AQUACULTURE POND MODELING FOR THE ANALYSIS OF ENVIRONMENTAL IMPACT AND INTEGRATION WITH AGRICULTURE: MODELING OF TEMPERATURE, DISSOLVED OXYGEN, AND FISH GROWTH RATE IN STRATIFIED PONDS USING STOCHASTIC INPUT VARIABLES

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ABSTRACT

A model has been developed for the prediction of water temperature, dissolved oxygen (DO), and fish growth using stochastically generated input weather variables. The model has been calibrated and validated using data from pond sites in Thailand, Honduras, and Rwanda. The model includes modules for the generation of weather parameter values, and for the calculation of water quality and fish growth. The weather parameters generated include hourly solar radiation, air temperature, wind speed, and wind direction. The water quality variables modeled include water temperature, DO, total ammonia nitrogen, and phytoplankton (in terms of chlorophyll *a*). For modeling purposes, the water column is divided into three layers, each of which is considered to be fully mixed. Temperature and DO are calculated separately for each of the three layers resulting in simulations of stratified ponds. Given the stochastic nature of the weather input variables, the model must be run a number of times for a given set of pond management conditions. Typically, the model is run 20 times for each data set. The probability distributions for water quality and fish yield can be calculated from the simulation results, providing the basis for the estimation of probability distributions that can be of use to pond managers, planners, researchers, and teachers.

INTRODUCTION

Computer models developed previously for aquaculture systems use deterministic approaches. Under a deterministic simulation, a single set of model results is obtained for a particular run. While this approach is satisfactory for many situations, it fails to provide information related to potential changes in model results caused by stochastic variations in parameters or processes. An aquaculture pond is exposed to weather parameters that undergo stochastic changes. These changes result in fluctuations in model outcomes and real system conditions. The model described here is a first attempt at generating probability distributions of critical model variables based on a deterministic model run with stochastically generated weather parameter values. The model includes a module for the stochastic generation of weather parameter values (wind, solar radiation, wind velocity, wind direction, air temperature) (Lu et al., 1998). The module was developed to make use of the weather data available for PD/A CRSP sites. Although weather data have been collected at PD/A CRSP sites for a number of years, the magnitude of the data base for a given site is limited relative to data sets required for previous stochastic weather parameter generation models.

The weather generation module is linked to a model used to simulate pond water temperature, dissolved oxygen (DO), phytoplankton, total ammonia nitrogen (TAN), and fish biomass. Water temperature and DO are simulated using deterministic models based on previously developed PD/A CRSP models (+Culberson, 1993). TAN and chlorophyll *a* are simulated based on mass balance calculations (Lee et al., 1991). Fish growth is calculated using a bioenergetic model (Bolte et al., 1995; Jamu and Piedrahita, 1996) that can account for growth based on natural food (phytoplankton) as well as on artificial feed and other food sources.

The model accounts for water quality stratification, and three layers are considered: top, middle, and bottom. Conditions within each layer are assumed to be uniform. Fish distribution in the water column is assumed to be uniform as long as DO concentration is above a critical value. If DO drops below the threshold in a given pond layer, the fish move to an adjacent layer in search for higher DO. If DO is below the threshold in all layers, the fish congregate in the surface layer.

This final report provides a general description of the model and each of its components. The description is followed by a presentation of sample results and a discussion of how these can be used.

WEATHER GENERATION MODULE

The model has been constructed based on the statistics of monthly daily clearness indices (K_t, defined as the ratio of the actual solar radiation to the clear-sky radiation) (Lu et al., 1998). The cumulative frequency distribution (CFD) of the daily clearness index for each month was been obtained from the PD/A CRSP database for each of the Honduras, Rwanda, and Thailand sites. The correlation of the CFD and monthly average daily clearness index was examined for each of the sites to test the procedure for the generation of hourly solar radiation values.

After the CFD curves of K_t are obtained from the historical data, the procedure for the generation of the hourly solar radiation values has two steps. The first step consists of generating solar radiation values for each day based on the

CFD of K_t for each month. In the second step, a series of hourly values is obtained by dis-aggregation of the daily value using a first order autoregressive model.

The data sets used to calculate the daily clearness index probability distributions cover periods of eight years (1984 to 1991), six years (1986 to 1991), and six years (1990 to 1995) for Honduras, Rwanda, and Thailand, respectively. However, the data sets are not complete, with data missing from periods of up to three months. The extraterrestrial solar radiation was calculated using the equations of Duffie and Beckman (1991), to allow the calculation of K_t and $\overline{K_t}$ (monthly average clearness index value).

Since the monthly CFD curves are of similar shapes, a single equation form was selected for all the CFD curves after exploratory analysis of the data (TableCurve™). The equation was selected on the basis of the quality of fit as indicated by the correlation coefficient (R^2). To reduce the number of equations used while also maintaining the accuracy of the model, it was decided to combine similar CFD curves into a single equation as long as the R^2 for the combined equation could be maintained above 0.98. The CFD curves were then normalized (Amato et al., 1986; Graham et al., 1988), and daily solar radiation values were generated from the normalized equations using an autoregressive model in which the clearness index value on a given day depended on the value for the previous day and on a random term (Lu et al., 1998).

Hourly values for solar radiation were generated from the daily values determined as indicated above using the approach proposed by Knight et al. (1991). The approach essentially breaks down the daily values according to the sunset hour angle and the hour angle (Duffie and Beckman, 1991) using an autoregressive model similar to the one used for estimating daily values.

WATER QUALITY MODEL

Water quality parameters modeled were temperature, chlorophyll *a*, DO, and TAN. The model used is based on a previous model (Culberson, 1993) in which temperature and DO were simulated for a stratified pond (three layers) over 24-h periods. The model was expanded so that additional water quality parameters could be simulated (chlorophyll *a* and TAN), and simulations could be carried out for a complete growing season while maintaining a time step of one hour. Weather variables upon which water quality parameter calculations are based were generated using the Weather Generation Module described above.

Temperature

Water temperature in the model is calculated based on energy balances for each of the water layers (Culberson, 1993). Potential energy inputs are through solar and atmospheric radiation and through sensible heat transfer from the air over the pond. Heat losses are through back radiation to the atmosphere, through the latent heat of evaporation of water from the pond, and through sensible heat transfer to the air over the pond. Heat may also be lost from the pond bottom layer by transfer to the pond sediment. Distribution of the heat energy through the water column is modeled with processes of diffusion (molecular, turbulent, and convective) and radiation. Distribution of radiant heat energy through the water column is modeled using the Beer-Lambert Law in which the light extinction coefficient is estimated from chlorophyll *a* values. The relationship between chlorophyll *a* and light extinction coefficient was developed from PD/A CRSP data sets (Jamu et al., 1999) and accounts for phytoplankton and non-phytoplankton contributions to light extinction.

Chlorophyll *a*

Chlorophyll *a* was chosen as the variable to represent phytoplankton biomass. Phytoplankton growth rate was considered to be a function of light intensity, nutrient concentration (TAN), temperature, and chlorophyll *a* concentration. Non-optimal conditions of light intensity, nutrients, and temperature result in a reduction in the growth rate of phytoplankton below its optimum level (maximum specific growth rate). The effect of light intensity on photosynthetic rate at any particular time is considered to be dependent on the light intensity to which phytoplankton are exposed for the three previous days. Phytoplankton "sink" terms include respiration, grazing by fish, settling to the sediments, and non-predatory mortality.

Dissolved Oxygen

Dissolved oxygen calculations were based on mass balances in which production, consumption, and transfer rates were simulated. Oxygen production was due to photosynthesis by phytoplankton. Consumption terms considered include phytoplankton respiration, fish respiration, organic matter oxidation, nitrification, and sediment respiration. Transfer terms include diffusion across the air-water interface, and diffusion between adjacent layers (molecular, turbulent, and convective diffusion as for the temperature calculations).

Total Ammonia Nitrogen

TAN calculations were based on a mass balance similar to that developed for dissolved oxygen. Potential TAN sources include fertilizers, fish excretion, and the breakdown of organic nitrogen in the water column or the sediments. Processes that contribute to a reduction in TAN include uptake by phytoplankton and nitrification. Diffusion to the atmosphere was neglected in the model and TAN was assumed to be uniformly distributed in a pond.

FISH GROWTH MODEL

The fish growth model uses bioenergetics calculations and is based on models proposed by Liu and Chang (1992), and later revised by others (Bolte et al., 1995; Jamu and Piedrahita, 1996). In the model, fish growth is estimated from the difference between the energy content of food intake and energy outputs from the fish. Food intake is considered to be a function of environmental parameters (temperature, DO, and TAN), fish characteristics (species, size, and feed preferences), and food concentration and composition (three types of food are considered: phytoplankton, non-phytoplankton, and supplied feed). The energy output is estimated as a single term representing excretion, wastes, and catabolism (Liu and Chang, 1992).

SAMPLE RESULTS

The process of model calibration and validation was carried out with data from Honduras, Rwanda, and Thailand. After initial testing, the model was run for Thailand data, and results were used to adjust model coefficients in the process of calibration (Table 1). Subsequent runs for other sites used the calibrated values obtained from the Thailand simulations, in addition to site-specific parameters and initial conditions. Initial conditions used for a given run were the mean values of measurements from replicate ponds. In all cases, the simulations were carried out for 150-day growing seasons, and each simulation run was repeated 20 times to obtain probability distributions for the outcome variables. Sample results presented below include water quality and fish growth variables.

Water Quality

The simulated water quality variables include temperature, chlorophyll *a*, DO, and TAN. Diel measurements of temperature and dissolved oxygen were collected at approximately two-week intervals, and those values were used to determine the accuracy of the simulations. The figures show the simulated values only for the days for which diel measurements were available for comparison. Temperature and DO simulations are presented here. Chlorophyll results have been presented previously (Lu and Piedrahita, 1999).

Table 1. Calibrated parameter values for the water quality model.

Parameter	Thailand	Rwanda	Honduras
Slope of PI Curve (mg C/(mg chla *(μmol m^{-2}))	0.05	0.04	0.03
Oxygen Consumption in Organic Matter Oxidation (mg O_2/mg OM)	3.0	3.0	1.08
Water Column O_2 Respiration Rate (mg O_2 m^{-2} h^{-1})	100	100	200
Non-phytoplankton Light Extinction Coefficient (m^{-1})	3.6	4.1	8.5
Chla Content (mg l^{-1} Chla/mg l^{-1} dry cell)	0.01	0.012	0.01

Simulation results can also be presented as frequency distributions. The frequency distributions are constructed by determining the frequency of obtaining a simulated value within a given range (after 20 simulations, each 150 days long). Frequency distributions are constructed for each depth and for each time of the day for which measurements are available, namely 0600 h, 1000 h, 1400 h, 1800 h, and 2200 h.

The impact of the stochastic variation in the weather variables can be seen in the variation of the simulation results obtained. In addition, the accuracy of the simulations in predicting measured conditions varied between sites and between experimental treatments.

<u>Temperature</u>
Temperature simulations are shown for the Thailand site (Figures 1 through 4). The data correspond to Experiment 4, Cycle 4, designed to test the effects of different fertilization rates on fish growth and water quality. The treatments used included fertilization with 44, 100, and 200 kg ha^{-1} wk^{-1} of chicken manure. The manure was supplemented with urea to maintain the ratio of carbon to nitrogen (C:N) at 5:1. Figures 1 through 3 show the temperature at the three depths for the 100 kg ha^{-1} wk^{-1} manure fertilization treatment. This treatment was used to calibrate the model. Figure 4 shows the surface water temperature for the 200 kg ha^{-1} wk^{-1} treatment. In general, there were substantial differences between the temperatures at the three depths, but there was little difference between the temperatures for the different fertilization treatments.

Differences between the three depths are easily observed with the frequency distribution curves (Figures 5, 6, and 7). In general, the distributions tend to be much tighter for the bottom layer than for the top layer. This is in agreement with observations of bottom conditions being more stable than surface or mid-water conditions. There is also an increased frequency (and probability) of excessively high temperatures in the surface layer.

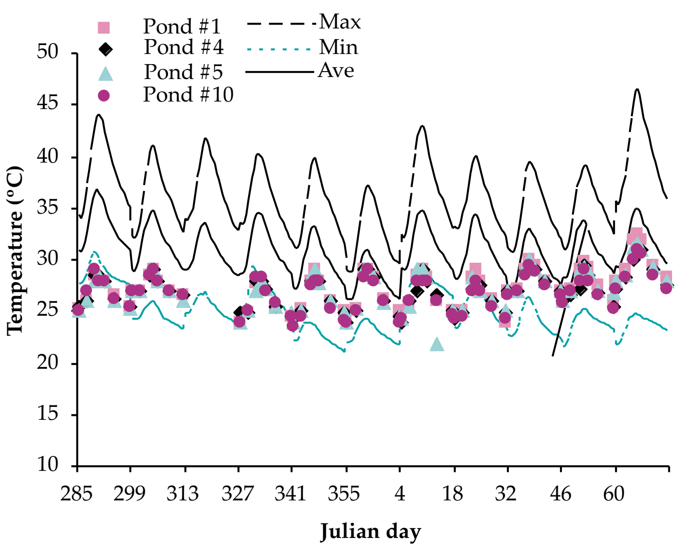

Figure 1. Simulated (curves) and observed (data points) temperature of the surface layer for the Thailand site under fertilization with 100 kg ha^{-1} wk^{-1} of chicken manure.

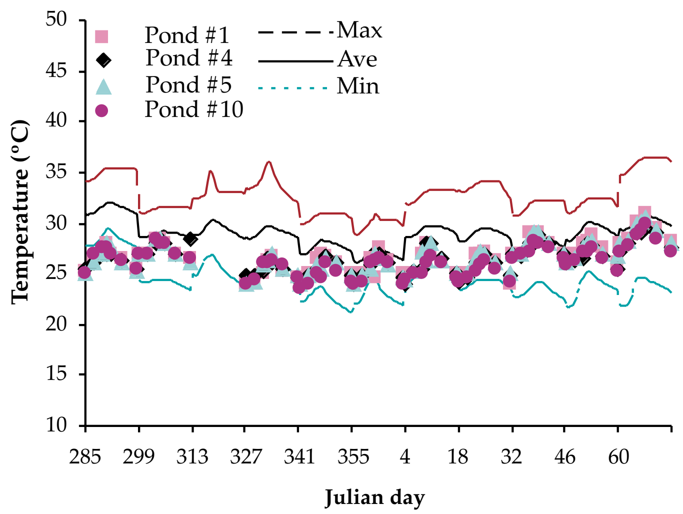

Figure 2. Simulated (curves) and observed (data points) temperature of the middle layer for the Thailand site under fertilization with 100 kg ha^{-1} wk^{-1} of chicken manure.

Dissolved Oxygen

In general, dissolved oxygen simulations were less accurate than those for temperature, as illustrated in Figures 8 and 9. This reflected the difficulties in simulating the processes associated with oxygen production (photosynthesis) and consumption (respiration by phytoplankton, fish, sediments, etc.). Frequency distributions (Figure 10) illustrate the usefulness of the stochastic simulations in quantifying the probability of having DO values outside a prescribed range needed by the fish. The frequency distribution (Figure 10) shows that during the evening there is a high probability of low DO even in the surface layer, but this probability is reduced considerably during the middle of the day. Comparison of the simulated and measured probability distributions (Figure 11) shows very good agreement. The results on Figure 11 are aggregated for the daylight hours (0600 h to 1800 h) due to the low number of measured values available in the database.

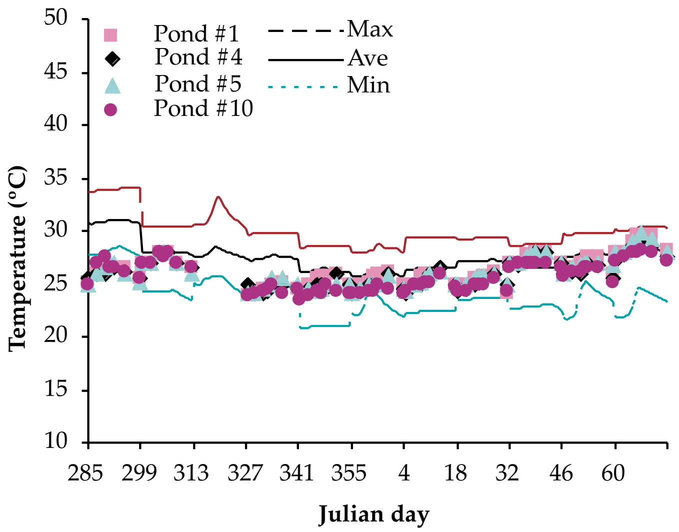

Figure 3. Simulated (curves) and observed (data points) temperature of the bottom layer for the Thailand site under fertilization with 100 kg ha^{-1} wk^{-1} of chicken manure.

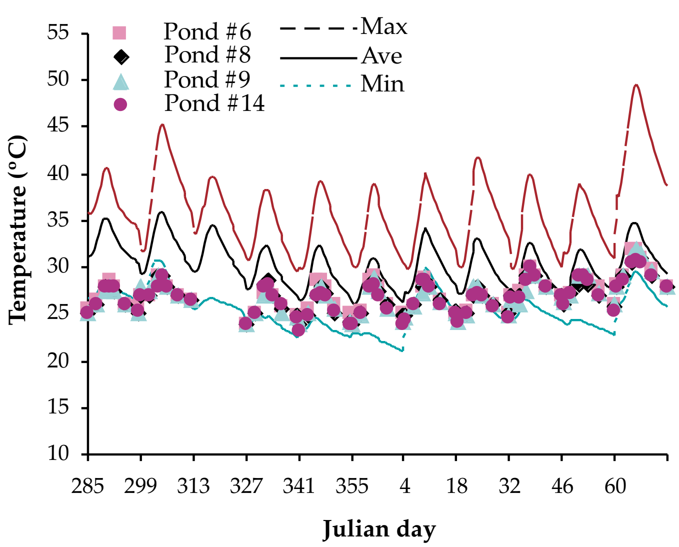

Figure 4. Simulated (curves) and observed (data points) temperature of the surface layer for the Thailand site under fertilization with 200 kg ha^{-1} wk^{-1} of chicken manure.

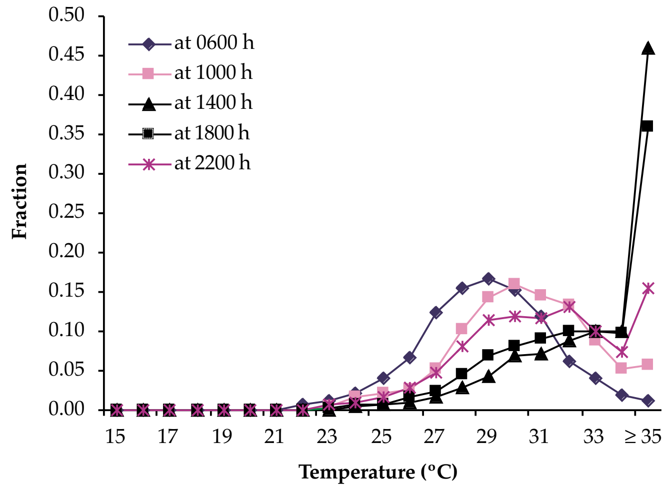

Figure 5. Frequency distribution curve for temperature of the surface layer for the Thailand site under fertilization with 100 kg ha^{-1} wk^{-1} of chicken manure.

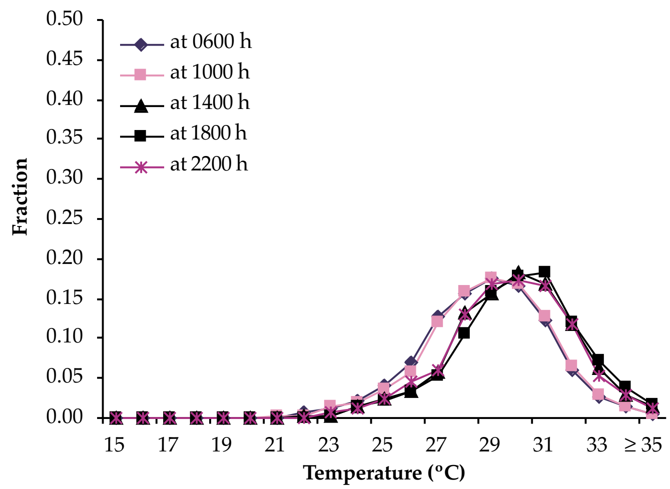

Figure 6. Frequency distribution curve for temperature of the middle layer for the Thailand site under fertilization with 100 kg ha^{-1} wk^{-1} of chicken manure.

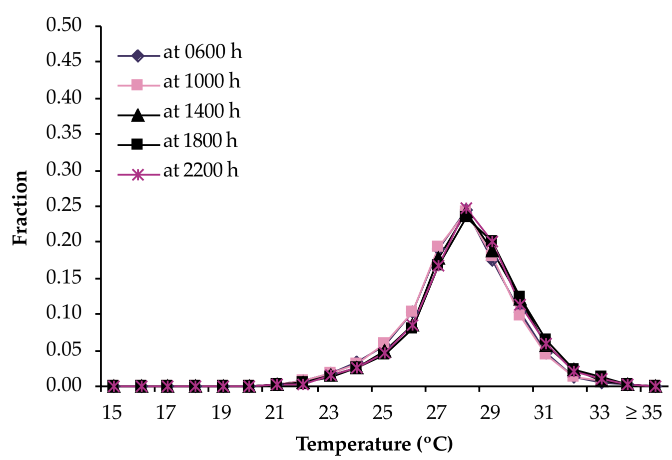

Figure 7. Frequency distribution curve for temperature of the bottom layer for the Thailand site under fertilization with 100 kg ha^{-1} wk^{-1} of chicken manure.

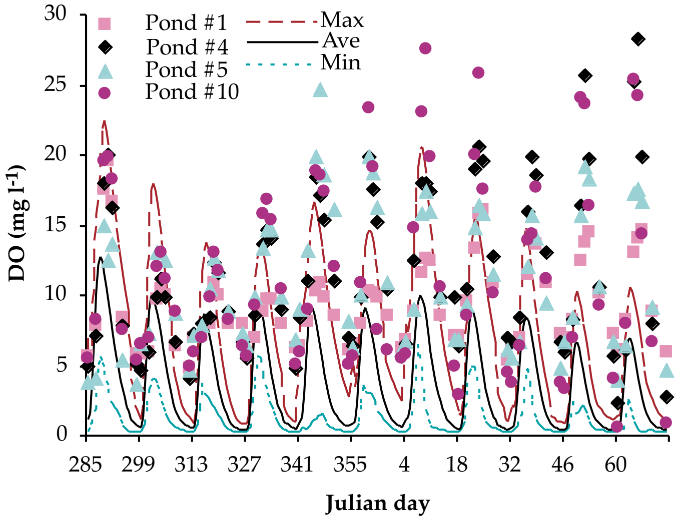

Figure 8. Simulated (curves) and observed (data points) DO of the surface layer for the Thailand site with 100 kg ha^{-1} wk^{-1} of chicken manure.

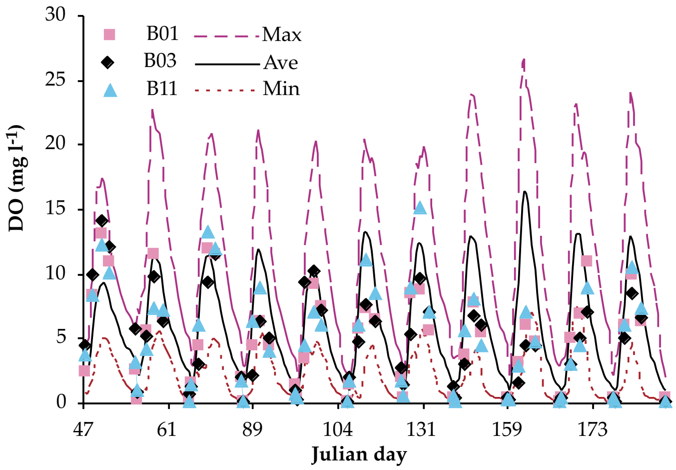

Figure 9. Simulated (curves) and observed (data points) DO of the surface layer for the Honduras site with 500 kg ha^{-1} wk^{-1} of chicken manure.

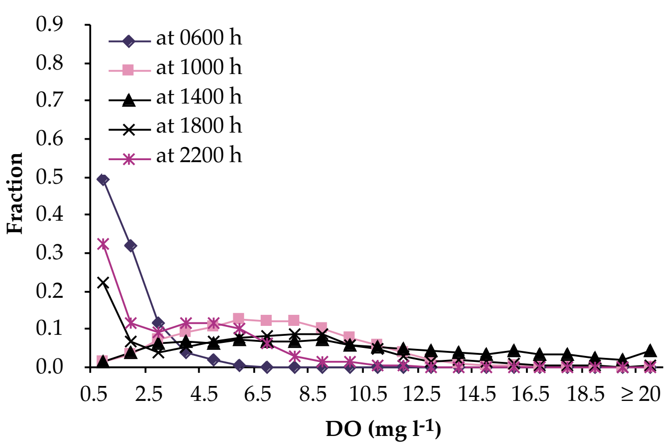

Figure 10. Frequency distribution curve for DO of the surface layer for the Honduras site under fertilization with 500 kg ha^{-1} wk^{-1} of chicken manure.

Fish Growth

Fish growth proved to be the most difficult parameter to simulate. Accuracy of the simulations varied considerably between sites and between pond treatments. In addition, data from some replicate ponds showed very high variability (Figure 12). This suggests that there are subtle differences between ponds receiving replicate treatments that are difficult to identify and that result in substantial differences in fish growth. These differences in fish growth between replicates were more noticeable for Thailand than for the other sites. For example, a simulation for the Rwanda site shows less variation between replicate ponds, and better agreement between the measured and simulated values (Figure 13).

Discussion

The generated weather variables constituted satisfactory stochastic data sets based on the available measurements for each PD/A CRSP site. However, agreement between simulated and measured values of water quality and fish growth varied considerably. The quality of the simulations varied between

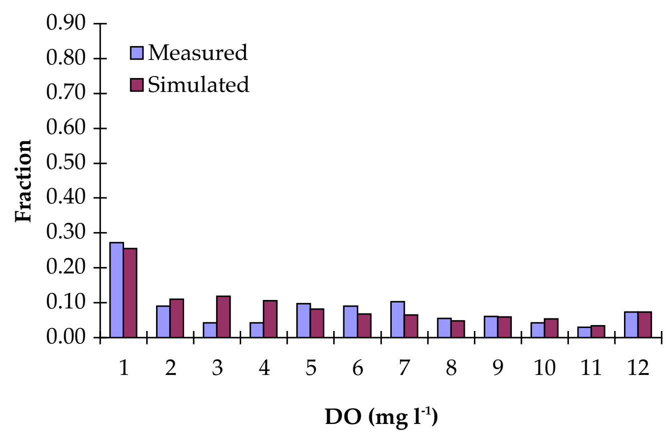

Figure 11. Frequency distributions for the daytime (0600 to 1800 h) measured and simulated surface DO for the Honduras site

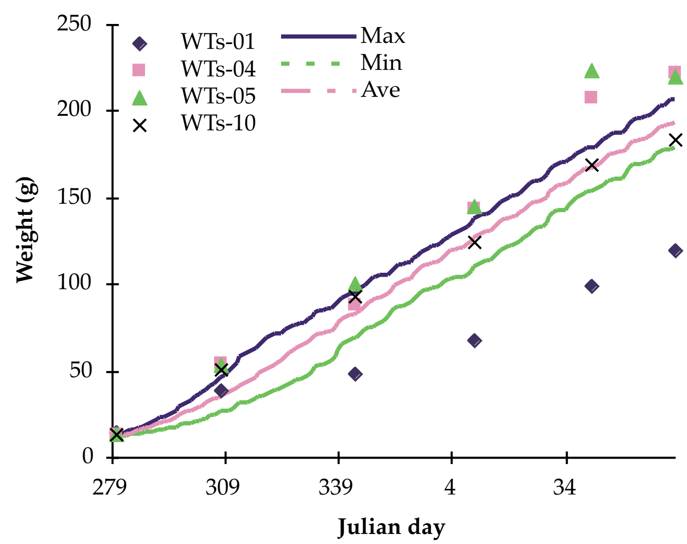

Figure 12. Fish growth simulation for the Thailand site under fertilization with 100 kg ha^{-1} wk^{-1} of chicken manure.

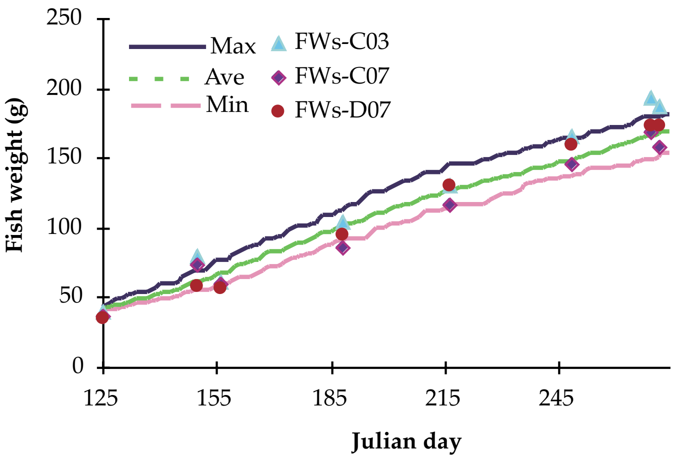

Figure 13. Fish growth simulation for the Rwanda site under fertilization with 500 kg ha^{-1} wk^{-1} of chicken manure and fresh cut grass.

sites and between treatments. Although the stochastic simulations account for much of the variability caused by weather fluctuations, there are variations between replicate ponds that could not be simulated with the model. These variations between ponds were particularly evident for the Thailand site, and their cause is unknown. Identifying the causes of variation between replicate ponds, and developing models to be able to predict the magnitude of that variation should be a goal for future research efforts.

Even with the limitations noted, the model developed can provide useful information on potential water quality and fish yields. The model can be used with data from different sites, and the results obtained are useful in identifying possible probability distributions for water quality variables and fish growth. The relatively modest data requirements for the weather generation submodel make possible the generation of stochastic weather values for sites for which limited data are available. As a result, the model can be run for potential sites as part of an analysis of possible yields from aquaculture ponds under a variety of treatment options.

ANTICIPATED BENEFITS

The model provides the possible ranges of water quality and fish growth in ponds using statistically generated weather values as inputs. The weather values are generated based on historical records for a particular site. The variability of water quality and fish yield for short and long terms also can be studied for varying feeding and fertilization regimes, size of fish at stocking and harvesting, pond location, and date of fish stocking and harvesting. The model will be useful in the planning of fish ponds, management of water quality, selection of pond site, and analysis of alternative pond management strategies.

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