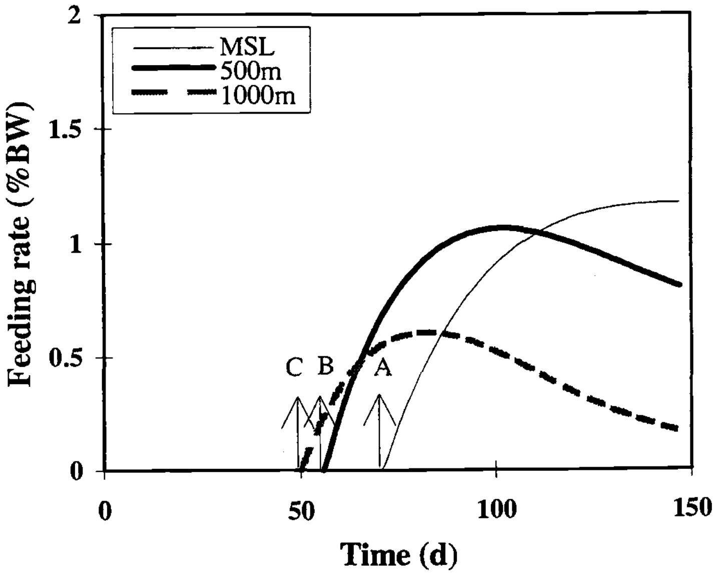

Figure 5.15. Feeding curves generated by the BE model for Nile tilapia that are assumed to use both natural and supplemental food resources in ponds located at three different elevations (MSL, 500m and 1000m). Points A, B, and C in the curves indicate when supplemental feeding should commence.

food requirements of fish decrease as they grow). However, the above feeding tables are not directly applicable to well fertilized ponds because they do not account for the proportion of natural food in the diet of pond fish. Further, although authors such as Hepher (1988) indicate that supplemental feeding rates developed for a given set of conditions should be adjusted according to local conditions (primarily ambient water temperatures, stocking density and fish size), it is unclear as to how the adjustments should be made. On the other hand, feeding curves (e.g., Fig. 5.15) generated by the BE model account for the combined effects of all of these factors, and clearly indicate that supplemental feeding rates in fertilized ponds may not necessarily decrease monotonously with increasing fish weight.

### Effects of stocking density

In the BE model, SD does not directly impact growth rates. Rather, stocking density affects the biomass of fish in a pond, which in turn is used to estimate the parameter $f_n$. Thus, for a given CFB, ponds stocked at higher densities may be expected to reach this biomass earlier, and require larger amounts of feed thereafter if a certain satiation level is to be maintained. These concepts are illustrated for the Nile tilapia in the model experiments below.

Fish were assumed to be cultured over a 150d grow-out period at El Carao. The CFB was set at 0.15 kg $m^{-3}$. The treatments are as follows: (i) SD of 1 fish $m^{-2}$, no feed (SD1-NF), (ii) SD of 1 fish $m^{-2}$, fish fed to full satiation after the CFB is reached (SD1-F), (iii) SD of 2 fish $m^{-2}$, no feed (SD2-NF), and (iv) SD of 2 fish $m^{-2}$, fish fed to full satiation after the CFB is reached (SD2-F). The non-fed treatments are included in this analysis to compare the effects of SD and supplemental feeding on $f_n$ as predicted by the BE model. For all the treatments, the initial stocking weight was set to 30g. Pond water temperature for use in the BE model were predicted using input data from the weather generator in POND.

Final predicted fish weights for the SD1-NF, SD1-F, SD2-NF, and SD2-F treatments were 224.0, 294.6, 147.2, and 294.6g respectively. These results are within the ranges for similarly treated ponds at El Carao (Green et al., 1994). Of more interest, however, are profiles for the natural food index (which corresponds to $f_n$ expressed on a percentage basis) obtained from the CFB-based function (Fig. 5.16). As expected, these curves indicate that increasing fish biomass causes the proportion of natural food in fish diet to decrease rapidly for all treatments. However, within each of the SD treatments, this trend is more pronounced for the fed ponds. Further, supplemental feed should perhaps be added earlier in ponds stocked at higher densities (compare points A and B in Fig. 5.16) because the CFB will be reached earlier. These concepts have previously been described by Hepher (1978), but not illustrated in a quantitative manner. Another advantage of the BE model, of course, is that it can be used to generate NFI profiles for other culture conditions (e.g., different species, temperature conditions, and/or management strategies). Feed requirements predicted by the BE model for the SD1-F and SD2-F treatments were 1118.8 and 5051.6 kg ha$^{-1}$ respectively. Although gross yields for the SD2-F treatment were about twice as high as those for the SD1-F treatment, local feed costs will determine whether use of the higher SD is economically superior. These types of comparative analyses may be of considerable use to aquaculture planners and managers.

The conclusions reached in the above discussion are valid only for conditions in which feed is added after the CFB is reached, and where natural food is preferred over supplemental feed. It is possible that profiles of the natural food index different from those indicated in Fig. 5.16 may be obtained when the fish species shows a marked preference for supplemental feed over natural food resources. An alternate approach that enables analysis of such preferences is described in Chapter 6.

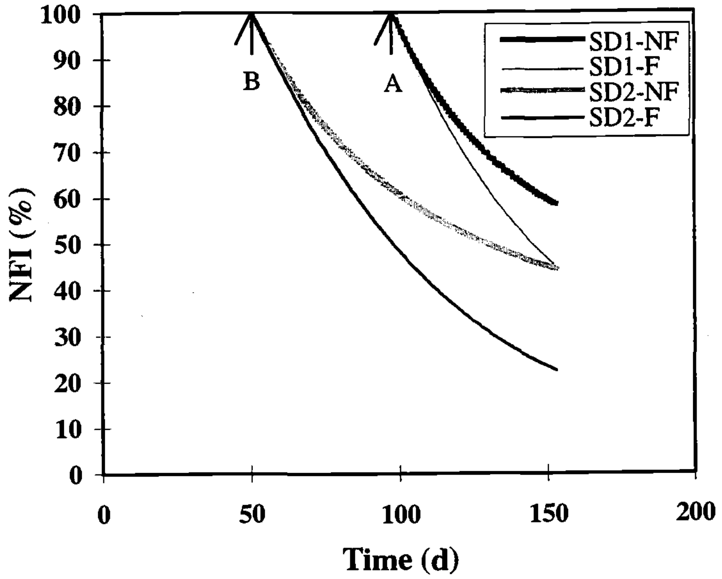

Figure 5.16. Natural food index (NFI) profiles for ponds stocked at 1 and 2 fish m$^{-2}$ which either did not receive feed (NF) or were fed (F). Points A and B indicate when supplemental feeding should commence in ponds stocked at 1 and 2 fish m$^{-2}$ respectively.

## Supplemental Feeding in Unfertilized Ponds

Simulations were conducted with the BE model to examine feeding rates at MSL, 500m and 1000m elevations in ponds that were not fertilized. Model assumptions were identical to those made for the comparison of fish growth in fertilized ponds at these elevations (see above), with the exception that Nile tilapia were fed to satiation from the beginning of the experiment and the contribution of natural food resources to the diet of fish was assumed to be zero.

The BE model generated somewhat different feeding curves for the MSL, 500m and 1000m sites (Fig. 5.17). Over time, feeding rates decreased from 7.1 to 2.1% BW $d^{-1}$ for

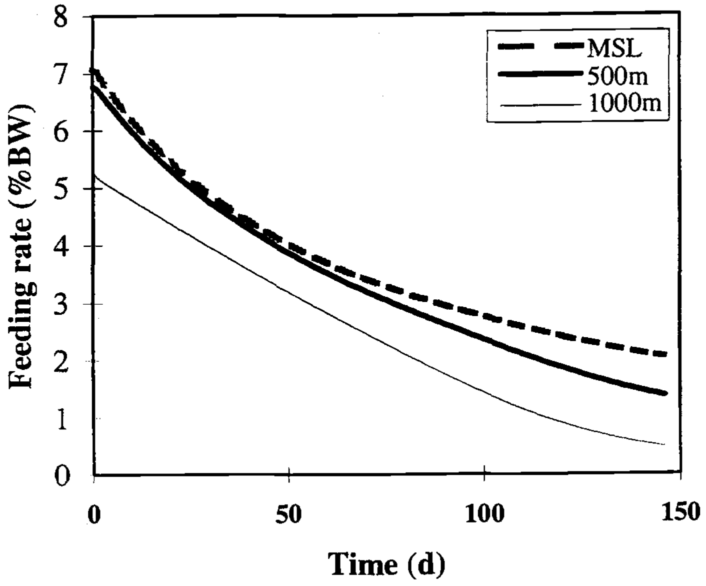

Figure 5.17. Feeding curves generated by the BE model for Nile tilapia in fed ponds located at three different elevations (MSL, 500m and 1000m).

the MSL site, from 6.6 to 1.4% BW $d^{-1}$ for the 500m site, and from 1.5 to 0.6% BW $d^{-1}$. Predicted feeding rates for the MSL and 500m sites are within the ranges reported in feeding tables for tilapia (Hepher, 1988; Lim, 1989). As noted by Goddard (1996), currently available feeding tables represent a general guide to feed intake and typically account only for differences in fish size and water temperature. They do not account for short- and long-term fluctuations in appetite associated with physiological and environmental factors. Such fluctuations are accounted for in the feeding curves generated by the BE model (e.g., Fig. 5.17).

Goddard (1996) also observed that extant feeding tables likely reflect maximum food intake by fish. However, depending on the economics of feeding and marketing, it may be necessary to reduce feed application rates. The BE model offers such capabilities in that different feeding curves can be generated by adjusting the parameter $f_t$. Such curves will likely be useful for making decisions regarding the intensity of the fish culture operation. A further advantage of the BE model is that feeding curves similar to those for tilapia can be generated by applying it to other species for which model parameters have been estimated.

As noted earlier, predicted fish weights obtained by use of the BE model for fed ponds (i.e., $f_n = 0$) are independent of SD. In reality, growth rates of fish stocked at high densities may be depressed due to accumulation of metabolites in the pond water, or because of behavioral changes. Such behavioral changes in fish cannot be easily addressed by the use of simulation models. However, it may be possible to address the effects of water quality variables (e.g., low DO, high UIA) by linking the BE model either to time-series data for these variables or to suitable models that describe the dynamics of such variables in aquaculture ponds. Until such refinements are made, stocking densities that are consistent with typical practices for the selected species should be used when fish growth in fed ponds is simulated with the BE model.

## Feed Quality

All the simulation experiments previously described assumed that the feed quality parameter $q$ was equal to 1.0. To examine the effects of this parameter on fish growth and feed requirements, model experiments were conducted assuming culture conditions as described for the feed only treatment in an experimental study conducted at El Carao (Green, 1992). Additionally, the following treatments were assumed: (i) a high quality feed (HQF; $q = 1.0$) expected to correspond to the pelleted ration used by Green (1992), and (ii) a low quality feed (LQF; $q = 0.7$).

For the HQF treatment, predicted fish weights at harvest and feed requirements were 266.7g and 9680 kg $ha^{-1}$ respectively. Corresponding experimental results reported by Green (1992) were 262.3g and 8971 kg $ha^{-1}$. Although predicted and observed fish weights are very similar, the predicted feed quantities are somewhat higher than the reported values perhaps due to differences between the fish biomass calculated from the BE model during the simulation run compared to the biomass estimated by Green (1992) on the basis of routine samplings. For the LQF treatment, predicted fish weights at harvest and feed requirements were 91g and 5288 kg $ha^{-1}$ respectively.

These results indicate that the use of a lower value for $q$ will lead to depressed fish growth rates, as might be expected with poor quality feeds. Apparently, model output is very sensitive to the value of $q$ used because decreasing its value from 1.0 to 0.7 caused a large difference in the estimated harvest weights and feed requirements. If results from actual experimental trials using different feed types are available, the appropriate value of $q$ to be used in the BE model could perhaps be more accurately determined by calibration. Such values can then be used in comparative analyses to gauge the economic benefits of using feeds of various qualities in pond aquaculture.

# CONCLUSIONS

A generalized bioenergetics model which accounts for the effects of key variables affecting fish growth in aquaculture ponds has been developed. The function used to estimate natural food consumption as a function of fish biomass appears to provide a reasonable estimate of the contribution of such resources to fish diet without the need for complicated mathematical formulations, and is particularly useful in estimating when supplemental feed addition should commence in ponds and the feed amounts required to reach a target feeding level. The model has been successfully calibrated and validated for five fish species under various production conditions, indicating that it is a relatively robust and flexible tool for describing fish growth in aquaculture ponds. Sensitivity analyses suggests that the model is very sensitive to three anabolic, one catabolic and two temperature parameters. As with other simulation tools, there are limitations in the applicability of the model to all culture conditions that may be found in ponds. Specifically, the current version of the BE model does not adequately represent the effects of stocking density in fed ponds, food preferences and artificial diets of differing quality on fish growth in ponds. Further work is also required to estimate appropriate parameters in the DO and UIA functions for different species.

On the other hand, simulation experiments suggest that the BE model can be of use in practical pond management situations including assessment of growth of different target fish species at various geographical locations, estimation of feed application rates, and examination of different stocking density regimes. Specifically, model experiments suggest that fertilized tilapia ponds stocked at higher rates will require supplemental feeding to be initiated earlier compared to those stocked at lower rates given a fixed target feeding level. Moreover, supplemental feed requirements to maintain this target feeding level increases rapidly with increasing fish biomass. The model experiments also generated different feeding curves (in terms of %BW of fish) for ponds assumed to receive feed only, or those receiving both fertilizer and feed. For fed-only ponds, model experimentation suggests that the use of traditional fixed feeding rates apparently leads to higher feed requirements, increased waste feed, and higher FCR's compared to satiation feeding rates for locations with different water temperature profiles. However, for fertilized and fed ponds, the feeding curves generated by the BE model do not decrease monotonously with increasing fish weight as is the case with published feeding tables, but are characterized by an initial increase followed by a gradual reduction or leveling-off in the feeding rates. This is because the BE model accounts for the amount of natural food in the diet of pond fish such as tilapia. Model experiment results have important implications for resource use efficiency in aquaculture farms. Further verification of the BE model under actual pond conditions would be beneficial in terms of generating data that can be used for further calibration, to critically evaluate model assumptions, and to examine the degree of correspondence between results obtained from model experimentation and those collected during field trials.

# CHAPTER 6

# MODELING FOOD CONSUMPTION BY FISH IN AQUACULTURE PONDS

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## ABSTRACT

Fish species like tilapias and carps consume different food resources such as phytoplankton, zooplankton and feed when cultured in aquaculture ponds. Changes in consumption of these resources are known to affect plankton structure in ponds, and may have implications for pond management strategies such as feeding and fertilization practices. Previously developed simulation models for pond ecosystems have not adequately addressed these issues. Therefore, a study was undertaken to incorporate a resource substitution function in an existing fish growth model, and to develop models to predict phytoplankton and zooplankton concentrations in aquaculture ponds. An iterative algorithm was also developed to estimate the contribution of supplemental feed in the diet of fish raised in ponds where natural food resources are available. Model experiments were then conducted to examine changes in the plankton structure of Nile tilapia (*Oreochromis niloticus*) ponds stocked at 1, 2 and 3 fish $m^{-3}$. These experiments assumed that the overall phytoplankton biomass in ponds can be divided into two pools (Pool A and B), of which the former was assumed to be the preferred type by tilapia. Simulation results indicate that the models would predict a decrease in natural food availability with increased fish biomass, as would be expected in real ponds. These results were caused by lower phytoplankton biomass in ponds with a higher fish standing crop, except in fed ponds where uptake of supplemental feed apparently allowed an increase in the overall phytoplankton biomass. Moreover, the resource substitution function also predicted a sharper decline in the biomass of the preferred form of phytoplankton (Pool A) as fish stocking density increases, followed by a reduction in the biomass of Pool B as a result of increased uptake of this resource. Model results are consistent with reports documenting phytoplankton changes in Nile tilapia tanks. The iterative algorithm converged to adequate estimates of supplemental feed uptake within 6-13 iterations. The model recommended a supplemental feed requirement from the beginning of the numerical experiment, which raises questions about the availability and quality of natural food resources during the initial phase of tilapia culture that should be

addressed in physical pond experiments. The resource substitution function appears to be an effective tool for predicting changes in the pattern of food consumption by pond fish. Complex pond aquaculture simulation models such as the ones presented herein are a powerful tool for understanding the behavior of pond ecosystems and provide opportunity for knowledge synthesis relevant to such systems.

## INTRODUCTION

Many fish species such as tilapias and carps commonly cultured in ponds derive a substantial portion of their dietary requirements from natural or endogenous food resources in ponds (Spataru, 1977; Hepher, 1978; Schroeder 1980; see also review by Colman and Edwards 1987). Consumption of these resources may be a function of either the species preference for various types of resources (such as phytoplankton and zooplankton), concentration of these resources in the pond (Svirezhev et al., 1984), fish species in the pond, and stocking densities (Milstein et al., 1985a, b; Colman and Edwards, 1987; Costa-Pierce, 1992). For example, silver carp can only harvest endogenous food resources that are larger than the spacing between their filtering apparatus (Spataru, 1977; Cremer and Smitherman, 1980; Opuszynski, 1981; Milstein et al., 1985a; Smith, 1985; Laws and Weisburd, 1990; see also review by Costa-Pierce, 1992). Many of these studies demonstrated that harvest of net-plankton (>10-30$\mu$m) by fish during the initial culture period resulted in a standing crop of nanoplankton (<10$\mu$m) that was essentially unavailable for fish consumption. Schroeder (1980) demonstrated that most pond fish species can switch from a preferred food resource to another one; however, reduced fish growth and yields may occur as a result of reduced food intake or poor nutritional quality of the switching feed.

In addition to the effects of fish species and their biomass (which determines the grazing intensity), endogenous food production also depends on environmental conditions (e.g., nutrient concentrations, temperature) and management practices (e.g., fertilization)

(Hickling, 1962; Hepher, 1978). Depending on the quality of supplemental feed added to the pond, there may be preferential feeding for this additional resource as well. Estimating the rates of natural food and supplemental feed consumption by pond fish is important in assessing the efficacy of fertilization and feeding practices. Moreover, models that enable quantification of such rates are likely to result in improved understanding of pond ecosystems under various other management practices as well (e.g., monoculture vs. polyculture).

Svirezhev et al. (1984) developed a simulation model that predicts endogenous food resource (phytoplankton, zooplankton, detritus and benthos) concentrations in fish ponds and the consumption of such resources by different carp species in polyculture. These authors assumed that each fish species had a high uptake probability of a *preferred* food resource until it was depleted to some critical concentration (due to over-grazing), at which point the fish would switch to another resource designated as the *substituting* food. Thus, for silver carp, phytoplankton was designated as the preferred food, and detritus the substituting food. However, this modeling approach which considers only two resources at any given time and is not easily extendible to multiple resources, appears to be inadequate to describe simultaneous consumption of several resources including supplementary feeds of differing quality. An alternate feeding function that does not have these limitations is the resource substitution function proposed by Tilman (1982). As with the uptake probability model of Svirezhev et al. (1984), use of this function also requires concentrations of the various food types to be available.

This paper focuses on the use of the Tilman function in the fish growth model (Chapter 5) to predict consumption of natural food resources and supplemental feed by pond fish. Models are also developed in this paper to predict concentrations of various natural food resources (phytoplankton and zooplankton) in ponds.

## MODEL DEVELOPMENT

In this section, only the functions developed to model food availability for pond fish are presented. Functions used to account for the effects of other variables (i.e., size, food availability, photoperiod, temperature, dissolved oxygen and unionized ammonia concentrations) on fish growth are documented elsewhere (Chapter 5). A description of the models that are used to predict concentrations of natural food resources in ponds is also presented. All of these models are implemented in the POND decision support software (see also Chapter 1).

### Fish Growth Model

According to Ursin (1967), the change in fish weight over time is given by:

$$\frac{dW}{dt} = HW^{m} - kW^{n} \tag{1.1}$$

where W = fish weight (g), H = coefficient of anabolism ($d^{1-m}$), m = anabolism exponent, k = coefficient of anabolism ($d^{1-n}$), and n = catabolism exponent.

The parameter *H* in Equation 1.1 can be expanded to consider daily ration, feeding catabolism and digestibility of the food consumed as follows (Ursin, 1967):

$$\frac{dW}{dt} = b(1-a)\,R - kW^{n} \tag{1.2}$$

where *a* = fraction of the food assimilated that is used for feeding catabolism (0-1), *b* = the efficiency of food assimilation (0-1), and R = daily ration (g $d^{-1}$), which is the sum of daily intake of endogenous or natural food ($R_n$) and supplemental feed ($R_s$). The term *b(1 - a)* in Equation 1.2 represents energy that is available for growth and fasting catabolism.

Daily ration is a function of fish size, the proportion of food consumed relative to satiation requirements ($f$) and environmental conditions (E):

$$R = h f E W^m \tag{1.3}$$

where $h$ = coefficient of food consumption.

The parameter $f$ as defined by Ursin (1967) is the ratio of the actual food intake rate (R) to the food intake rate at complete satiation ($R_{max}$). In ponds that receive supplemental feed, $f$ is the sum of the proportion of natural food resources ($f_n$) and feed ($f_s$) in the diet, with associated intake rates given by the product of each of these proportions and $R_{max}$ (e.g., $R_n = f_n R_{max}$). For fed ponds, it is also convenient to define a target or satiation feeding level ($f_t$; 0-1), which is essentially a control parameter that can be used to adjust the amount of feed added to a pond.

The parameter $f_n$ was modeled by Liu and Chang (1992) on the basis of a function developed by Ivlev (1961), who observed that food intake by fish tends to increase asymptotically with resource availability. Liu and Chang (1992) used a fertilizer richness parameter as a measure of available endogenous food resources. However, their approach assumes that endogenous food availability depends on the number of fish in a pond whereas it is really a function of fish biomass or standing crop (Hepher, 1978). This author showed that in carp ponds, adequate endogenous food appears to be produced in properly fertilized ponds during the early phase of fish culture thus allowing satiation feeding (i.e., $f = 1$), but that once the fish biomass (FB) or standing crop in the pond exceeds the "critical standing crop" (CFB), endogenous food availability declines until the carrying capacity of the pond is reached. Based on Hepher's observations, we have previously estimated $f_n$ from the CFB for a pond (see also Chapter 5). However, the CFB approach does not account for consumption of different food types. The Tilman feeding function is expected to be useful in addressing this problem. This function is essentially an extension of Monod uptake kinetics to multiple resources (Tilman, 1982). Use of the

Tilman function requires calculation of the specific consumption rate of various food resources by fish ($\mu_F$; $d^{-1}$) as follows:

$$\mu_F = \sum_{i=1}^{N} \mu_F^{max} \left( \frac{\frac{F_i}{c_i}}{1 + \sum_{j=1}^{N} \frac{F_j}{c_j}} \right) \tag{1.4}$$

where $\mu_F^{max}$ = maximum specific consumption rate ($d^{-1}$) calculated as $R_{max}/W$, $F_i$ = effective concentration of the i<sup>th</sup> food resource, $c_i$ = half-saturation constant for uptake of the ith food resource, and N = total number of food resources being considered. There is no restriction on the number of food resources that can be considered in Equation 1.4. Further, the half-saturation constants are a measure of food preference because lower values force a more rapid uptake of the associated resource. Therefore, adjustment of $c_i$ for different food resources provides a means of ranking these resources according to their preference by the target fish species. Units for $F_i$ and $C_i$ depend on the resource under consideration (e.g., gC $m^{-3}$ for phytoplankton, g $m^{-3}$ for zooplankton). Because there may be minimum threshold concentrations below which fish cannot consume a particular resource, the term 'effective concentration' was used in the current study for $F_i$. This term denotes the concentration of the resource *i* that is actually available for fish uptake, and is calculated by subtracting the associated threshold concentration $t_i$ from $F_i$.

Supplemental feeding rates in aquaculture are typically expressed in terms of the percent body weight (%BW) of the fish or in terms of kg $ha^{-1}$, and not on a volumetric basis. However, because the Tilman function requires resource concentrations, it is assumed that the 'concentration' of supplemental feed in Equation 1.4 can be expressed in dimensionless terms by the use of $f_s$. Consequently, the half-saturation constant for feed is also dimensionless.

The resource substitution function also permits calculation of the specific consumption rates of individual resources as follows:

$$\mu_{A,F} = \mu_F^{max} \left( \frac{\frac{F_i}{c_i}}{1 + \sum_{j=1}^{N} \frac{F_j}{c_j}} \right) \qquad (1.5)$$

where $\mu_{A,F}$ refers to the specific consumption rate ($d^{-1}$) of the particular food resource $A$ (phytoplankton, zooplankton, bacteria or supplemental feed) by fish. Calculations involved in estimating $f_n$ and $f_s$ by use of the Tilman function for ponds where only natural food resources are available, and those where supplemental feed is also added, are discussed below.

## Pond with Natural Food Only

If only natural resources are consumed, the sum of the specific consumption rates calculated by the use of Equation 1.5 reflects overall natural food consumption ($\mu_{n,F}$) for a particular fish population (lot) in the pond, and $f_n$ is given by:

$$f_n = \frac{R_n}{R_{max}} = \frac{\mu_{n,F} W}{R_{max}} \qquad (1.6)$$

For fertilized ponds, $f_n$ as calculated above replaces $f$ in Equation 1.3.

## Ponds with Natural Food Plus Supplemental Feed

In contrast to feed calculations used in Chapter 5 where the composition of fish and feed is assumed to be identical, the ratio of the dry matter content of fish ($DM_{fish}$; g dry matter per g fish) to the dry matter content of feed ($DM_{feed}$; g dry matter per g feed) is used herein to account for differences in the composition of supplemental feed and fish. Thus, an inherent assumption of the Ursin model (i.e., the compositions of fish and their dietary sources are identical) continues to be retained in part because it is still assumed that the composition of various endogenous food resources is similar to that of fish. This is due to the difficulty in gauging the composition of such resources as well as their large variability (Hepher, 1988; Lim, 1989). A complication introduced by the use of the dry matter contents of fish and feed is that it becomes necessary to distinguish between rates relevant to fish (as g fish $d^{-1}$) and those that are relevant to feed (as g feed $d^{-1}$). As in the simpler version of the fish growth model (Chapter 5), feed requirements may either be estimated or specified by the user.

### *Feed Requirements Estimated by the Fish Growth Model*

If supplemental feed requirements are to be estimated for lots of fish which can also consume endogenous resources, $f_n$ is calculated by Equation 1.6. The working assumption is that feed addition is not required unless $f_n < f_t$ (i.e., $f_s = 0$ and $f = f_n$). However, once $f_n$ drops below $f_t$, the approach used herein automatically adds feed as an additional pool to the list of specified natural food resources and estimation of supplemental feeding rates is accomplished by an iterative algorithm (Table 6.1) combined with the resource substitution function (Equation 1.4). The aim of the iterative algorithm is to estimate R as the sum of $R_n$ ($= \mu_{F,n} \times W$; g fish $d^{-1}$) and $R_s$ ($= \mu_{F,s} \times W$; g fish $d^{-1}$), where $\mu_{F,s}$ is the specific feed consumption rate from Equation 1.5. This enables calculation of $f_s$ and $f$.

An iterative method is required because the proportion of supplemental feed in the diet consumption is not known *a priori* and cannot be automatically assumed to equal $f_t - f_n$. This is because the proportion of supplemental feed in the diet is likely to be a function of fish species preference for feed among other factors. For example, if feed is

Table 6.1. Pseudo-code for the iterative algorithm used to estimate supplemental feed consumption by pond fish.

```
// Initial value for the supplemental feeding rate
$R_s = R_t - R_n$;
// Fraction of diet from supplemental feed
$f_s = (R_t - R_n)/R_{max}$;
// Difference between $R_t$ and R
$\Delta R = 0$;
// Tolerance level for convergence
tol = 0.05 * $R_t$;

while( TRUE )
    {
    // Is $R_t > R$?
    if $\Delta R > 0$
        // Increase proportion of supplemental feed in diet
        $f_s = f_s * (1.0 + \Delta R)$;
    if $\Delta R < 0$
        // Decrease proportion of supplemental feed in diet
        $f_s = f_s * 0.95$;
    // Evaluate Equations 1.4 and 1.5 with endogenous food resource pools and $f_s$
    representing the proportion of supplemental feed in the fish diet
    Evaluate $\mu_F$
    // Compute new feeding rate
    $R = W * \mu_F$;
    // Update difference between $R_t$ and R
    $\Delta R = R_t - R$;
    // If convergence criteria are met, exit the while loop
    if ($\Delta R > 0$ AND $\Delta R <$ tol )
        exit;
    }
```

added to a pond with fairly abundant natural food (although inadequate to meet $f_t$), some species may preferentially consume supplemental feed whereas others may not. In other words, the proportion of $f_n$ in the diet of a given fish species will likely differ depending on whether feed is present or not.

As with most iterative methods, it is necessary to provide an initial guess for the parameter to be estimated ($R_s$ in this case) and to define stopping criteria. Setting $R_s$ equal to the difference between the target feeding rate $R_t$ (g fish $d^{-1}$) and the natural food consumption rate ($R_n$) provided adequate convergence during trial simulations. The stopping criteria are: (i) $R_t \geq R$, and (ii) $(R_t - R) < tol$, a tolerance parameter which is arbitrarily set to 5% of $R_t$ (Table 6.1). The first criterion ensures that the specified target feeding level $f_t$ is not exceeded, and the second one facilitates (faster) convergence to an acceptable value for R.

Once $f_s$ is estimated, daily supplemental feed ($R_a$; g feed $d^{-1}$) to be added for a particular lot is given by:

$$R_a = \frac{W\,f_s}{q} \times \frac{DM_{fish}}{DM_{feed}} \tag{1.7}$$

where $q$ = a feed quality coefficient (0-1). The amount of feed wasted ($R_w$; g feed $d^{-1}$) is obtained as the product of $R_a$ and the proportion of waste feed $(1 - q)$.

### *Feed Requirements Specified*

When supplemental feeding rates are specified (as %BW $d^{-1}$), $R_a$ is known. However, if a given pond contains more than one lot, it is difficult to estimate the amount of feed reaching the fish within each lot even if identical feeding rates are specified. For instance, a pond may contain two populations (e.g., tilapia and carp), each being fed at the same rate on a %BW basis. However, the actual feed consumed by fish within each lot will likely differ because of differences in fish size and appetite. In such situations, the total amount of feed added to the pond is calculated and then averaged over the number of lots in it to arrive at a single rate ($R_a$) for each lot. Feed that may be available for daily uptake ($R_{avail}$; g fish $d^{-1}$) is then calculated as follows:

$$R_{avail} = q\,R_a \times \frac{DM_{feed}}{DM_{fish}} \tag{1.8}$$

The additional variable $R_{avail}$ is required because $f_s$ in the iterative algorithm (Table 6.1) is initially set to the ratio of $R_{avail}$:$R_{max}$, unless $R_{avail} > R_{max}$, in which case $f_s$ is forced to one because consumption cannot exceed fish appetite. As before, actual consumption rates of supplemental feed ($R_s = \mu_{F,s} \times W$) and endogenous food ($R_n = \mu_{F,n} \times W$) are then calculated by the use of the resource substitution function (Equations 1.4 and 1.5). Finally, the amount of feed wasted $R_w$ (g feed $d^{-1}$) is estimated as follows:

$$R_W = (1 - q)\; R_a + \left[ \left( R_{avail} - R_S \right) \times \frac{DM_{fish}}{DM_{feed}} \right] \tag{1.9}$$

Note that $R_w$ under conditions of excess feeding comprises two components: (i) a fraction of the applied feed that is unavailable for consumption, and (ii) an estimate of feed supplied in excess of satiation.

## Models of Natural Food Resources

Fish such as tilapia and carp can consume various kinds of natural foods such as phytoplankton, zooplankton, detritus and benthos in aquaculture ponds (e.g., Ivlev, 1961; Hickling, 1962; Reich, 1975; Hepher, 1988). For simplicity, the current study assumed that phytoplankton and zooplankton are the two primary groups of natural food resources available for consumption. In part, this was because model experiments concentrated on the Nile tilapia (*Oreochromis niloticus*), which is primarily a plankton feeder (Caulton, 1982). However, this species also consumes detritus (Bowen, 1982); we therefore assumed that ponds would also contain steady state concentrations of this resource (referred to as bacteria hereafter) that is available for uptake by tilapia.

For modeling purposes (as indicated in Chapter 1), ponds in the POND software are assumed to be continuously stirred tank reactors (CSTR) with unsteady flow. The differential equation expressing the change in concentration of state variables like phytoplankton and zooplankton in such reactors (e.g., Benefield and Randall, 1980; McDuffie, 1991) is given by:

$$\frac{dC}{dt} = \frac{Q_i C_i}{V} - \frac{Q_o C_o}{V} + R_c - \frac{C}{V}\frac{dV}{dt} \tag{2.1}$$

where C = concentration of the material (e.g., gC $m^{-3}$ for phytoplankton and g $m^{-3}$ for zooplankton), $Q_i$ = influent rate ($m^3$ $d^{-1}$), $Q_o$ = effluent rate ($m^3$ $d^{-1}$), $C_i$ = material concentration in the influent (g $m^{-3}$), $C_o$ = material concentration in the effluent (g $m^{-3}$), V = pond volume ($m^3$) and $R_c$ = sum of the source and sink processes affecting the material (e.g., g $m^{-3}$ $d^{-1}$). In the current study, we assumed that ponds are operated at steady state volumes without flow. Thus, it only becomes necessary to address the $R_c$ term for phytoplankton and zooplankton.

## Phytoplankton

As previously discussed, pond experiments have shown that grazing of phytoplankton by pond fish can result in depletion of net-plankton and accumulation of nanoplankton (which either cannot be consumed or efficiently harvested). This suggests that ponds can be assumed to contain two pools of phytoplankton (designated as Pool A and B in this study). Processes that are considered in modeling these two pools (discussed below) in aquaculture ponds are identical, with the exception that fish are assumed to have different preferences for Pools A and B.

Based on previous work (e.g., Di Toro et al., 1971) the following differential equation can be developed to express changes in phytoplankton over time (dP/dt; gC $m^{-3}$ $d^{-1}$):

$$\frac{dP}{dt} = PGR - PRR - PDR - FPR - ZPR \tag{2.2}$$

where PGR = phytoplankton growth rate (or gross primary productivity), PRR = phytoplankton respiration rate, PDR = phytoplankton death rate, FPR = consumption rate of phytoplankton by fish, and ZPR = consumption rate of phytoplankton by zooplankton.

PGR is a function of light ($\lambda$), temperature ($\tau$) and nutrient limitations as well as the daily photoperiod scaler ($\pi$) (e.g., Steele, 1962; Straskraba and Gnauck, 1985). Nutrients typically considered to be limiting in freshwater ponds are nitrogen, phosphorus and carbon; their respective limitation terms are denoted as $\nu_n$, $\nu_p$, and $\nu_c$. The general equation for PGR is then given by:

$$\mathrm{PGR} = \mu_P^{max} \times \min(\lambda, \tau, \nu_n, \nu_p, \nu_c) \times \pi \times P \qquad (2.3)$$

where $\mu_P^{max}$ = maximum specific phytoplankton growth rate ($d^{-1}$), and P = phytoplankton biomass (gC $m^{-3}$). The daily photoperiod (h) at different sites can be obtained from sunrise and sunset hour angle calculations (Hsieh, 1986), and $\pi$ then estimated as photoperiod/24. A photoperiod of 12h for instance would result in $\pi = 0.5$. It should be noted that several functions (de Groot, 1983; Straskraba and Knauck, 1985; see also Chapter 4) can be used to assess the effects of multiple limiting factors on phytoplankton growth. For simplicity, Liebig's minimum factor rule is assumed to apply.

Temperature dependence of phytoplankton (and zooplankton) growth rates is based on the "skewed normal" function of Lehman et al. (1975) and Svirezhev at al. (1984):

$$\tau = \begin{cases} \exp\left\{-4.6\left[(T_{opt} - T)/(T_{opt} - T_{min})\right]^4\right\}, & \text{if } T < T_{opt} \\ \exp\left\{-4.6\left[(T - T_{opt})/(T_{max} - T_{opt})\right]^4\right\}, & \text{if } T \geq T_{opt} \end{cases} \qquad (2.4)$$

where $T_{min}$, $T_{opt}$ and $T_{max}$ are the minimum, optimum and maximum temperatures for growth (assumed to be the same for phytoplankton and zooplankton).

Nutrient limitation of phytoplankton growth can be approximated by the use of the Monod equation to describe Michaelis-Menten enzyme kinetics (Dugdale, 1967). Droop

(1973) used a slight modification of the Monod equation to account for nutrients that are actually available for algal uptake. Because such threshold concentrations may exist for nitrogen, phosphorus and carbon in ponds as well, the Droop equation is used to describe the growth limitation term in Equation 2.3 for each of the three primary nutrients ($\nu_S$) as follows:

$$\nu_S = \frac{(S - S_0)}{k_S + (S - S_0)} \tag{2.5}$$

where S, $S_0$ and $k_S$ are respectively the ambient concentrations, threshold concentrations and half-saturation constants for the nutrient being considered.

The light limitation term ($\lambda$) for aquaculture ponds can be approximated using the following expression (Piedrahita et al., 1993):

$$\lambda = \frac{e}{\varepsilon} \exp\left[1 - \exp\left(\frac{I_o}{I_{sat}}\right)\right] \frac{1}{d} \tag{2.6}$$

where $\varepsilon$ = the light extinction coefficient, $I_o$ = photosynthetically active light radiation (PAR; Einst $m^{-2}$ $d^{-1}$), $I_{sat}$ = optimum or saturating solar radiation (Einst $m^{-2}$ $d^{-1}$), and d = pond depth (m). Smith (1980) assumed $I_{sat}$ to be equal to 30% of the daily PAR. Trial simulations for the current study suggested that setting $I_{sat}$ = 50% of the daily PAR would be more appropriate.

The coefficient $\varepsilon$ can be estimated using the following expression (e.g., Poole and Atkins, 1929):

$$\varepsilon = \frac{c}{SDV} \tag{2.7}$$

where *c* = a constant and SDV = secchi disk visibility (m). The value of *c* ranges from 1.2 to 2.7 (Straskraba and Knauck, 1985). A value of 2.0 was assumed for this study. SDV was predicted by the use of the following function (see also Appendix II):

$$\mathrm{SDV} = \frac{\alpha}{(\mathrm{Chl}\text{-}a + \mathrm{T})^{\beta}} \times \frac{1}{100} \tag{2.8}$$

where Chl-*a* = chlorophyll *a* concentration (mg $m^{-3}$), *T* = baseline turbidity (Chl-*a* equivalents), and $\alpha$ and $\beta$ are non-linear regression parameters. Chl-*a* is estimated by converting the phytoplankton biomass (P in gC $m^{-3}$) using the chlorophyll-*a* to carbon ratio. According to Reynolds (1984), this ratio can vary from 12.5 to 50; an intermediate value of 30 was used in this study.

Phytoplankton respiration (PRR) is typically estimated as function of water temperature and biomass (Di Toro et al., 1971; Lehman et al., 1975). The former group of authors used a linear function to express this relationship; however, because respiration rates tend to increase exponentially with temperature (Thomann et al., 1975), we used the following expression (Tchobanoglous et al., 1991) to estimate PRR:

$$\mathrm{PRR} = \mathrm{k}_{\mathrm{p}}^{\mathrm{r}}\ \mathrm{P} \tag{2.9}$$

$\mathrm{k}_{\mathrm{p}}^{\mathrm{r}}$ is a temperature dependent parameter given by (Tchobanoglous et al., 1991):

$$\mathrm{k}_{\mathrm{p}}^{\mathrm{r}} = \mathrm{k}_{\mathrm{p},20}^{\mathrm{r}} \times \theta_{\mathrm{i}}^{(\mathrm{T}-20)} \tag{2.10}$$

where $\mathrm{k}_{\mathrm{p},20}^{\mathrm{r}}$ ($d^{-1}$) and $\theta_i$ are constants. The latter is commonly assumed to have a value of 1.024 (Tchobanoglous et al., 1991).

Phytoplankton death (PDR) is assumed to be biomass dependent as follows (Di Toro et al., 1971):

$$\mathrm{PDR} = \mathrm{k}_{\mathrm{p}}^{\mathrm{d}}\ \mathrm{P} \tag{2.11}$$

where $\mathrm{k}_{\mathrm{p}}^{\mathrm{d}}$ is the phytoplankton death parameter ($d^{-1}$).

The rate of consumption of phytoplankton by fish (FPR) is obtained from Equation 1.5 after conversion into the required units (i.e., gC $m^{-3}$) as follows:

$$\mathrm{FPR} = \mu_{\mathrm{P,F}} \times \mathrm{FB} \times \mathrm{F}_{\mathrm{car}} \tag{2.12}$$

where $\mu_{P,F}$ is the specific consumption rate ($d^{-1}$) of the phytoplankton by fish, FB = fish biomass or standing crop (g fish $m^{-3}$), and $F_{car}$ is the carbon content of fish (gC per g fish) assumed to be 0.10 (Ryther, 1969).

As discussed below, Equations 1.4-1.5 are also used to describe zooplankton feeding. Hence, the rate of phytoplankton consumption by zooplankton (ZPR) is obtained in a manner analogous to Equation 2.12 as follows:

$$\mathrm{ZPR} = \mu_{\mathrm{P,Z}} \times \mathrm{Z} \times \mathrm{Z}_{\mathrm{car}} \tag{2.13}$$

where $\mu_{P,Z}$ is the specific phytoplankton consumption rate by zooplankton ($d^{-1}$), Z = zooplankton biomass (g $m^{-3}$), and $Z_{car}$ is the carbon content of zooplankton (gC per g zooplankton) assumed to be 0.063. This value is based on the assumption that the moisture content of zooplankton ranges from 85-90% (Creswell, 1993) and that organic carbon represents about 50% of zooplankton on a dry matter basis.

## Zooplankton

Di Toro et al. (1975) provide the following differential equation to express changes in zooplankton with time (dZ/dt; g $m^{-3}$ $d^{-1}$):

$$\frac{dZ}{dt} = \mathrm{ZGR} - \mathrm{ZRR} - \mathrm{ZDR} - \mathrm{FZR} \tag{3.1}$$

where ZGR = zooplankton growth rate, ZRR = respiration rate, ZDR = death rate, and FZR = consumption rate of zooplankton by fish. ZRR and ZDR are calculated using Equations 2.9-2.11 and the relevant parameter values are assumed to be identical to those for phytoplankton.

ZGR is a function of food consumption, temperature and biomass (Di Toro et al., 1971). The resource substitution function (Equation 1.4) is also used to estimate the specific consumption rate of the two pools of phytoplankton as well as bacteria by zooplankton ($\mu_Z$; $d^{-1}$) by substituting the appropriate parameters including $\mu_Z^{max}$ (the maximum specific zooplankton growth rate; $d^{-1}$). Half-saturation constants and minimum threshold concentrations for zooplankton uptake of these resources are assumed to be different from those for fish. The effects of temperature ($\tau$) are assessed using Equation 2.4. The expression for ZGR is as follows:

$$ZGR = \mu_Z \times \tau \times Z \tag{3.2}$$

In a manner analogous to phytoplankton uptake by fish (Equation 2.12), FZR is given by:

$$FZR = \mu_{Z,F} \times FB \times F_{car} / Z_{car} \tag{3.3}$$

where $\mu_{Z,F}$ is the specific consumption rate ($d^{-1}$) of the zooplankton by fish.

## MODEL VERIFICATION

The models developed to analyze food consumption by pond fish constitute the sets of Equations 1-3 presented above, and are implemented in the decision support system POND (Chapter 1). As previously indicated, only the functions used in the fish growth model to express natural food and supplemental feed uptake have been presented in detail because the other components of this model (including species parameters) are described in Chapter 5.

Adequate verification of the models presented herein requires routine time-series data pertaining to fish growth, phytoplankton and zooplankton biomass, water temperature, water flow rates (if applicable), nutrient concentrations, and feed application. It would also be necessary to classify phytoplankton on the basis of their size. Data of this nature are either rarely collected in pond experimental trials or not reported in the published literature.

Nevertheless, the models have been used to examine Nile tilapia growth in earthen aquaculture ponds located at Bang Sai, Thailand (14°45' N, 100°32' E). The primary focus of the verification trials was to examine whether the models developed herein were capable of generating results that are consistent with observations of fish growth and their food consumption patterns in aquaculture ponds. In other words, the main interests in this study were on the use of simulation models as tools to understand pond ecosystems rather than to accurately predict system performance, and to examine implications of model output for pond management.

Ponds of area 220 $m^2$ at the Bang Sai site were stocked at 1, 2 and 3 fish $m^{-2}$ treatments respectively, and were fertilized with chicken manure at 500 kg $ha^{-1}$ $wk^{-1}$ (DM basis). These treatments are designated as SD1, SD2 and SD3 respectively. Other experimental details are given by Diana et al. (1990). Tilapia growth and survival data in the above ponds were extracted from the aquaculture database maintained by the Pond Dynamics/Aquaculture Collaborative Research Support Program (PD/A CRSP). Daily water temperature for use in verification trials was predicted by use of the model described in Chapter 2; weather data required as input to the latter model were also extracted from the PD/A CRSP database. Ponds were assumed to be maintained at steady state volumes and the flow terms in Equation 2 were set to zero. Because of the lack of data on phytoplankton and zooplankton biomass in the CRSP database, initial conditions listed in Table 6.2 were assumed for the simulation runs. The initial conditions for fish weight and water temperature in Table 6.2 are, however, the mean values for the ponds as reported in the PD/CRSP database.

The simulations assumed that nutrient concentrations (i.e., nitrogen, phosphorus and carbon) were such that phytoplankton growth limitation by these nutrients would not occur (i.e., $v \rightarrow 1$ in Equation 2.3). Table 6.2 also lists various parameters that were used in the simulations. With the exception of the parameters $T$, $\alpha$ and $\beta$ (which were fitted to SDV and chl-a measurements for Bang Sai; Appendix II), the rest of the model parameters were either obtained by calibration or assumed. An additional numerical experiment was conducted for Bang Sai ponds stocked at 2 fish $m^{-2}$ using the same conditions as described above, with the exception that fish were fed to 80% satiation with a supplemental diet. This treatment is designated as SD2F.

## RESULTS AND DISCUSSION

Final predicted fish weights were 191.9, 136.1, and 106.8g for fertilized ponds stocked at 1, 2 and 3 fish $m^{-2}$. Weights predicted for the lowest SD compared favorably with observed harvest weights of 189.7g (Diana et al., 1990); at the other two densities, predicted weights exceeded observed weights by about 20g. For the SD2F pond, the final fish weight was 303.9g, which is comparable to the mean weight of 301g reported by Diana et al. (1993) for fertilized and fed ponds at the Bang Sai site. Reasons for the discrepancy between observed and predicted fish weights for the SD2 and SD3 treatments are unclear, but may in part be due to errors in the estimation of the amount of natural food actually consumed by fish. Profiles for the natural food index (NFI) (which corresponds to $f_n$ expressed on a percentage basis) for all the four treatments simulated are indicated in Fig. 6.1.

These profiles suggest that the total amount of natural food in the diet of Nile tilapia (as predicted by the models developed herein) may exceed the amount that one may expect this species to derive from actual ponds stocked at 2 and 3 fish $m^{-3}$, particularly towards the end of the simulation period. For example, NFI reached a maximum of about 62% satiation in both SD2 and SD3 treatments (Fig. 6.1). Although this proportion

Table 6.2. Initial state variable conditions and parameter values used in the Bang Sai simulations of tilapia growth.

| Symbol | Description | Value | Units |
|---|---|---|---|
| *Variables* | | | |
| W | Fish weight | 33.0 | g |
| $P_a$ (Pool A) | Biomass of phytoplankton Pool A | 7.0 | gC $m^{-3}$ |
| $P_b$ (Pool B) | Biomass of phytoplankton Pool B | 2.0 | gC $m^{-3}$ |
| Z | Biomass of zooplankton | 1.0 | g $m^{-3}$ |
| B | Biomass of bacteria | 2.0 | g $m^{-3}$ |
| *Parameters* | | | |
| <u>Fish</u> | | | |
| $c_{P(A),F}$ | Half-saturation constant for phytoplankton Pool A uptake | 2.0 | gC $m^{-3}$ |
| $c_{P(B),F}$ | Half-saturation constant for phytoplankton Pool B uptake | 6.0 | gC $m^{-3}$ |
| $c_{Z,F}$ | Half-saturation constant for zooplankton uptake | 2.0 | g $m^{-3}$ |
| $c_{B,F}$ | Half-saturation constant for bacteria uptake | 6.0 | g $m^{-3}$ |
| $c_{S,F}$ | Half-saturation constant for supplemental feed uptake | 0.05 | -- |
| $t_{P(A),F}$ | Threshold concentration for phytoplankton Pool A uptake | 2.0 | gC $m^{-3}$ |
| $t_{P(B),F}$ | Threshold concentration for phytoplankton Pool B uptake | 2.0 | gC $m^{-3}$ |
| $t_{Z,F}$ | Threshold concentration for zooplankton uptake | 1 | g $m^{-3}$ |
| $t_{B,F}$ | Threshold concentration for bacteria uptake | 1 | g $m^{-3}$ |
| $t_{S,F}$ | Threshold concentration for supplemental feed uptake | 0 | -- |
| $DM_{fish}$ | Dry matter content of fish | 18.5 | % |
| $F_{car}$ | Carbon content of fish | 10 | % |
| <u>Phytoplankton</u> | | | |
| $T_{min}$ | Minimum temperature for phytoplankton growth[a] | 20.0 | °C |
| $T_{max}$ | Maximum temperature for phytoplankton growth[a] | 35.0 | °C |
| $T_{opt}$ | Optimum temperature for phytoplankton growth[a] | 30.0 | °C |
| c | Secchi constant | 2.0 | -- |
| $\alpha$ | Intercept parameter for SDV function | 80.22[b] | -- |
| $\beta$ | Slope parameter for SDV function | 0.33[b] | -- |
| T | Baseline turbidity | 3.37[b] | mg $m^{-3}$ |
| $\mu_P^{max}$ | Maximum specific phytoplankton growth rate | 2.25 | $d^{-1}$ |
| $k_{p,20}^{r}$ | Phytoplankton respiration parameter[a] | 0.1 | $d^{-1}$ |
| $k_P^d$ | Phytoplankton death parameter[a] | 0.05 | $d^{-1}$ |
| Chl-*a*:C | Chlorophyll-a to Carbon ratio | 30 | -- |

[a] Same parameter value used for zooplankton.

[b] For use in Equation 2.8 as parameterized for Bang Sai (see Appendix II).

Table 6.2. Continued.

| Symbol | Description | Value | Units |
|---|---|---|---|
| **Zooplankton** | | | |
| $\mu_Z^{max}$ | Maximum specific zooplankton growth rate | 0.3 | $d^{-1}$ |
| $c_{P,Z}$ | Half-saturation constant for uptake of phytoplankton[c] | 4.0 | $gC\ m^{-3}$ |
| $c_{B,Z}$ | Half-saturation constant for uptake of bacteria | 2.0 | $g\ m^{-3}$ |
| $t_{P,Z}$ | Threshold concentration for uptake of phytoplankton[c] | 1.0 | $gC\ m^{-3}$ |
| $t_{B,Z}$ | Threshold concentration for uptake of bacteria | 1.0 | $g\ m^{-3}$ |
| $Z_{car}$ | Carbon content of zooplankton | 6.3 | % |
| **Feed** | | | |
| $DM_{feed}$ | Dry matter content of supplemental feed | 10 | % |
| q | Feed quality coefficient | 1.0 | -- |

[c] Assumed to be the same for both phytoplankton pools.

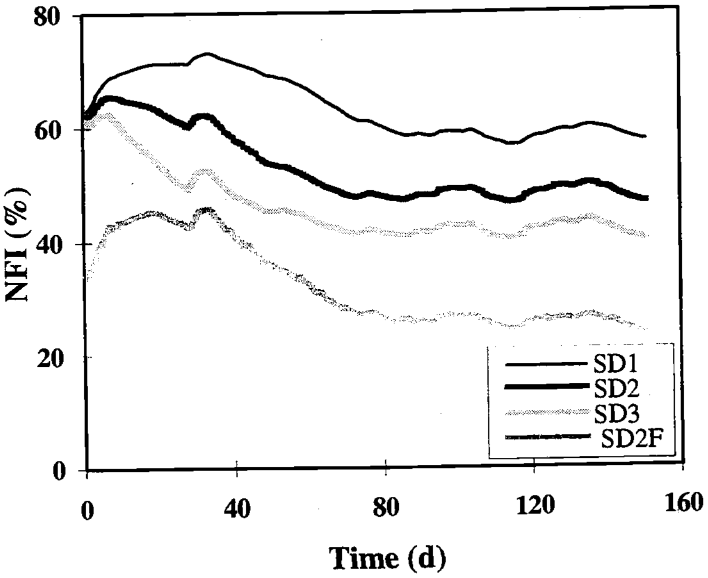

Figure 6.1. Profiles of the natural food index (NFI) in tilapia ponds.

dropped fairly quickly after the maximum values were reached, particularly for the SD3 treatment (Fig. 6.1), the models suggest that the fish were still able to harvest enough natural food to enable NFI's of about 40-45% until the end of the simulation runs. Tilapia growth data presented by Diana et al. (1990) suggest that the fish gained very little weight during the last month of culture in the SD2 and SD3 treatments implying that available natural food was perhaps sufficient to only meet maintenance requirements. Because data relevant to natural food availability were not collected by Diana et al. (1990), it is difficult to assess whether the predicted NFI profiles (Fig. 6.1) are realistic. An alternate hypothesis is that the simulation models have not been appropriately calibrated. For the SD2F treatment, however, the models predict a downward shift in the proportion of natural food in the diet compared to the SD2 treatment (Fig. 6.1) apparently caused by the consumption of supplemental feed.

Examination of the biomass of individual natural food resources suggests that changes in the consumption patterns of the two pools of phytoplankton are the main reason for differences in fish production among the four treatments (Figs. 6.2-6.4). In the SD1 treatment, the biomass of phytoplankton Pool A increased slightly at the beginning of the simulation, and then began to decline after about 40d (Fig. 6.2). The biomass of phytoplankton Pool B, however, increased steadily with time suggesting that this resource (as predicted by the simulation models) was not harvested to a substantial extent by tilapia. In the SD2 treatment, the decline in the biomass of phytoplankton Pool A was more rapid, and Pool B after an initial increase remained more or less constant (Fig. 6.3) due to grazing pressure of the fish. Profiles of the two phytoplankton pools in the SD2F treatment (Fig. 6.3) are more similar to those obtained for the SD1 treatment (Fig. 6.2) presumably due to the consumption of supplemental feed as previously indicated. It would appear that the addition of supplemental feed to fertilized ponds containing a filter feeder such as tilapia results in an increase in phytoplankton biomass. At the highest SD, the biomass of Pool A dropped sharply before reaching steady-state conditions whereas the Pool B increased slightly at the beginning of the simulation, and then began to decline gradually as consumption of this resource by fish increased (Fig. 6.4). In general, the resource substitution function predicted lower phytoplankton biomass in ponds with a higher standing crop of fish, except in the fed ponds where uptake of supplemental feed apparently allowed an increase in the overall phytoplankton biomass.

Although absolute changes in zooplankton are less pronounced (Fig. 6.5) presumably because the minimum threshold concentration for uptake of this resource by fish was assumed to be the same as the initial zooplankton biomass (Table 6.2), discernible patterns in the consumption of this resource by tilapia also can be observed. For the treatments without feed, there is a trend towards slightly lower zooplankton biomass with increasing fish density; for the SD2F treatment, the zooplankton biomass is marginally higher than the SD2 treatment (Fig. 6.5). These results are similar to the trends for the two phytoplankton pools (Figs. 6.2-6.4) discussed above. The two sharp declines in zooplankton biomass for all the four treatments within the first month or so of the

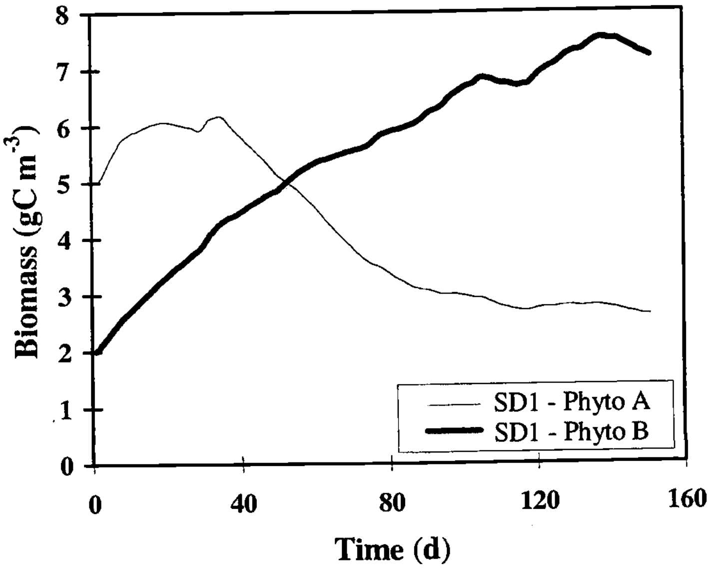

Figure 6.2. Simulated profiles of phytoplankton Pool A and Pool B in fertilized tilapia ponds stocked at 1 fish m$^{-2}$.

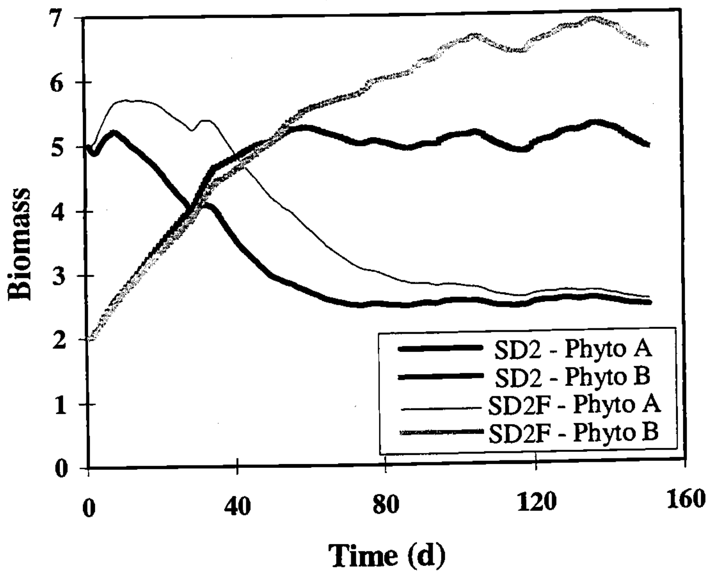

Figure 6.3. Simulated profiles of phytoplankton Pool A and Pool B in tilapia ponds stocked at 2 fish m$^{-2}$. SD2 refers to the treatment in which only fertilizer was added, whereas feed was also used in the treatment labeled SD2F.

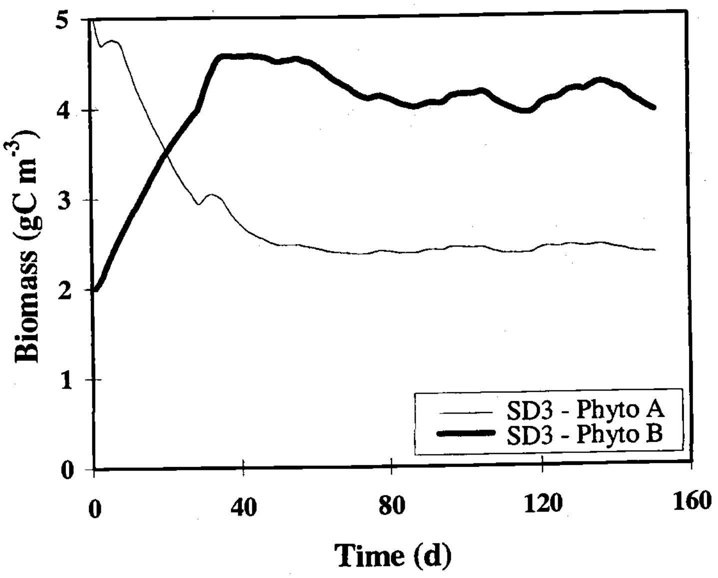

Figure 6.4. Simulated profiles of phytoplankton Pool A and Pool B in fertilized tilapia ponds stocked at 3 fish m$^{-2}$.

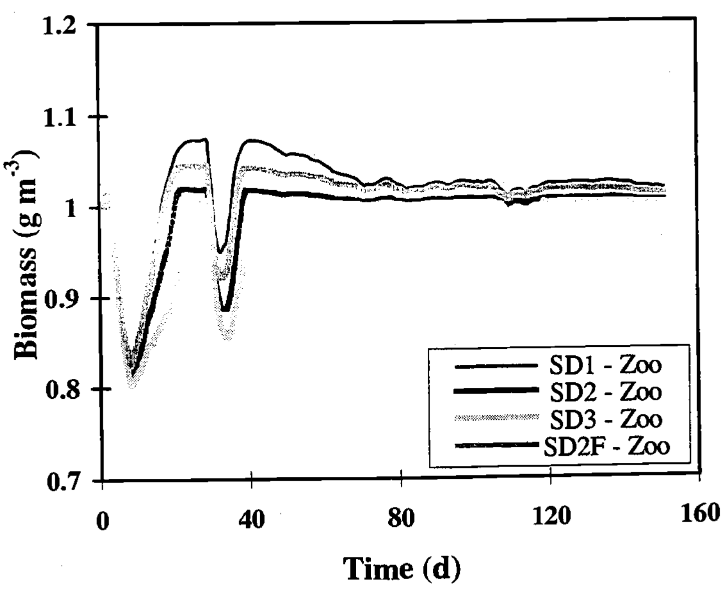

Figure 6.5. Simulated profiles of zooplankton in tilapia ponds.

simulations were associated with low water temperatures as predicted by the heat balance model (Chapter 2). Similar trends, although not to the same extent, can be observed for the phytoplankton pools as well (Figs. 6.2-6.4).

Diana et al. (1990) did not measure biomass changes of different pools of plankton in their ponds, and it is therefore difficult to directly evaluate the model output generated in the current analysis. However, comparison of model results to those reported by Colman and Edwards (1987) and Colman et al. (1990) is instructive. Experimental work with Nile tilapia in septage loaded tanks as reported by the former group of authors indicated a decrease in algal biomass in tanks with the highest fish biomass. Similar results were also reported by Colman et al. (1990). In both of the above studies, a shift in dominance towards smaller algal species was observed over time, presumably due to increased consumption of net-plankton. The simulations conducted herein clearly demonstrates the suitability of the resource substitution function as a tool to predict such shifts in the consumption of natural food resources by fish such as tilapia. As previously noted, the function is especially advantageous over the approach used by Svirezhev et al. (1984) because it can be used for multiple resources and food preferences are inherently captured in the half-saturation constants. Further, although the numerical experiments were limited to tilapia, it should be possible to calibrate the resource substitution function for other fish species, and to examine patterns of food consumption under mono- and polyculture situations. Such analyses may be useful in determining the appropriate mix of species for a given set of pond environmental and management conditions.

In terms of phytoplankton biomass profiles for the SD2F treatment, there are no published reports on size structure changes of plankton in fertilized and fed Nile tilapia ponds. Therefore, it is difficult to assess whether the increased biomass of phytoplankton predicted by the models (Fig. 6.3) is a trend that occurs in actual ponds. Phytoplankton blooms commonly occur in fed aquaculture ponds (Boyd, 1990). Such blooms are problematic in terms of oxygen depletion and the accumulation of off-flavor compounds in species such as channel catfish raised in the Southern US (Tucker and Robinson, 1990). The occurrence of blooms in such systems is apparently the result of high nutrient concentrations (due to high feeding rates), rapid increases in phytoplankton biomass, and possibly the lack of efficient filter feeders to lower this biomass.

Diana et al. (1993) reported the accumulation of unionized ammonia as well as low dissolved oxygen levels in fed and fertilized Nile tilapia ponds at Bang Sai. Such trends often occur in static ponds with a large phytoplankton population where the net productivity is low or when plankton die-offs occur (Boyd, 1990; Delince, 1992). If similar conditions did consistently occur in the ponds maintained by Diana et al. (1993), it may indicate that tilapia preferentially consumed supplemental feed, resulting in lower grazing pressure on phytoplankton and therefore an increase in their biomass. Results obtained for the SD2F treatment (Fig. 6.3) are consistent with this hypothesis in that models developed herein predicted large phytoplankton biomass compared to similar ponds that were not fed (i.e., the SD2 treatment). Moreover, increased nutrient concentrations do not account for the higher phytoplankton biomass predicted by the models for the SDF2 treatment because all the simulation runs assumed that the ponds were not nutrient limited. In other words, changes in the consumption of natural food by tilapia as manifested by the simulation models are primarily caused by the availability of supplemental feed in the SD2F treatment.

The iterative algorithm (Table 6.1) used to calculate supplemental feed consumption provided relatively rapid convergence throughout the SD2F simulation. However, the number of iterations required to converge to adequately accurate estimates of supplemental feed consumption in the SDF2 treatment (Fig. 6.6) appears to be inversely correlated with the NFI predicted for this treatment (see Fig. 6.1). Thus, more iterations seem to be necessary when the difference between NFI and the target feeding level (80% satiation in this case) is large. This trend may also have been caused by predicted changes in the proportions of the various natural food items (particularly phytoplankton Pool A and Pool B) consumed by tilapia over time.

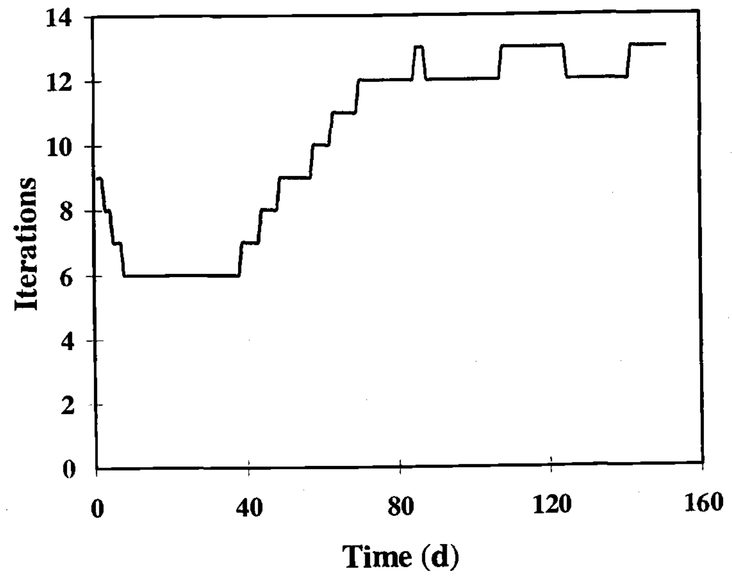

Figure 6.6. Number of iterations required to converge to an adequate estimate of supplemental feed consumption in the SD2F simulation.

An interesting outcome of the SD2F simulation is that the models suggest a supplemental feed requirement right from the beginning of the experiment (Fig. 6.7). In Chapter 5, we used an estimate of the critical standing crop or fish biomass (CFB; kg $m^{-3}$) to judge whether supplemental feed addition is required in fertilized ponds. Following Hepher (1978), this approach assumes that natural food is adequate to meet fish requirements until the CFB for a given pond is reached, and that feed addition was only required thereafter. A CFB of 0.078 kg $m^{-3}$ (roughly equivalent to 790 kg $ha^{-1}$) was estimated (see also Chapter 5) from data reported in the PD/A CRSP database for the fertilized ponds at Bang Sai that were stocked at 2 fish $m^{-2}$. This CFB apparently occurred around day 30 after stocking. In other words, the simplified fish growth model would recommend supplemental feed addition in such ponds only after a month of culture.

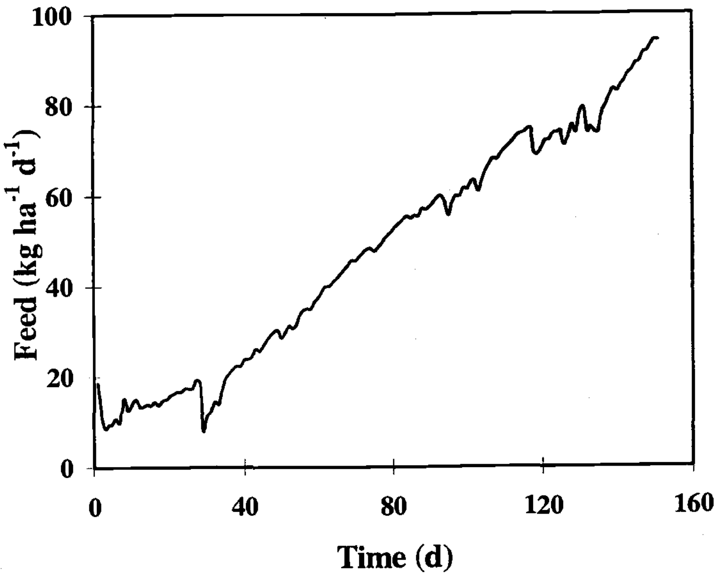

Figure 6.7. Supplemental feed requirements estimated during the SD2F simulation.

In part, the differences in the initiation of supplemental feeding between the simplified growth model (Chapter 5) and the more complex simulation models described herein for the same experiment could be due to errors in CFB estimates. CFB is assumed to occur at the point when individual fish growth rates reaches a maximum (Hepher, 1978). Diana et al. (1990) sampled fish at intervals about a month and the value of CFB (i.e., 0.078 kg $m^{-3}$) was estimated (see also Chapter 5) to correspond to fish biomass at the end of the first month of culture. However, the CFB may have actually occurred prior to the end of the first month of culture, in which case the simplified growth model described in Chapter 5 would have recommended the addition of supplemental feed prior to the end of the first month of culture. More frequent sampling (e.g., every two weeks) during the first two months or so of tilapia culture in ponds should help in clarifying this issue. It is also possible that the fish biomass at stocking exceeded the CFB, as suggested by Diana (in press). This author synthesized results from a variety of PD/A CRSP fertilization and feeding experiments with tilapia in Thailand. In some of these experiments, fish were sampled at biweekly intervals. His analysis indicated that there were differences in the growth response of this species from virtually the beginning of a variety of experiments which used the following treatments: fertilizer only, fertilizer plus feed, and feed only. Diana (in press) concluded that the CFB must have occurred very early on in the culture period when fish were in a size range of 30-40g. Results obtained in the SD2F simulations herein tend to support Diana's conclusions.

Alternate hypotheses to explain Diana's (in press) observations, as well as the differences in the initiation of supplemental feeding predicted by the approach used herein and that used in Chapter 5 are that the quantity and/or quality of natural food produced in the fertilized ponds at Bang Sai may not have been adequate to meet all the requirements of tilapia during the initial phase of culture (irrespective of the stocking size), or that fish may not be able to harvest natural food as efficiently as being offered exogenous feed. These possibilities raise questions as to whether the conclusions drawn by Hepher (1978) following his development of the critical standing crop concept based on carp experiments are necessarily applicable to intensive and semi-intensive culture of other fish species such as Nile tilapia. For instance, results obtained herein and those discussed by Diana (in press) may very well be caused by one or more of the following reasons: (i) natural food in some ponds is not adequate in terms of quantity, despite fish biomass being relatively low, (ii) species such as tilapia may not be feeding upto satiation in ponds where natural food is apparently plentiful, because the efficiency at which such resources can be harvested is low, and (iii) lower nutritional value of available natural food compared to that of a complete artificial feed (i.e., an issue of food quality).

## CONCLUSIONS

As noted by several ecological modeling practitioners (e.g., Straskraba and Gnauck, 1985; Haefner, 1996 among others), simulation tools can generate information that is beneficial in terms of understanding system behavior, translating such understanding into improved management practices, designing better experiments and improving the original models. Results obtained in this study are encouraging from the viewpoint of using complex pond aquaculture simulation models for such purposes. Specifically, the models predicted a decrease in phytoplankton biomass with an increase in the standing crop of fish in fertilized tilapia ponds. This result is consistent with the tank culture work of Colman and co-workers (Colman and Edwards, 1987; Colman et al., 1990).

Moreover, the models predict a change in the dominant phytoplankton pool within such ponds, a finding that is also consistent with the experience of many pond aquaculture researchers. Interestingly, the models suggest that adding supplemental feed to tilapia ponds results in a shift in food consumption patterns accompanied by an increase in phytoplankton biomass that is independent of the nutrient concentrations in ponds. Further, supplemental feed addition appears to be required even within the early phase of tilapia culture, a finding is contrary to the arguments of Hepher (1978) and the results obtained by the use of a simplified function to estimate natural food availability (Chapter 5). These results have practical implications for feeding practices because pond aquaculture managers are often interested in determining when supplemental feeding should commence in fertilized ponds.

The verification trials described in this paper must be considered preliminary, and it is important to conduct physical experiments to further validate and refine the models developed herein. Such experiments may initially be conducted at microcosm or mesocosm levels because better control can be exerted in such systems, prior to being done in experimental or production ponds. In particular, it would be beneficial to further examine changes in the size structure and biomass of plankton as fish standing crop increases under both fertilized and fed conditions. It would also be useful to conduct similar experiments with various fish species under polyculture conditions. Routine monitoring of water quality conditions in these systems can also generate data that will be useful both in terms of understanding the performance of aquaculture systems, and in the refinement of the models developed herein to address overall system performance.

One of the drawbacks of simulation models is the need to parameterize them periodically to new conditions (Richter and Sondgerath, 1990; Haefner, 1996). This is a particularly complex and tedious procedure for parameter-rich models such as the ones described in this paper. In conjunction with the verification experiments suggested above, it would be very beneficial to further refine recent parameter estimation techniques (e.g., Sequeira and Olson, 1995; see also Chapter 7) so as to enable automatic calibration of more complex simulation models (such as the ones developed during this study) for different culture conditions.

Finally, the verification trials conducted demonstrate the power of combining data analysis and synthesis via a combination of physical and simulation model experimentation, wherein the latter raise questions that can be examined by specific pond experiments. Results from such pond experiments can then be used in an iterative manner to refine the simulation models by including the new knowledge gained. This scheme of data collection, analysis and synthesis could also include other modeling techniques such as stochastic models, qualitative approaches, and rule-based systems.

# CHAPTER 7

# APPLICATION OF GENETIC ALGORITHMS FOR PARAMETER ESTIMATION OF A FISH GROWTH MODEL

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## ABSTRACT

Manual parameterization of complex simulation models is time-consuming, tedious and complicated because of interactions among variables considered and the large parameter space to be searched. Numerical parameter estimation techniques that have been used in lieu of manual calibration require partial derivative evaluations. Because of the difficulties in accurately estimating partial derivatives for complex simulation models that consider several variables, the use of genetic algorithms (GA) to automatically calibrate a fish growth model for five species important in pond aquaculture was explored. The objective function chosen for GA testing was the minimization of the absolute error between observed and predicted fish growth. Implementation details of the GA technique developed during the study are presented. Parameters were generated by the GA's in relatively short time periods and provided good correspondence between fish weight predicted by the model and observed data for all the five species. GA-based parameter estimation appears to be an appropriate approach for the automatic calibration of complex simulation models, a finding that is consistent with previous research efforts.

## INTRODUCTION

The use of simulation models that have been calibrated for one set of fish culture conditions to other locations or for other candidate fish species is often impeded by the need to manually adjust model parameters for the new set of culture conditions. However, estimating suitable parameters for complex, nonlinear simulation models such as the fish growth model described in Chapter 5 by manual calibration is extremely tedious because of the potentially high degree of interaction among variables, and the large size and dimensionality of parameter spaces to be searched. Piedrahita (1990) also noted the need to develop methods for parameter estimation of aquaculture simulation models other than manual calibration.

Several approaches have been developed in the past to estimate parameters for nonlinear, ordinary differential equation based (ODE) simulation models (Bard, 1974; Press et al., 1992). Richter and Sondgerath (1990) and Marsili-Libelli (1992) have demonstrated the use of some of these methods for parameterizing ecological models. Traditional parameter estimation approaches typically involve the specification of an objective function (e.g., error sum of squares between predicted and observed values) that is to be minimized, and a procedure for finding a set of parameters which in fact minimize this function. Thus, model parameter estimation may be considered to be an 'optimization' problem. In general, numerical algorithms for minimizing objective functions require evaluation of partial derivatives of the function with respect to each of the parameters to be estimated. For relatively large nonlinear models, such derivative evaluations can rarely be accomplished analytically, and are usually calculated numerically (Bard, 1974). However, it is difficult to achieve accurate results with numerical methods for derivative calculations, and the techniques that do exist tend to be relatively computation-intensive. In general, the difficulties associated with these methods has severely limited their application in biological models (Haefner, 1996).

Recently, however, a variety of nonlinear optimization strategies that may be broadly categorized as evolutionary computation techniques and which show considerable promise for parameter estimation of nonlinear biological models have been developed (Schwefel, 1981, 1995; Haefner, 1996). Genetic algorithms (GA's) represent an evolutionary computation technique that attempts to circumvent the problems of traditional parameter estimation methods (Schwefel, 1981; Davis, 1992). Within the agricultural sciences, GA's have previously been used as a tool for parameter estimation of a simulation model for cotton (Sequeira and Olson, 1995). The need to extend applications of the fish growth model (Chapter 5) to a variety of pond aquaculture species stimulated a study that examined the use of GA's to estimate suitable bioenergetic parameters for these species.

## MODEL PARAMETERS

The fish growth model (Chapter 5) can be used to examine the effects of fish weight, food availability, and environmental variables on growth. The model has been implemented in the Microsoft Windows-based decision support software POND (Bolte et al., 1995). In its simplest form where the dissolved oxygen and unionized ammonia concentrations are assumed to be such that fish growth is not adversely affected, a total of 10 parameters are required for each species (Table 7.1). Five fish species which are of considerable interest in pond aquaculture were chosen to examine the suitability of a GA-based parameter estimation technique for the fish growth model. The selected species were Nile tilapia (*Oreochromis niloticus*), tambaqui (*Colossoma macropomum*), pacu (*Piaractus mitrei*), common carp (*Cyprinus carpio*), and channel catfish (*Ictalurus punctatus*). Parameter estimation for the model requires time-series data pertaining to fish growth, water temperature, and feed application. Data sources that were used to estimate best-fit parameters for the five species and brief details regarding the actual experiments are listed in Table 7.2. Additional details regarding fish culture conditions in these experiments are summarized in Chapter 5.

## GENETIC ALGORITHMS

### Background

Only a brief review of GA's is presented here because more detailed discussions are available elsewhere (e.g., Holland, 1975; Davis, 1992; Michalewicz, 1992; Schwefel, 1995). GA's are based on the process of natural selection which tends to favor the propagation of those organisms that are better suited for a particular environment (Holland 1975). Such propagation occurs via the promotion of genes that cause the organism to become better adapted to its environment. The performance measure used to judge the success of an organism is its *fitness* - in genetics, this refers to the ability of the

Table 7.1. Listing of fish growth model parameters estimated by use of the GA's, together with their biological interpretation.

| Bioenergetic Parameter | Biological interpretation |
|---|---|
| Anabolism exponent ($m$) | Describes the relationship between fish weight and anabolic processes |
| Food consumption coefficient ($h$) | Rate parameter for food consumption |
| Efficiency of assimilation ($b$) | Proportion of food intake (gross energy) that is available as metabolizable energy |
| Feeding catabolism coefficient ($a$) | Proportion of the food assimilated (metabolizable energy) that is used to process it |
| Catabolism exponent ($n$) | Describes the relationship between fish weight and catabolic processes |
| Minimum catabolism coefficient ($k_{min}$) | Rate parameter for catabolism at the minimum temperature for the species |
| Temperature parameter ($s$) | A constant that describes temperature effects on catabolism |
| Minimum temperature scaler ($T_{min}$) | Lower temperature limit below which fish will not feed |
| Maximum temperature scaler ($T_{max}$) | Upper temperature limit above which fish will not feed |
| Optimum temperature scaler ($T_{opt}$) | Temperature at which food consumption reaches a maximum |

Table 7.2. Data sources used to estimate parameters for the five fish species together with relevant experimental details.

| Fish Species | Site | Period Simulated | Treatment | Data Source |
|---|---|---|---|---|
| Nile tilapia[a] | El Carao, Honduras | 27/7/89 to 21/12/89 | Feed + Fertilizer (CL1)[b]<br>Feed + Fertilizer (CL3)[c] | Teichert-Coddington et al., (1991) |
| Tambaqui | Pirassununga, Brazil | 1/10/84 to 13/6/85 | Feed | Lima et al. (1988) |
| Pacu | Itiquira, Brazil | 26/4/86 to 11/03/87 | Feed | Merola and Pagan-Font (1988) |
| Common carp | Golysz, Poland | 10/6/72 to 10/10/72 | Feed | Szumiec (1979a), Szumiec (1979b) & Szumiec and Szumiec (1985) |
| Channel catfish | Stoneville, MS, USA | 1/5/94 to 1/10/94 | Feed | Robinson and Li (1995) |

[a] Data for this species were extracted from the tropical aquaculture database maintained by the Pond Dynamics/Aquaculture Collaborative Research Program.

[b] CL1 refers to the treatment in which chicken litter was used for the first month of culture followed by feed.

[c] CL3 refers to the treatment in which chicken litter was used for the first three months of culture followed by feed.

organism to survive and reproduce, measured as the number of offspring of the individual which survive to reproduce.

GA practitioners use terminology that is borrowed from genetics. Thus, the term *individual* or *genotype* is used to represent a member of a population. These individuals are also called *chromosomes* because GA's typically consist of only a single chromosome (i.e., the population is made up of single chromosome individuals), which in turn is made up of genes located at certain places called *loci* on the chromosome. These genes can assume different states called *alleles*. The key aspects of adaptation that are exploited by GA's are (i) the chromosomes contain all the information that the population has found to be useful in adapting to its environment, and (ii) as long as there is scope for increased adaptation to their environment, the proportion of fit structures will continue to rise (i.e., fitness increases).

Traditionally, GA implementations involve the use of chromosomes that are represented as binary vectors (i.e, bit strings). These strings are manipulated by the use of genetic operators, namely "crossover" and "mutation" (Holland, 1975), to enable evolution of suitable solutions to the problem being analyzed. In the former, genes of two parent chromosomes are swapped to produce two offspring which may have very different characteristics. In mutation, bits are selected at random and altered so that a 1 becomes 0 or vice versa.

For optimization problems, it is assumed that each chromosome in a GA represents a potential solution to the problem. If the problem is one of parameter estimation and there are $n$ parameters, the chromosome is set up as an array of length $n$ with each element in the array (i.e., a gene) corresponding to one of the parameters to be estimated. The GA proceeds by setting up an initial population of individuals, evaluating each chromosome by estimating its "fitness" in relation to the optimization problem by the use of the objective function, selecting a new population of individuals from the existing one in a manner that is proportional to their fitness, and reproducing the chromosomes using genetic operators such as crossover and mutation (Davis, 1992). The procedure is then repeated for each new population until a population of individuals with a higher mean fitness than the original population results. The best individual in the final population will likely represent a highly evolved solution to the problem being solved. The link between the problem and the population of chromosomes is the objective function which provides a measure of the performance (i.e., fitness) of each chromosome in relation to the problem. The evaluation function thus plays an analogous role to the environment which a natural organism may encounter.

The basic assumptions of GA's in problem solving are related to the conventional concept of evolution. That is, (i) potential solutions to a problem can be represented as a population of single chromosome individuals, (ii) at any given time, the individuals in the current population are the repository of information that has proven useful in adapting successfully to its environment, and (iii) individuals which have a higher fitness reproduce more often than those with lower fitness so that the new population tends to have a higher average fitness compared to the previous one. This is because GA's implicitly assume that the best solutions are likely to occur in the region which contains a relatively high proportion of good solutions; therefore, they tend to sample these solutions more than others.

## Implementation Details

Implementation of GA's for optimization problems vary depending on the requirements of the specific problem that is being analyzed (Davis, 1992; Haefner, 1996). However, in general, all GA's including the one implemented in the current study follow the steps indicated in Figure 7.1. Specific features of the GA used herein are discussed below. The GA code used for the study was programmed in Borland® C++, and accessed

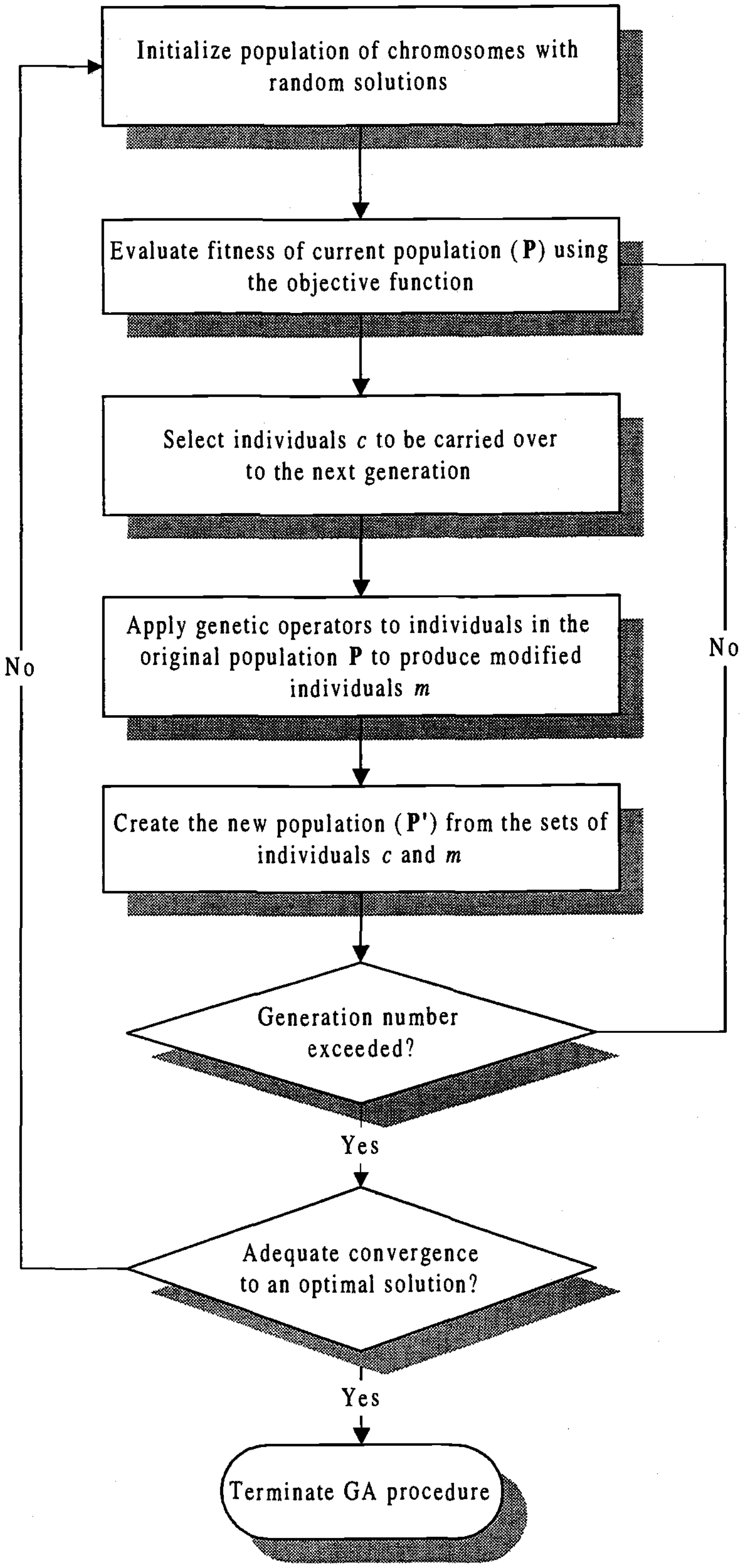

Figure 7.1. Steps involved in GA-based optimization.

from within the POND software. Parameter estimation was accomplished on an IBM-compatible personal computer with a Pentium CPU.

## Objective Function and Fitness Evaluation

A variety of objective functions can be used in parameter estimation techniques relevant to dynamic simulation models (Bard, 1974; Press et al., 1992). These functions typically involve the minimization of some measure of ‘goodness of fit’. Commonly used objective functions (e.g., Bard, 1974; Press et al., 1992) include minimization of (i) the absolute error between observed (O) and predicted (P) data, (ii) the sum of the squared error between O and P data, or (iii) the chi-square estimate between O and P data. Sequeira et al. (1994) compared various goodness of fit measures for GA-based parameter estimation, and concluded that minimization of the absolute error between O and P data resulted in the most consistent behavior of the GA’s. Consequently, this measure which can be stated as follows was used in the current study:

$$\sum_{i=1}^{m} \left|P_i - O_i\right| \tag{1}$$

where $P_i$ and $O_i$ refer to the predicted and observed fish weights respectively at the $i$th sampling time, and $m$ = total number of observations. Because growth data were typically measured at intervals of two to four weeks for all species, observed fish weights were linearly interpolated to enable computation of the objective function at each time step (one day) of the simulations.

The absolute error calculated from Equation 1 is used as a measure of the fitness of each individual in a population. Ranking of the population is also based on the fitness of its individuals (a lower absolute error indicating a more fit individual) Another statistic that is used to evaluate GA's is the average fitness of each generation which is the sum of the fitness of all individuals divided by the population size.

## Representation

As previously indicated, chromosome representation in GA's has primarily been accomplished by the use of binary vectors. This approach was also used by Sequeira and Olson (1995). However, there is evidence to suggest that floating point representations of chromosomes are computationally more efficient for numerical optimization problems, produce more consistent results among runs, are more precise, and are conceptually closer to the problem space compared to binary vectors (Michalewicz, 1992). Chromosomes for the current study were therefore represented as floating point arrays of length *n* with each element (gene) corresponding to one of the parameters.

## Genetic Operators

Our GA code uses two operators namely crossover and mutation. A one-point crossover mechanism that works as follows was used. First, the number of allowable crosses is determined. This is a constant number for each GA run obtained as the product of the crossover rate (a control parameter that is user-specified) and the population size divided by two. For this work, the crossover rate was set to 0.25 (i.e., 25% of the individuals were assumed to be available for crossover). Secondly, to ensure that individuals with higher fitness were preferentially selected for crossover, selection of these individuals was accomplished by ranking the current population according to fitness, and then stochastically sampling this population using an exponential distribution with a mean obtained as the product of the number of individuals and another control parameter that was arbitrarily set to 0.20. Use of this value implies that the upper 20% of the population has a higher probability of being selected for crossover. Thirdly, once the individuals were selected, the cleavage point was stochastically determined on the basis of a uniform distribution, the range of which was set to the number of parameters (10 in the current study) minus one, which ensures at least a minimal exchange of 'genetic material'. Finally, one-point crossover between two individuals (C1 and C2) occurs by exchanging the material beyond the cleavage point in individual C1 with that of C2, and vice versa (Fig. 7.2). This final step is repeated for all the allowable crosses in the current generation.

Mutation is assumed to occur on the basis of all the genes in the population, which is given by the product of the number of genes per individual (i.e., the parameter count equal to 10 here) and the population size. The number of allowable mutations is then given by the product of a user-specified parameter, the mutation rate, and the total number of genes in the population. The genes to be mutated in each generation are stochastically selected on the basis of a uniform distribution with a maximum value equal to the number of allowable mutations. The new or 'mutated' value of the parameter represented by the gene selected for mutation is obtained as a uniform random number that is within the allowable range for the specific parameter.

### Selection Strategy

A number of different approaches have been used to select individuals that appear in the next generation during a simulation run (see review by Michalewicz, 1992). These include deterministic approaches such as the elitist strategy in which the best chromosome is always carried over to the next generation and variants around this general idea. Stochastic approaches have also been used in which individuals with higher fitnesses have an increased probability of appearing in the next generation. We used a modified version of the elitist strategy by specifying a carryover rate of 0.20, which

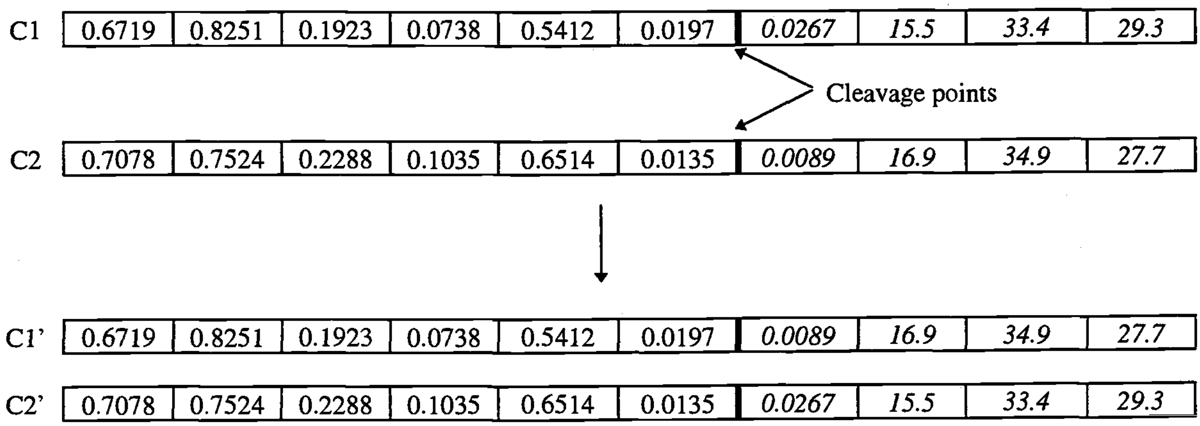

Figure 7.2. Schematic representation of a one-point crossover exchange between two individuals C1 and C2 from the current population, which results in two different individuals C1' and C2' that enter the next population.

implies that a proportion (20%) of the individuals in the current generation ranked on the basis of their fitnesses have to be carried over to the new generation. For the typical population size of 20, this implies that the four best individuals in the current generation would be selected into the new generation.

## Parameter Estimation Procedures

GA settings used in this study are summarized in Table 7.3. Parameter estimation for the fish growth model proceeded according to the general procedure for GA-based parameter estimation of simulation models (Fig. 7.3). More specifically, the steps involved in parameter estimation for all the fish species in this study were as follows:

1. An initial population of individuals was created by uniform random sampling from the allowable range for each of the parameters to be fitted. Allowable parameter values for each of the five fish species were established on the basis of literature-derived information for the individual species and from trial simulation runs in which model parameters were adjusted to obtain reasonable predictions of fish growth. Parameters for which baseline values were established from literature sources (Table 7.4) included those relevant to the relationship between temperature and fish growth (i.e., the parameters $T_{min}$, $T_{max}$, $T_{opt}$ and $s$ in Table 7.1). The parameter ranges to be searched for all the parameters were typically set to ± 25% of the baseline values.
2. The fitness of each individual in the current population was evaluated by the use of Equation 1, with the observed values of fish weights for each of the species obtained from the sources listed in Table 7.2. This step involves a simulation run for each of the individuals in the population.
3. Next, a new population of individuals was created by applying the genetic operators and selection strategy described earlier. The fitness of this new population was then evaluated as indicated in Step 2 above.
4. Once the preset number of generations (i.e., maximum number of GA iterations) was reached, a final simulation run was made with the best individual and model predictions compared to observed fish weights.

Table 7.3. GA settings used for automatic calibration of the fish growth model.

| Setting | Value/Method |
|---|---|
| Number of generations | 20 |
| Chromosome length | 10 |
| Population size | 20 |
| Crossover rate | 0.25 |
| Crossover type | One point |
| Mutation rate | 0.15 |
| Carryover rate | 0.20 |
| Selection strategy | Elitist based on carryover rate |
| Fitness criteria | Minimization of absolute differences |

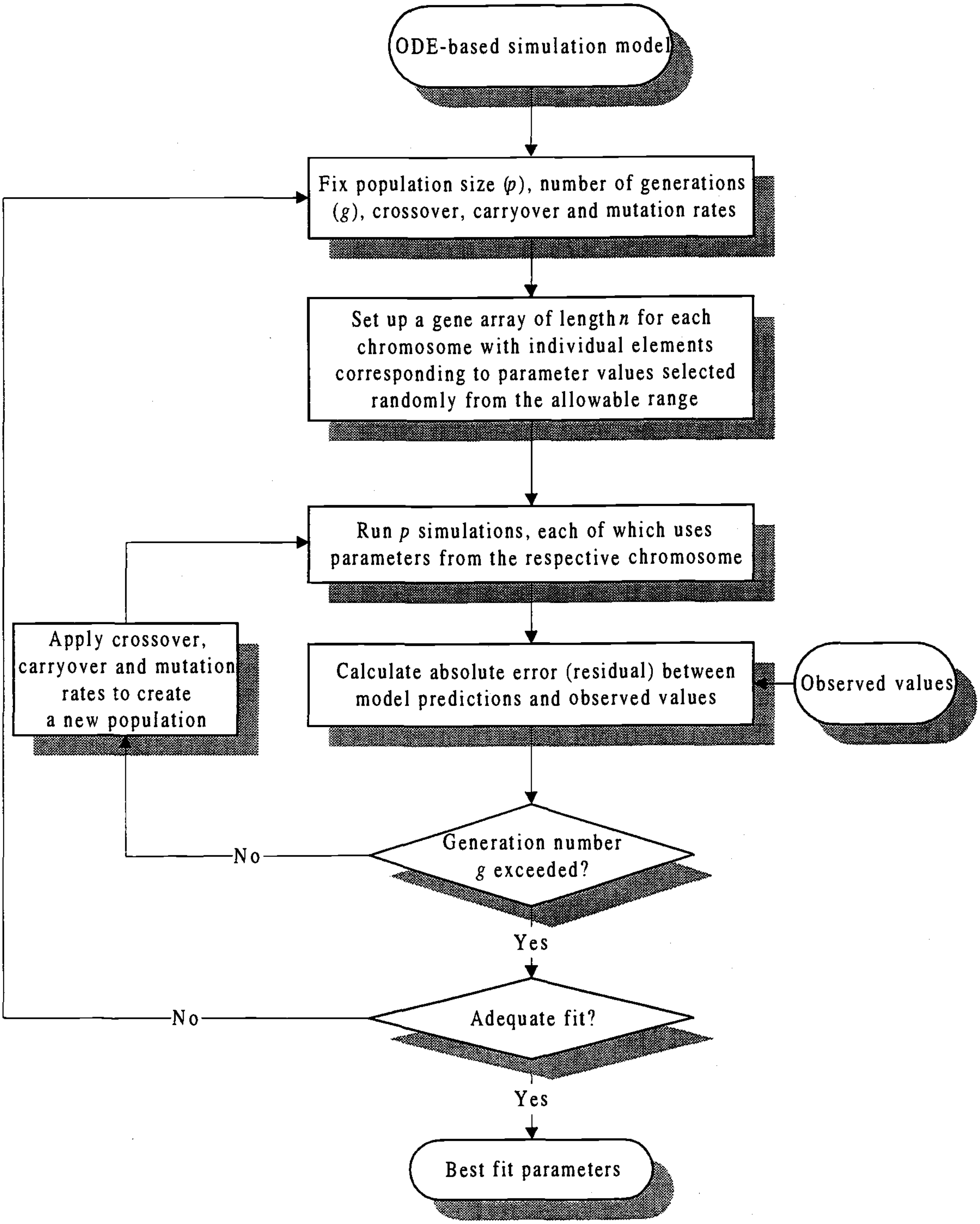

Figure 7.3. Procedure for GA-based parameter estimation of a simulation model.

Table 7.4. Data sources used to arrive at baseline values of the temperature parameters for the five fish species chosen for analysis.

| Fish Species | Data Source |
|---|---|
| Nile tilapia | Gannam and Phillips (1992), Denzer (1967), Caulton (1982) |
| Tambaqui | Saint-Paul (1989), Lovshin (1995) |
| Pacu | Saint-Paul (1989) |
| Common carp | Szumiec and Szumiec (1985), Hepher (1988) |
| Channel catfish | Tucker and Robinson (1990) |

## RESULTS AND DISCUSSION

The GA-based parameter estimation technique resulted in adequate convergence for all the five species tested. Results obtained for each species are presented below, followed by analyses of various GA statistics collected during the course of the parameter estimation.

### Nile tilapia

The individual with the best-fit parameters (Table 7.5) resulted in good predictions of Nile tilapia growth compared to the observed weights (Fig. 7.4). Final fish weights were not substantially different from the mean of the observed weights (Table 7.6). Periods of slow growth predicted by the model for both the CL1 (chicken litter for one month followed by feed) and CL3 (chicken litter for three months followed by feed) treatments used by Teichert-Coddington et al. (1991) were apparently caused by low water temperatures (in the range of 19-22°C). Such trends are difficult to observe in actual growth data because of the relatively long sampling intervals (about four weeks) used by the above authors.

Table 7.5. Best-fit model parameters estimated using GA's for five fish species.

| Bioenergetic Parameter | Nile tilapia | Tambaqui | Pacu | Common carp | Channel catfish |
|---|---|---|---|---|---|
| *Anabolism Parameters* | | | | | |
| Efficiency of assimilation ($b$) | 0.7108 | 0.6695 | 0.7719 | 0.7129 | 0.7865 |
| Anabolism exponent ($m$) | 0.6277 | 0.6855 | 0.7154 | 0.6722 | 0.6327 |
| Food consumption coefficient ($h$) | 0.4768 | 0.2863 | 0.2415 | 0.3282 | 0.2885 |
| *Catabolism Parameters* | | | | | |
| Feeding catabolism coefficient ($a$) | 0.0559 | 0.1057 | 0.0529 | 0.0786 | 0.1133 |
| Catabolism exponent ($n$) | 0.8373 | 0.5336 | 0.5332 | 0.5166 | 0.5118 |
| Minimum catabolism coefficient ($k_{min}$) | 0.0104 | 0.0146 | 0.0094 | 0.0104 | 0.0227 |
| Temperature parameter ($s$) | 0.0288 | 0.0110 | 0.0290 | 0.0027 | 0.0119 |
| *Temperature Scalers* | | | | | |
| Minimum ($T_{min}$) | 18.7 | 14.4 | 17.5 | 10.1 | 13.3 |
| Maximum ($T_{max}$) | 39.7 | 38.6 | 31.4 | 36.2 | 36.0 |
| Optimum ($T_{opt}$) | 32.4 | 29.0 | 28.1 | 30.6 | 30.8 |

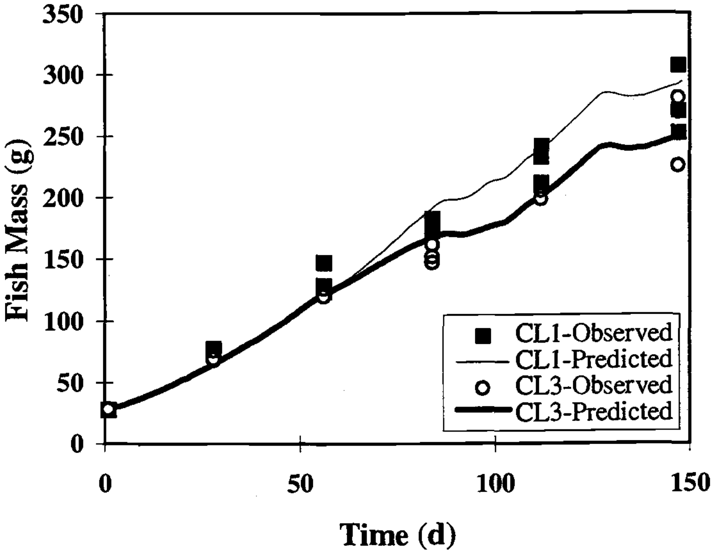

Figure 7.4. Calibration results for Nile tilapia at El Carao, Honduras.

Table 7.6. Final observed (O) fish weights compared to those predicted (P) by the growth model for five fish species. The percent relative error was calculated as [(P - O)/O] × 100.

| Fish Species | Final fish weights (g) | | Percent relative error |
|---|---|---|---|
| | Observed | Predicted | |
| Nile tilapia | 276.4 | 294.2 | +6.4 |
| | 258.4 | 251.4 | -2.7 |
| Tambaqui | 298.0 | 304.6 | +2.2 |
| Pacu | 699.6 | 727.9 | +4.0 |
| Common carp | 400.0 | 401.8 | +0.5 |
| Channel catfish | 463.0 | 454.6 | -1.8 |

## Tambaqui

Best-fit model parameters for tambaqui (Table 7.5) resulted in the growth profile shown in Figure 7.5. Although the relative error (calculated as indicated in Table 7.6) between the final fish weight predicted by the growth model with the above parameters and the actual harvest weight reported by Lima et al. (1988) was only about 2.2%, there is a tendency for predicted fish weights to be slightly lower than observed weights during the entire simulation except towards the end (Fig. 7.5). It is possible that the estimated model parameters are not adequate to accurately predict growth of this species when temperatures are within the optimum range for this species, or that the model is not flexible enough to accomodate the growth of tambaqui. Nevertheless, the set of best-fit parameters produces a growth profile for tambaqui that does closely follow the pattern of observed weights.

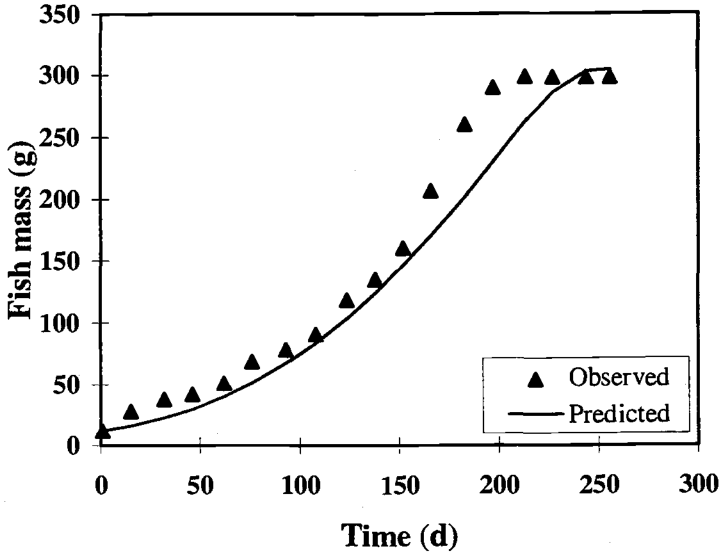

Figure 7.5. Calibration results for tambaqui at Pirassununga, Brazil.

## Pacu

For this species, there was a close correspondence between observed data and weights predicted using the set of best-fit parameters (Fig. 7.6; Table 7.5). Among the five species chosen for parameter estimation, this species was cultured for the longest time period of close to 11 months (Table 7.2) and it might therefore be expected that there would be an appreciable difference between the final observed weight at harvest and that predicted by the growth model. However, because the GA-based calibration procedure generated a good set of parameters for pacu, the relative error between the actual and predicted harvest weights was only 4% (Table 7.6). The good fit may in part be attributable to more frequent sampling weights reported by Merola and Pagan-Font (1988), use of which likely reduces any errors that may be introduced by applying linear interpolations to observed weights so as to calculate the absolute error (Equation 1).

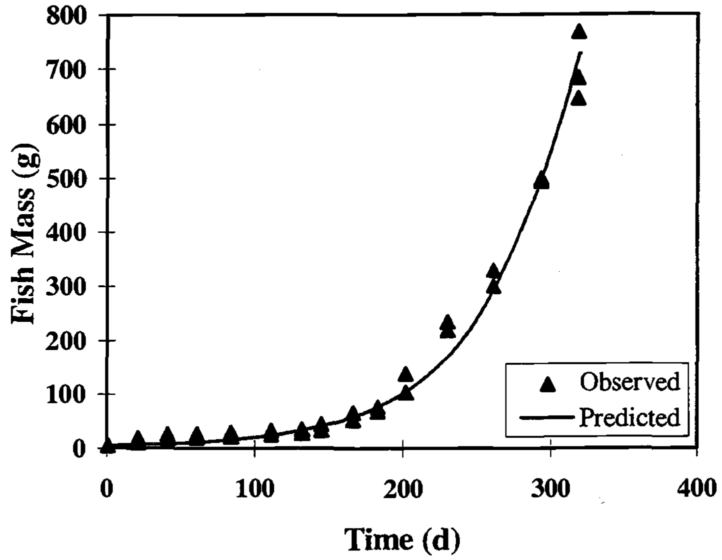

Figure 7.6. Calibration results for pacu at Itiquira, Brazil.

## Common Carp

Excellent correspondence between fish weights predicted by the use of the calibrated model and observed weights was obtained for this species throughout the simulation period (Fig. 7.7), and the relative error was the lowest among the five fish species tested (Table 7.6). Slower growth rates towards the end of the simulation period were presumably due to low water temperatures, a trend that was accurately predicted by the set of growth parameters for the common carp.

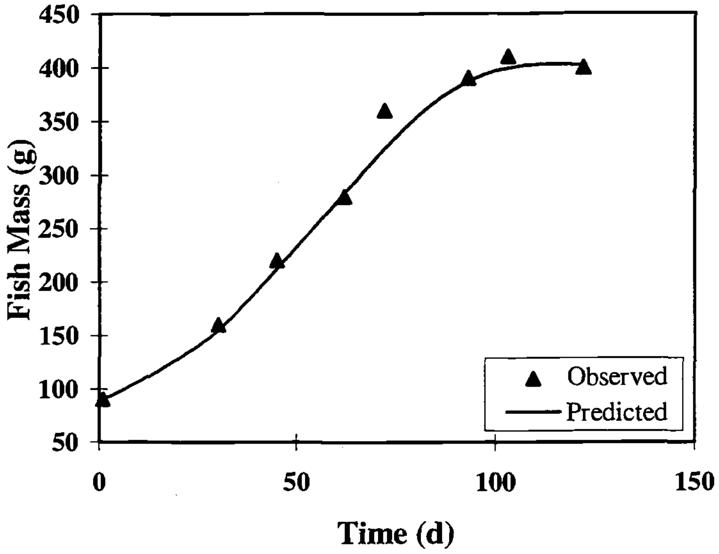

Figure 7.7. Calibration results for common carp at Golysz, Poland.

### Channel Catfish

Best-fit parameters generated by the GA (Table 7.5) resulted in model predictions that compared very favorably with observed weights (Figure 7.8). The final harvest weight predicted by the growth model was only marginally lower than the actual weight reported by Robinson and Li (1995; Table 7.6).

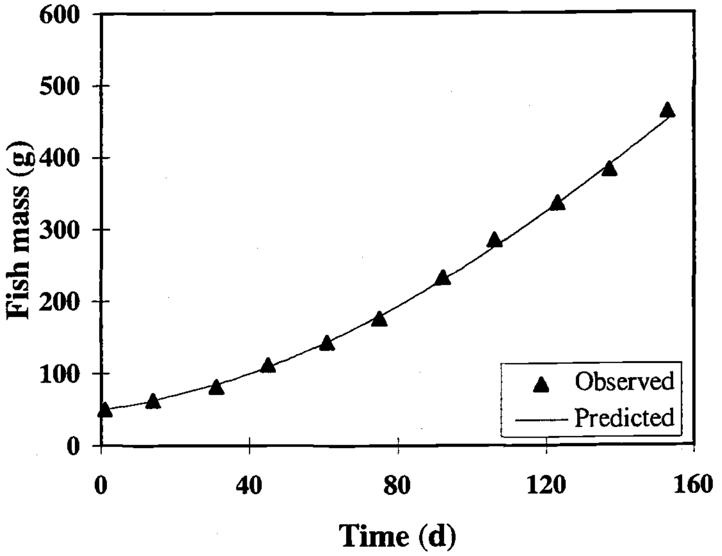

Figure 7.8. Calibration results for channel catfish at Stoneville, Mississippi, USA.

### GA Performance

As indicated above, GA's proved to be an acceptable approach for the complex task of automatically calibrating the nonlinear fish growth model described in Chapter 5. Moreover, the technique generated suitable parameters for the five species which were cultured under different conditions. Thus, the technique appears to adequately address site-specific characteristics (e.g., temperature, feeding rates, etc.) while parameters are being estimated, which is consistent with the observations of Sequeira and Olson (1995).

Three statistics were collected during the current study to further assess the performance of the GA-based parameter estimation technique: the average fitness of the extant population, the individual with the best fitness in the current population (prior to the carryover individuals being blended in), and the fitness of the best individual from the commencement of the GA run. The latter two statistics are respectively referred to as the best current fitness and best cumulative fitness in the remainder of this paper. Similar patterns for these three statistics were obtained for all the fish species; discussion is therefore limited to results for tilapia and pacu.

After a slight increase in values for the average fitness in the first generation for tilapia (Fig. 7.9), this statistic decreases sharply until the sixth generation, following which its value is more or less constant. For pacu, the trend for average fitness values is similar, although the overall tendency is towards a slight decrease with an increase in the generation number (Fig. 7.10). Trends obtained for this statistic are similar to those obtained by Sequeira and Olson (1995). The slight increases even towards the end of the GA runs (Figs. 7.9-7.10) are likely due to mutation, which can actually create individuals whose fitness may be much lower (i.e., high absolute error in the current context) than expected (Michalewicz, 1992) much in the same way that unfit stuctures can show up in natural populations.

Trend in the best current fitness statistic are fairly similar to the average fitness for both species, but the actual value as expected is substantially lower (Figs. 7.9-7.10). The best cumulative fitness shows a sharp decline within the first few generations for both tilapia (Fig. 7.9) and pacu (Fig. 7.10); thereafter, its value changes very slowly. For the former species, the best individual was obtained in generation 14 whereas the best individual for pacu was obtained in generation 19. It is possible that an individual with even better fitness could have been obtained for pacu if the generation size was larger. However, because growth model predictions for this species using the best individual were very good (Fig. 7.6), it was decided that substantial benefits would not accrue by increasing the generation size and repeating the parameter estimation procedure.

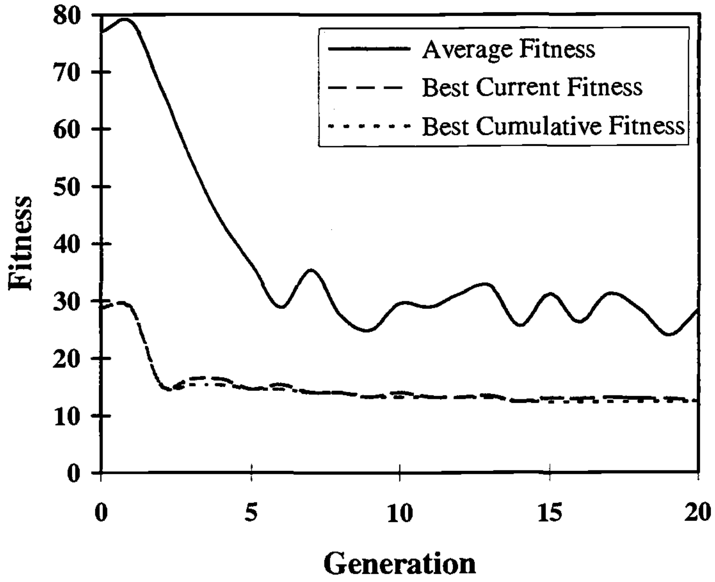

Figure 7.9. GA statistics for tilapia.

The absolute values of the GA statistics collected for tilapia (Fig. 7.9) and pacu (Fig. 7.10) differ substantially. This appears to be a surprising result given that a better growth model fit was apparently obtained for the latter species (compare Figs. 7.4 and 7.6). However, the higher values for pacu are explained by the fact that the duration of experiment for tilapia was only 147d (Teichert-Coddington et al., 1991) whereas Merola and Pagan-Font (1988) cultured pacu for 321d (Table 7.2). Because the absolute error

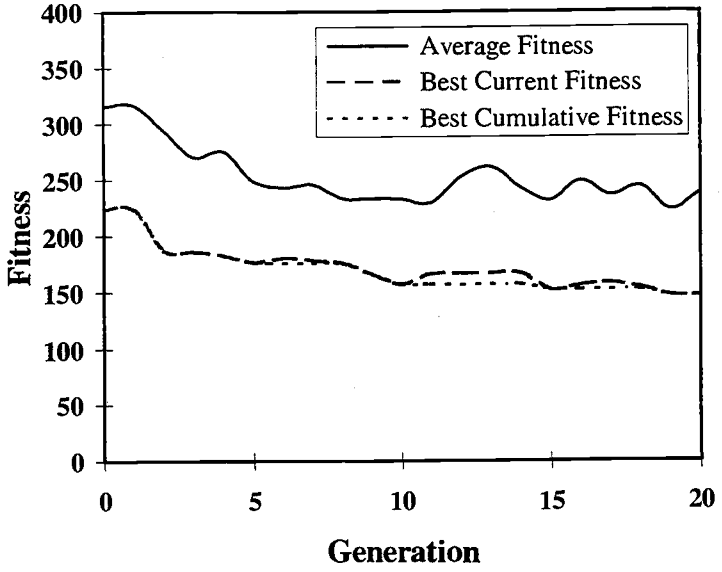

Figure 7.10. GA statistics for pacu.

represents the sum of the errors over an entire simulation (Equation 1), its value may increase with the simulation duration.

An additional performance measure for any parameter estimation method is the time required to obtain a sufficiently calibrated model. In the current context, this performance measure is especially important because the fish growth model is packaged within a decision support framework and the parameter estimation package will likely be used by pond aquaculture managers to either adjust parameters in accordance with site-specific conditions for one of species that the model has already been calibrated for, or to generate best-fit parameters for new fish species. In other words, relatively rapid model calibration is desirable. Convergence to the best individuals in the current study was typically obtained within about 30-45 minutes for all the species considered, a time frame that should be satisfactory under most conditions.

It is important to note that Sequeira and Olson (1995) actually estimated only five parameters (out of a total of 50) for the cotton model GOSSYM using GA's, whereas the current study has demonstrated that GA-based model calibration can be used to estimate a larger number of parameters (i.e., a total of 10 for the fish growth model). This has considerable significance for ecosystems models where the number of parameters may be very large, and where manual calibration is particularly tedious and time-consuming. For such models, calibration by numerical techniques (as previously pointed out) is also difficult. Apart from parameterizing models using GA's alone, it may be possible to combine available optimization techniques to generate the most suitable set of parameters. For instance, Davis (1992) discusses the combined use of expert systems, numerical techniques and GA's for industrial problems. Such an approach has yet to be explored for parameter estimation of complex ecological models and may very well be useful because each of the above optimization techniques have some inherent advantages. For instance, expert systems may be useful in setting parameter ranges to explore as well as in automatically evaluating optimal parameters. Numerical techniques can be very powerful particularly when derivative evaluations are possible, whereas GA's are useful in identifying parameter spaces where good solutions exist.

## CONCLUSIONS

A GA-based technique for calibration of a nonlinear fish growth model has been developed. The technique generated parameters for five fish species within relatively short time periods. These parameters resulted in good correspondence between fish growth predicted by the model and observed data. GA-based parameter estimation is a useful mechanism for the automatic calibration of complex simulation models, a finding that is consistent with previous research efforts.

# CONCLUSIONS

Research presented in this dissertation has dealt with the POND decision support system, and the development, verification and use of pond simulation models that have been implemented within this software. The POND framework apparently represents the first effort to integrate simulation models and economic analysis capabilities into a unified software tool specifically targeting pond aquaculture systems. This is a major departure from traditional analysis tools in which simulation model development and economic analysis capabilities have been viewed as separate activities. For instance, available pond simulation models which were developed either by the use of conventional programming tools (e.g., Cuenco et al., 1985; Cacho, 1990) or within software specifically designed for implementing simulation models (e.g., Piedrahita, 1990; van Dam and Penning De Vries, 1995) have not been linked to economic analysis tools. Similarly, economic analysis tools previously developed for aquaculture (e.g., Gempesaw et al., 1992) have transferred to the software user the responsibility of providing inputs about proposed farm operations. In other words, users of such tools are assumed to be familiar about the extent of resource use in the farm under consideration, whereas POND attempts to generate estimates of resources used in the form of simulation model outputs.

Another distinct feature of the POND software is that it is specifically designed to enable analysis of entire facilities. That is, the software provides capabilities to represent a physical aquaculture system which consists of a specific geographical location, source water quality, pond(s) associated with the site, fish lot(s) or populations (comprising one or more species) associated with each pond, and a soil type for each pond. This scheme of facility representation, coupled with the simulation models and the enterprise budget package in the software enables rapid analysis of facilities under a wide variety of potential operating conditions.

Simulation models implemented within the POND framework are organized hierarchically into three levels according to their complexity, availability of input data and output resolution requirements. From the viewpoint of information representation, manipulation and application, this scheme of model organization has allowed a single, generic analysis tool to meet the decision-making needs of different user groups such as pond aquaculture planners, managers and researchers.

However, there are a number of areas where future work on software improvement (apart from continued model verification which is discussed in detail below) is required. Firstly, the POND software in its current form is primarily a facility-level simulator wherein users can represent existing or planned pond facilities and explore different production scenarios. For management applications, such types of analyses can greatly benefit from linking the POND software to database tools which contain real-time information collected during routine farm operations. Apart from the obvious advantages of automation, use of actual farm data would be particularly beneficial for short-term management forecasting tasks relevant to practices such as pond fertilization and feeding. A second shortcoming of POND is that the economic analysis capabilities of the software are currently limited to enterprise budgeting. It would be beneficial to improve these capabilities to include cost-benefit, risk assessment and optimization techniques. Thirdly, the POND software does not presently enable analysis of other production systems (e.g., integrated animal and crop farming) which are often closely allied with pond aquaculture practices, particularly in developing countries. Addition of such functionality will likely be useful to aquaculture development planners and other decision-makers.

As indicated in Chapter 1, the more complex models in POND have yet to be fully verified. This is an area that should receive priority, in part because detailed simulation models offer a powerful mechanism for conducting various types of experiments and generating information that is useful both in understanding pond ecosystems and improving management practices. Further, a current weakness of the POND simulation models is that they do not adequately address the prediction of water quality in ponds. In particular, arriving at estimates of dissolved oxygen and unionized ammonia levels is important because these two variables often set the limits of fish production in more intensive aquaculture operations. Such estimates are required to assess the effects of reduced fish output as well as ameliorative strategies (e.g., aeration, water exchange, etc) on the economic performance of a given facility. Simulation models capable of generating realistic water quality profiles will also enable users of decision support systems such as POND to analyze effluent management practices in aquaculture facilities (e.g., shrimp farms) where substantial water exchange may occur, with potentially serious consequences for the surrounding environment.

With regard to the simulation models that have been presented in this dissertation, the water temperature model (Chapter 2) appears to be a very useful tool for predicting both long-term daily and short-term diurnal temperature profiles in aquaculture ponds that are assumed to be completely mixed. Previously developed temperature models have not provided this dual functionality. The model generated daily and diurnal temperature profiles with a reasonable degree of accuracy at geographically distinct sites in Thailand, Honduras and Rwanda suggesting that it is a relatively robust tool. As expected, daily water temperature predictions were more accurate when actual weather measurements were used as model input compared to data obtained from the POND weather generator. Sensitivity analyses indicated that among the various weather variables required as inputs, the water temperature model is most sensitive to air temperature, followed by relative humidity and short-wave solar radiation. Increased accuracy in water temperature projections can be expected when measurements of these three weather variables are available as input to the model. Potential applications of the model relevant to long-term daily water temperature projections include regional-scale assessment of aquaculture potential for species with different temperature preferenda, species selection for specific locations, estimation of feed and fertilizer requirements, and water quality management. The capabilities of the model to generate diurnal temperature profiles are likely to be of more interest to researchers involved in the analysis of ponds via the use of complex systems models. In the context of research applications, however, it may be more beneficial to explore the use of stratified water temperature models such as those developed by Losordo and Piedrahita (1991) or Culberson and Piedrahita (1992) especially if comprehensive weather datasets are available.

The water budget model (Chapter 3) is apparently the first attempt to synthesize observations on pond water sources and sinks into an analysis tool that should have general applicability to assess water requirements for most pond aquaculture facilities. These facilities may include operations that depend on routine water replenishment to maintain desired depths, are rainfed, or maintain a constant flow through the ponds. Water gains considered in the model include regulated inflow, precipitation and runoff, whereas water losses include evaporation, seepage, effluent discharge, and overflow. Verification of the model at locations in Thailand and Honduras suggests that sufficiently accurate estimates of pond water requirements can be obtained provided comprehensive weather datasets that include air temperature, precipitation, relative humidity and wind speed measurement are available as inputs. However, this requirement is not a particular disadvantage because such weather datasets are increasingly becoming available from various locations world-wide. A current weakness of the water budget model, especially relevant to situations where water gain by runoff may be important (e.g., rainfed aquaculture), is that it requires an estimate of the curve number for the surrounding soil, land use and hydrologic conditions. Such estimates can be obtained from published tables, but it may very well be appropriate to develop a simple expert system which can recommend curve numbers based on qualitative information provided by model users and embed it within POND.

Nevertheless, the water budget model is relatively flexible and can easily be adapted for different locations and/or seasons. Its use requires minimal measurements from ponds compared to previous pond water budget studies, a particular advantage for situations where analysis of water requirements is to be done in the planning phase of aquaculture operations before actual ponds exist. The model may also find use in regional-scale planning and analysis of water resources for pond aquaculture.

The fertilization model (Chapter 4) developed during this research effort is conceptually similar to a previous approach (Lannan, 1993) in that it is based on limnological principles and is a responsive management strategy (i.e., one designed to account for ambient pond water conditions prior to recommending fertilizer application). However, it differs from the study cited above in that (a) an estimate of the light-limited gross primary productivity is used as the starting point for evaluating fertilizer needs rather than the maximum net productivity, (b) the model accounts for the effects of temperature and nutrient limitations on algal productivity (and therefore fertilizer needs), and (c) recycling of nitrogen and phosphorus in ponds is more fully considered in estimating nutrient requirements. Evidence for a kinetic response of algal growth to concentrations of dissolved inorganic carbon, nitrogen and phosphorus in fertilized ponds was also presented in Chapter 4.

Verification of the fertilization model at locations in Honduras, Thailand and the Philippines suggests that fertilizer application rates generated by the model are likely to be more conservative than those obtained by the use of approach developed by Lannan (1993). It is also expected that improved consideration of nutrient cycling will reduce the probability of unionized ammonia accumulation (potentially detrimental to fish growth) in ponds. Field trial of the fertilization model for different locations should, however, be undertaken to confirm verification results. Nevertheless, these results do support previous observations in that responsive fertilization strategies are likely to result in better nutrient utilization in ponds compared to traditional fixed input approaches, and should lead to improved fertilizer use efficiency.

The development of a management-oriented fish bioenergetics model (Chapter 5) has been a key focus area of the research presented in this dissertation. The model accounts for the effects of key variables (fish size, water temperature, photoperiod, dissolved oxygen and unionized ammonia) on fish growth in aquaculture ponds. The function developed to estimate natural food availability as a function of fish biomass is consistent with evidence from fertilized ponds, and appears to provide a reasonable estimate of the contribution of such resources to fish diet. The function has proven useful in estimating when supplemental feed addition should commence in ponds and the feed amounts required to reach a desired feeding level.

The fish bioenergetics model has been successfully calibrated and validated for five fish species namely Nile tilapia (*Oreochromis niloticus*), tambaqui (*Colossoma macropomum*), pacu (*Piaractus mesopotamicus*), common carp (*Cyprinus carpio*), and channel catfish (*Ictalurus punctatus*) under various production conditions, suggesting that it is a relatively robust and flexible tool for describing fish growth in aquaculture ponds. Application of the model to different pond species represents a departure from most of the previously developed fish growth models which have typically been calibrated only for one species. Sensitivity analyses suggests that the model is very sensitive to six out of a total of 10 parameters. As with other systems analysis tools, there are limitations in the applicability of the model to all culture conditions that may be found in ponds. Specifically, the current version of the model does not adequately account for the effects of stocking density in fed ponds, food preferences and artificial diets of differing quality on fish growth in ponds. These represent areas for future work, which should also include parameterization of the dissolved oxygen and unionized ammonia functions for different species.

Various simulation experiments conducted with the fish bioenergetics model point to its applicability in practical pond management situations such as growth potential of different fish species at various geographical locations, estimation of feeding rates, and examination of different stocking density regimes in fertilized ponds with or without supplemental feed addition. Specifically, these experiments demonstrate that fertilized tilapia ponds stocked at higher rates will require supplemental feeding to commence earlier compared to those stocked at lower rates assuming the same target feeding level. Numerical experiments with the fish bioenergetics model also resulted in different feeding curves (in terms of percent body weight of fish) for ponds assumed to receive feed only, or those receiving both fertilizer and feed. For fed-only ponds, model experimentation suggests that the use of traditional fixed feeding rates (as percent body weight of fish) apparently leads to higher feed requirements, increased waste feed, and higher food conversion ratios compared to satiation feeding levels which account for variations in water temperature among different locations. However, for fertilized and fed ponds, the predicted feeding curves do not steadily decrease with increasing fish weight (as is the case with published feeding tables), but are characterized by an initial increase followed by a gradual reduction in the feeding rates. This is because the energetics model accounts for the contribution of natural food to the diet of pond fish such as tilapia. These findings have important implications for feed management practices and the efficiency of feed use in aquaculture farms. As with the other models developed herein, further verification of the fish bioenergetics model under actual pond conditions would be beneficial.

In contrast to the models described in Chapters 2-5 of this dissertation, where the focus was on the applied aspects of simulation modeling (e.g., in pond management and planning tasks), Chapter 6 dealt with the development and use of more complex models to understand pond ecosystems. The fish growth model used in the latter chapter is similar to the one described in Chapter 5, with the exception that a resource substitution function (Tilman, 1982) was used to analyze the consumption of various food resources, endogenous and exogenous, in aquaculture ponds. Chapter 6 also documents the development of models for phytoplankton and zooplankton from the available literature.

Simulation experiments conducted with these models predicted changes in the dominant phytoplankton pool of fertilized Nile tilapia ponds that are consistent with the experience of pond aquaculture researchers. These changes were more pronounced in ponds stocked at higher fish densities, and were correlated with increased fish biomass in the ponds. The overall phytoplankon biomass was also lower in ponds stocked at higher densities. An interesting outcome of the model experiments was that the addition of supplemental feed to tilapia ponds resulted in a shift in food consumption patterns accompanied by an increase in phytoplankton biomass that is independent of the nutrient concentrations in ponds. Further, supplemental feed addition appears to be required even within the early phase of tilapia culture, a finding is contrary to the arguments of Hepher (1978) and the results obtained by the use of the simplified function that was used in Chapter 5 to estimate natural food availability. It is unclear whether this finding is simply an artifact of the over-estimation of critical standing crops in tilapia ponds, or whether growth of the Nile tilapia in fertilized and fed ponds is more rapid during the initial phase of culture compared to ponds that receive only fertilizers. If the latter situation does occur in actual ponds, it may be necessary to further examine the underlying causes such as inadequate quantity/quality of natural food in fertilized ponds (which in turn may be related to pond water quality) and poor grazing efficiency of fish on natural food assemblages. Efforts should also be undertaken to enhance the pond systems models embodied in Chapter 6 by including descriptions of pond water quality (as discussed earlier), and parameterizing the models for different fish species as well as culture conditions.

The issue of simulation model parameterization is one of the main factors that has limited the use of such models in applied research fields such as aquaculture. The amount of time and effort expended in manually calibrating the fish bioenergetics model (Chapter 5) during the early part of the research presented in this dissertation motivated the development of the automated GA-based parameter estimation technique described in Chapter 7. As with other parameter estimation techniques, the GA-based method also requires an objective function to be optimized, which in this study was the minimization of the absolute error between predicted and observed fish weights. However, in contrast to more traditional numerical optimization algorithms that are used for parameter estimation, the GA-based technique does not require partial derivative evaluations of the objective function. The technique consistently generated parameters which resulted in good correspondence between fish growth predicted by the bioenergetics model and observed data for all the five fish species tested within relatively short time periods. In the future, this technique should be used to calibrate the more detailed pond ecosystem models such as those described in Chapter 6. Apart from applications to the current work, the GA-based technique should also be of use in parameterizing other complex ecological models.

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# APPENDICES

# APPENDIX I

# GENERATION OF WEATHER DATA FOR POND SIMULATIONS

The water temperature and water budget simulation models described in Chapters 2 and 3 of this dissertation require several weather data inputs, including short-wave solar radiation, air temperature, cloud cover, wind speed, relative humidity and precipitation. A simple weather generator has been implemented in POND to provide users of the decision support system with an alternate means of obtaining some of these data (discussed below) if locally measured values are unavailable. Although more sophisticated weather generators are available to predict the required weather data (e.g., Richardson and Wright, 1984; Geng et al., 1988), we have chosen not to use them because their parameterization requires several years of historical data.

Suitable methods to generate relative humidity and precipitation data could not be identified; the former variable is therefore assumed to be a constant when the weather generator is used. When simulations are conducted, relative humidity should be set to the mean of observed values if they are available or a value of 75% (which is likely to be adequate for most locations) can be assumed. When the POND weather generator is used, precipitation is assumed to be zero.

## Short-wave solar radiation

The method used to calculate short-wave solar radiation ($\phi_s$) in POND is principally based on the calculations given by Wunderlich (1972; cited in Fritz et al., 1980). According to this author, $\phi_s$ can be calculated as:

$$\phi_s = \frac{I_{sc}}{r_{es}^2} \sin \alpha \, A_t^m (1 - 0.65\, C_c^2) \qquad (1.1)$$

where $I_{sc}$ = solar constant ($1.2043 \times 10^5$ kJ m$^{-2}$ d$^{-1}$), $\alpha$ = solar altitude (radians), $A_t$ = atmospheric transmission coefficient, m = optical air mass, $r_{es}$ = relative distance between the earth and sun, and $C_c$ = fraction of the sky that is covered by clouds at the site (0-1).

The relative distance between the earth and sun varies on a daily basis because of the elliptical nature of the earth's orbit, and can be approximated by (Ryan and Stolzenbach, 1971):

$$r_{es} = 1 + 0.017 \cos\left[\frac{2\pi(186 - JD)}{365}\right] \qquad (1.2)$$

where JD = Julian day of the year (1-365).

Solar altitude ($\alpha$) is the angle between the sun's rays and a horizontal surface on earth (Hsieh, 1986), and is given by:

$$\sin \alpha = \sin L_t \sin \delta + \cos \delta \cos L_t \cos h_a \qquad (1.3)$$

where $L_t$ = site latitude, $\delta$ = declination of the sun, and $h_a$ = hour angle, all of which are expressed in radians.

Solar declination ($\delta$), which changes on a daily basis, refers to the angular distance between the center-to-center line from the sun to the earth, and the projection of this line on the equatorial plane of the earth (Hsieh, 1986). By convention, the declination is considered to be positive in the northern hemisphere, and negative in the southern hemisphere. It can be calculated as (Henderson-Sellers, 1984):

$$\delta = 0.4093 \sin\left[\frac{2\pi\,(JD - 79.75)}{365}\right] \tag{1.4}$$

The hour angle of a given point on the earth's surface is the angular distance through which the earth must turn to bring the meridian of the point directly below the sun, and can be calculated as (Fritz et al., 1980):

$$h_a = \frac{(t_s - 12)\,\pi}{12} \tag{1.5}$$

where $t_S$ = true solar time (h), which refers to the angular movement of the sun across the sky. Local solar noon occurs when the sun is immediately above the meridian of the site. $t_S$ can be calculated from the local clock time at the site ($t_L$), an astronomical correction term or the equation of time ($A_{ct}$), and a longitude correction term ($L_{ct}$), all of which are expressed in h, as follows (Hsieh, 1986):

$$t_s = t_L + A_{ct} + L_{ct} \tag{1.6}$$

The astronomical correction term accounts for variations in daylength caused by changes in the velocity of the earth as it revolves in an elliptical orbit around the sun, and is given by (Hsieh, 1986):

$$A_{ct} = \frac{9.87 \sin 2\beta - 7.53 \cos\beta - 1.5 \sin\beta}{60} \tag{1.7}$$

where $\beta = 0.01726\,(JD - 81)$.

The longitude correction term ($L_{ct}$) accounts for the time taken by the sun to traverse 1° of longitude (4 min), and is computed as (Hsieh, 1986):

$$L_{ct} = \frac{L_s - L_g}{15} \tag{1.8}$$

where $L_S$ = standard meridian for the time zone (°), and $L_g$ = site longitude (°).

The atmospheric transmission coefficient is a function of the geographic location of a site and time of the year, and may be empirically calculated as (Fritz et al., 1980):

$$A_t = 0.0685 \cos\left[\frac{2\pi (JD + 10)}{365}\right] + 0.80 \tag{1.9}$$

The optical air mass varies with the barometric pressure, and therefore with altitude (z, in m). Following Kasten (1964; cited in Fritz et al., 1980), *m* is given by:

$$m = \frac{[(288 - 0.0065\,z)/288]^{5.256}}{[\sin\,\alpha + 0.15(a + 3.885)]^{-1.253}} \tag{1.10}$$

Once $\phi_s$ has been calculated by the use of equations (1.1-1.10), it is necessary to account for short-wave reflectivity ($A_s$; see Equation 6 in Chapter 2) to arrive at the solar radiation that actually penetrates into the pond water ($\phi_{sn}$). Henderson-Sellers (1984) suggests that it is adequate to assume $A_s = 0.06$ for mean daily calculations of $\phi_{sn}$.

However, it may be desirable to account for the effects of solar altitude angle and cloud conditions on $A_s$ in which case the following expression (Fritz et al., 1980) can be used:

$$\phi_{sn} = \phi_s \left[1 - x\,(57.3\,\alpha)^y\right] \tag{1.11}$$

where the term $x\,(57.3\,\alpha)^y$ corresponds to $A_s$, with x and y being empirical factors, values of which are dependent on the cloud cover ($C_c$; Table AI.1). Cloud cover data to estimate the factors x and y are generated by the procedures that are described later in Section 3 below.

Table AI.1. Cloud type, cloud cover values ($C_c$), and estimates of empirical factors (x and y) from Fritz et al. (1980).

| Cloud type | $C_c$ | x | y |
|---|---|---|---|
| Clear | 0.0 | 1.18 | - 0.77 |
| Scattered | 0.1-0.5 (0.5)[1] | 2.20 | - 0.97 |
| Broken | 0.6-0.9 (0.75)[1] | 0.95 | - 0.75 |
| Overcast | 1.0 | 0.35 | - 1.45 |

[1] Represent the actual $C_c$ values used in POND depending on the selected cloud type.

Daily vs. Diurnal mode

POND allows users to perform both daily and diurnal simulations. In the former type of simulation, diurnal trends in variables such as short-wave solar radiation and air temperature are ignored and the mean values of these variables are used as model input. There are minor differences between short-wave solar radiation predictions under each of these simulation scenarios.

To arrive at total daily insolation values for daily simulations, it is necessary to integrate Equation 1.1 over the time period between sunrise and sunset. To avoid these additional calculations during daily simulations, it is assumed that the maximum incident short-wave solar radiation ($\phi_{s,\max}$) occurs at the local solar noon (i.e., when $h_a = 0$) and that incident radiation during daylight hours has a symmetrical profile around this maximum value. Thus, the mean solar radiation during daylight hours is given by $\phi_{s,\max}$ /2. This value needs to be further scaled by the photoperiod *p* to arrive at the daily average as follows:

$$\phi_s = p\left[\frac{\phi_{s,max}}{2}\right] \qquad (1.12)$$

*p* is expressed as the fraction of a day that is daylight and can be calculated as $-h_r/\pi$ (Hsieh, 1986), where $h_r$ = local sunrise angle given by:

$$h_r = -\cos^{-1}(-\tan L_t \tan \delta) \qquad (1.13)$$

The sunset hour angle ($h_s$) is equivalent to $h_r$ but with the sign reversed, and is positive by convention (Hsieh, 1986).

For diurnal simulations, $\phi_s$ is set to zero at night, and is estimated during daylight hours (i.e., when $h_r \leq h_a \leq h_s$) as follows (Monteith, 1973):

$$\phi_s = \phi_{s,max} \sin(\pi t / p) \qquad (1.14)$$

where *t* is the time (d) elapsed since sunrise.

Finally, for both daily and diurnal simulations, $\phi_s$ is adjusted for short-wave reflectivity (see Equation 1.11 above) to arrive at estimates of $\phi_{sn}$.

## Air Temperature

Air temperature is required to estimate two components of the energy balance (net long-wave atmospheric radiation and conductive heat flux) used to predict water temperature in ponds (see Chapter 2). As with the other weather parameters, air temperature is difficult to predict because of seasonal and diurnal trends. Therefore, we use empirical equations developed by other researchers to predict daily and diurnal air temperature.

Daily vs. Diurnal mode

The following polynomial equations (Straskraba and Gnauck, 1985), which only require latitude, altitude, and Julian Day inputs are used to predict mean air temperature ($T_a$; °C) for daily simulations:

$$T_{am} = 25.92 + 0.4893\,L'_t - 0.02739\,L'^{2}_t + 0.0001782\,L'^{3}_t \tag{2.1}$$

$$T_{aa} = 1.536 + 0.05735\,L'_t - 0.01296\,L'^{2}_t + 0.0001312\,L'^{3}_t \tag{2.2}$$

$$T_a = T_{am} + T_{aa} \sin\left[\frac{\pi\,(JD + P_a)}{180}\right] - T_r z \tag{2.3}$$

where $T_{am}$ = annual air temperature mean (°C), $T_{aa}$ = semiamplitude of annual air temperature variations (°C), $T_r$ = temperature change with each 100m rise in altitude above mean sea level (usually in the range 0.5-0.8), $L'_t$ = correction factor applied to the site latitude (= $|L_t - 3.4|$; with $L_t$ in degrees), and $P_a$ = phase angle (220° for the Northern hemisphere and 100° for the Southern hemisphere).

For diurnal simulations, values of air temperature at each time step ($T_{ad}$) are required during numerical integration. If the maximum ($T_{amax}$) and minimum ($T_{amin}$) air temperatures are known (e.g., from weather files), diurnal temperatures at different times of the day can be calculated under the assumption that air temperature follows a more or less sinusoidal pattern (Card et al., 1976). If it is additionally assumed that $T_{amin}$ and $T_{amax}$ occur at 0600h and 1500h respectively, the Card algorithm reduces to the following expression (Culberson and Piedrahita, 1992):

$$T_{ad} = T_{dm} + (T_{a\,max} - T_{a\,min}) \times 0.4484 \times \left\{ \sin\left(\frac{\pi(t_L - 2.7489)}{12}\right) + 0.2706 \times \sin\left[2\left(\frac{\pi(t_L - 2.7489)}{12}\right)\right]\right\} \tag{2.4}$$

If $T_{amax}$ and $T_{amin}$ data are not available, they are approximated as follows:

$$T_{a\,max} = T_{dm} + \left(\frac{T_{amp}}{2}\right) \tag{2.5}$$

$$T_{a\,min} = T'_{dm} - \left(\frac{T_{amp}}{2}\right) \tag{2.6}$$

where $T_{amp}$ = typical daily temperature amplitude or mean difference between $T_{amin}$ and $T_{amax}$ (°C). In the POND weather generator, $T_{amp}$ is assumed to be constant for the period of simulation.

## Cloud Cover

Values for the fraction of the sky that is covered by clouds ($C_c$) are required for each day of the simulation, for both direct use in the water temperature model (Chapter 2) and to estimate the empirical factors x and y (Equation 1.11; see also Table AI.1) for short-wave solar radiation prediction. Models suitable for the prediction of such data could not be identified.

Some simplified methods are therefore provide to arrive at $C_c$ values for use in POND simulations. For example, when weather data are generated, users may optionally select the type of cloud cover (clear, broken, scattered or overcast) that best matches the season to be simulated, in which case the appropriate values of $C_c$, x and y from Table AI.1 are automatically used in Equations 1.1 and 1.11.

However, like other weather variables, the degree of cloudiness at any given site tends to vary both seasonally and diurnally, and is a function of air humidity, cloud altitude and cloud density. In addition, the degree of cloudiness may also vary in a random fashion. Therefore, use of a single cloud category for a full season may not adequately reflect changing weather conditions.

The alternative approach provided in POND is to generate cloud cover data from a normal distribution wherein users are required to specify whether the season is predominantly wet or dry. If wet conditions are assumed, $C_c$ values are drawn from a normal distribution with a mean of 0.625 and standard deviation of 0.1. The lower and upper bounds enforced on $C_c$ for wet season simulations are 0.25 and 1 respectively. Values for x and y corresponding to the stochastic values of $C_c$ are then set based on the cut-off point of $C_c$ for each category indicated in Table AI.1. Thus, if the generated value of $C_c$ is greater than 0.9, overcast conditions are assumed ($x = 0.35$, $y = -1.45$; Table AI.1). Similarly, for dry conditions, $C_c$ values are drawn from a normal distribution with a mean of 0.375 and standard deviation of 0.1; lower and upper bounds enforced on $C_c$ for such simulations are 0 and 0.75 respectively. Thus, if the stochastically generated value for $C_c$ is less than 0.1, we assume clear conditions ($x = 1.18$, $y = -0.97$; Table AI.1).

It should be noted that the statistically valid approach for examining the effects of a stochastic random variable on simulation results is to run the model repeatedly (at least 30 times), and summarize the state variables (e.g., water temperature) in the form of a mean and standard deviation. This applies to stochastic analysis of wind speed as well (see below). At this time, we have not examined the effects of these stochastic approaches on the distribution of water temperature profiles in ponds.

### Wind Speed

Wind speed (in m $s^{-1}$) data at reference height of 2m are required to estimate evaporative and conductive heat flux from a pond (see Chapter 2). Such data are not often collected in aquaculture facilities, with the possible exclusion of research sites. Further, wind patterns also exhibit substantial seasonal and diurnal trends, and may also vary in a stochastic manner. A suitable model to predict wind speeds has not been identified for use in POND.

If users do not have local wind speed measurements, they may either assume a constant mean wind speed for simulation runs or make use of an approach similar to stochastic cloud cover generation (as discussed in Section 3 above). If the latter approach is used, users are required to specify both the mean and standard deviation for the distribution of wind speed. POND then generates normally distributed random values of wind speed for the simulation runs.

# APPENDIX II

# A METHOD TO ESTIMATE SECCHI DISK VISIBILITY FROM CHLOROPHYLL *A* CONCENTRATIONS IN FISH PONDS

## BACKGROUND

Almazan and Boyd (1978) developed a simple model to express the relationship between chlorophyll *a* and Secchi disk visibility in earthen ponds from Central and Southern Alabama. The relationship is of the form:

$$\mathrm{Chl}\text{-}a = \frac{\mathrm{a}}{\mathrm{SDV}^{\mathrm{b}}} \tag{1}$$

where Chl-$a$ = chlorophyll $a$ concentration (mg m$^{-3}$), SDV = Secchi disk visibility (SDV; m), and $a$ and $b$ are non-linear regression parameters. Using regression fitting procedures, $a$ and $b$ were estimated by the above authors to be 19.14 and 1.976 respectively.

This simple model is useful in estimating phytoplankton density when SDV measurements are available. However, for pond systems modeling efforts where phytoplankton is one of the state variables, it is often important to estimate SDV based on the current phytoplankton biomass. This is because typical phytoplankton models (see also Chapter 6) require the use of light extinction coefficients to account for the effects of ambient light conditions on plankton growth; such coefficients can be indirectly estimated from SDV measurements (e.g., Poole and Atkins, 1929).

Thus, contrary to the approach used by Almazan and Boyd (1978), SDV becomes the variable dependent on phytoplankton biomass. Once a suitable function has been developed to express this dependency and the necessary parameters estimated for different locations, it is expected that the predicted values of SDV can be used to approximate light extinction coefficients in simulated ponds.

An effort was undertaken to develop such a function and parameterize it for several locations maintained by the Pond Dynamics/Aquaculture Collaborative Research Support Program (PD/A CRSP).

## METHODS

SDV (cm) and chlorophyll *a* (mg $m^{-3}$) data were extracted from the aquaculture database maintained by the PD/A CRSP for sites in Thailand (Bang Sai), Honduras (El Carao) and Rwasave (Rwanda). Data from all the ponds for the experiments conducted by CRSP researchers during Work Plan 5 (PD/A CRSP, 1989) were pooled together for these sites (see also Table AII.1). Averages of SDV were used for situations when two measurements of this variable were made.

Table AII.1. PD/A CRSP data sources for SDV and chlorophyll *a* data.

| Site | Start Date | End Date |
|---|---|---|
| Bang Sai (Thailand) | April 10, 1989 | March 19, 1991 |
| El Carao (Honduras) | November 11, 1989 | March 17, 1990 |
| Rwasave (Rwanda) | February 19, 1990 | December 12, 1990 |

As expected, data for all the locations (Figs. AII.1-AII.3) indicate an inverse relationship between SDV and chlorophyll *a*. Further examination of the relationship between SDV and chlorophyll *a* data for these sites suggests that, particularly for El Carao (Fig. AII.2), some factor other than phytoplankton density influences light penetration. Although plankton density is the primary source of turbidity in ponds, mud turbidity (either due to the water source or fish-induced bioturbation) may also be important under certain conditions (Boyd, 1979). A suitable expression to account for the additional source of turbidity appears to be of the form:

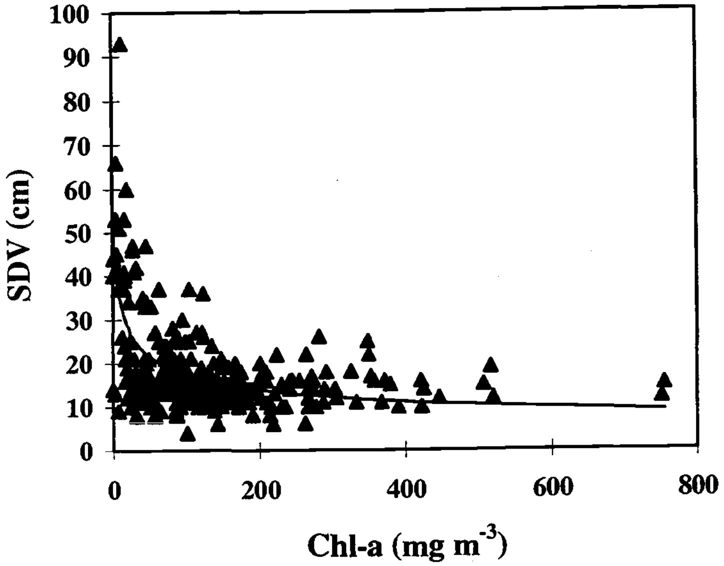

Figure AII.1. Relationship between Secchi disk visibility and chlorophyll *a* concentrations for Bang Sai, Thailand.

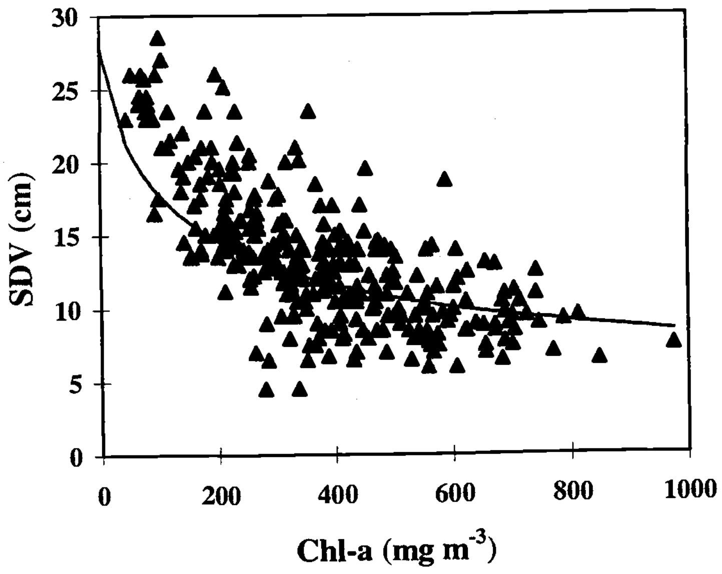

Figure AII.2. Relationship between Secchi disk visibility and chlorophyll *a* concentrations for El Carao, Honduras.

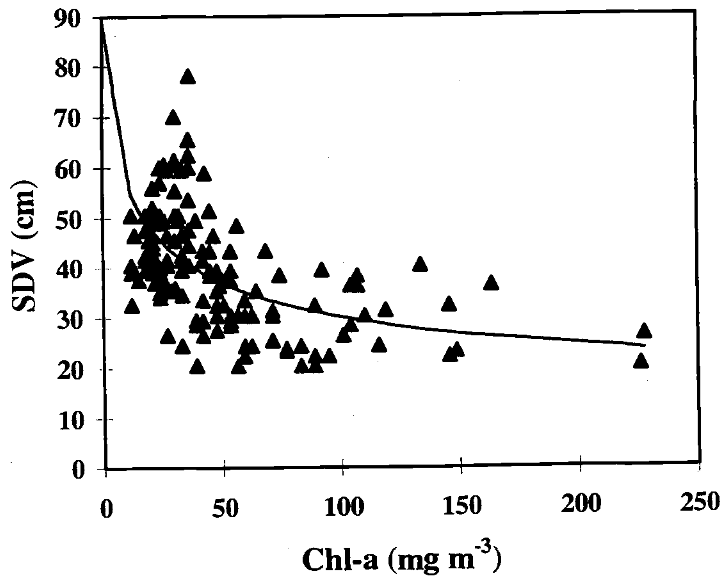

Figure AII.3. Relationship between Secchi disk visibility and chlorophyll *a* concentrations for Rwasave, Rwanda.

$$\mathrm{SDV} = \frac{\alpha}{(\mathrm{Chl}\text{-}a + \mathrm{T})^{\beta}} \tag{2}$$

where SDV is expressed in cm, *T* = baseline turbidity (Chl-*a* equivalents), and α and β are non-linear regression parameters. The parameter *T* is assumed to be a measure of the non-plankton turbidity inherent in the pond for the given location. Low values of *T* imply that phytoplankton-derived turbidity is the major factor influencing light penetration (as appears to be the case for Bang Sai; Fig. AII.1).

### Parameter Estimation

The parameters α, β and *T* in Equation 2 were estimated using Marquardt's method for non-linear regression in the statistical package *SAS* (SAS, 1988) applied to the SDV and Chl-*a* data for the three CRSP locations.

## RESULTS

Model fits obtained using Equation 2 are shown in Figs. AII.1-II.3. These fits (Table AII.2) in general had relatively high $r^2$ values. The parameter β appears to be more or less constant among the three sites with a range of 0.31-0.38 (Table AII.2). The parameter α is essentially an intercept term in Equation 2, and does vary from site to site (Table AII.2). Finally, as expected, the baseline turbidity estimate differs substantially among these sites, and is particularly high in El Carao. This parameter shifts the function curve along the x-axis (compare Figs. AII.1 and AII.2).

Table AII.2. Regression model parameters estimated from PD/A CRSP data for Bang Sai, El Carao and Rwasave.

| Site | $\alpha$ | $\beta$ | $T$ | $r^2$ |
|---|---|---|---|---|
| Bang Sai (Thailand) | 80.218 | 0.331 | 3.373 | 0.83 |
| El Carao (Honduras) | 114.727 | 0.376 | 43.693 | 0.94 |
| Rwasave (Rwanda) | 124.739 | 0.306 | 3.000 | 0.95 |

In summary, the function developed appears to be adequate to predict SDV values provided Chl-*a* measurements (or estimates in the case of phytoplankton modelling) are available. The function does not, however, address the possibility of the parameter *T* changing with pond conditions (e.g., different fish species or seasonal mud turbidity in the source water). This situation can be addressed if measurements of *T* are also made in ponds over time.