Modeling of Temperature and Dissolved Oxygen in Stratified Fish Ponds Using Stochastic Input Variables

Interim Work Plan, DAST Study 4

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Introduction

A model is being developed using stochastic input variables for the simulation of temperature, dissolved oxygen (DO), and fish growth in stratified fish ponds. Two major modifications have been made from the previous version of the model during the past year: the procedure for generating daily and hourly solar radiation data was changed; and oxygen consumption by nitrification was separated from the water column respiration term. In the previous model, the procedure for generating solar radiation values was based on the mean and variance of historical data for each day; however, the recorded data available through the PD/A CRSP Central Database have many missing values. This, in part, is due to the fact that weather data were collected only when pond experiments were being conducted. A new statistical method has been used with the data to develop a procedure for generating solar radiation values for stochastic pond simulations. For short term simulations, oxygen consumption rate by nitrification and decomposition of carbonaceous organic matter can normally be combined into a single, temperature dependent term. For the long term simulations (approximately one growing season) currently being carried out, these two oxygen consuming processes need to be considered separately, and the model has been modified to include the two terms.

Model Structure

The model includes sub-models for generation of weather values,simulation of temperature, DO, and fish growth. The temperature and DO sub-models are based on the work of Losordo (1988) and Culberson (1993) and have been modified for long-term simulations as described by Santos Neto and Piedrahita (1995). Additional modifications have been implemented to the dissolved oxygen model regarding phytoplankton simulations (Lu and Piedrahita, 1996). The fish growth model has been described by Jamu and Piedrahita (1996). The new procedure developed for the generation of solar radiation values and the separation of the water column oxygen consumption from nitrification are described in this report.

Model to Generate Solar Radiation Values

The goal of this research is to develop a water quality model which can predict the variability of water quality and fish growth associated with weather conditions at a given location. To achieve this goal, it is essential that the weather parameters used to execute the water quality and fish growth models accurately represent conditions at the chosen site. Conventional methods for generating weather parameters are based on probability distributions generated from long term records for a given site. However, the data available through the PD/A CRSP database do not fulfill the requirements of conventional weather prediction methods; data have not been collected for enough years, and since data were collected only while pond experiments were in progress, many of the years for which data are available are incomplete. The method developed and presented here is based on the monthly groupings of the data.

Previous researchers have found that the monthly cumulative probability distributions of clearness index (clearness index, K_t, is defined as the ratio between solar radiation at a particular site and theoretical, extraterrestrial solar radiation) are independent of location and month (Liu and Jordan, 1963). The monthly cumulative distributions were found to be functions of monthly average clearness

$$K_t(n) = F^{-1}[G(\chi(n))] \tag{1}$$

where,

$F^{-1}[] =$ the inverse function of $F[K_t]$, the cumulative probability function which is obtained from the measured data,

$$G[\chi(n)] = 0.5 + 0.5 * \mathrm{erf}(\chi(n)/\sqrt{2}) \tag{2}$$

$\mathrm{erf}(\chi) =$ error function defined as

$$\mathrm{erf}(\chi) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\chi} \left(e^{-t^2/2}\right) dt \tag{3}$$

$\chi(n) =$ random number generated using a first order autoregressive model

$$\chi(n) = \rho \cdot \chi(n-1) + \omega \tag{4}$$

r = autocorrelation coefficient of lag one between two consecutive days

w = normal distribution random number with a mean of zero and a variance of $1 - \rho^2$

$$K_h = K_m - \frac{\sigma_{kt}}{1.58} \ln\left[\frac{1}{0.5(1+\mathrm{erf}(\frac{\varepsilon}{\sqrt{2}}))} - 1\right] \tag{5}$$

where,

K_h = generated hourly solar radiation value at time h

$$K_m = K_i - 1.167K_i^3(1-K_i) + 0.979(1-K_i)\exp[\frac{-1.141(1-K_i)}{K_i \cos\theta_Z}] \tag{6}$$

K_i = generated daily solar radiation value on day i

q_z = zenith angle

$$\sigma_{kt} = 0.1557\sin(\frac{\pi K_i}{0.933})$$

ε = normally distributed random number with a mean of zero and a standard deviation of one.

index, $\overline{K_t}$ (Liu and Jordan, 1963). Because the probability distribution of clearness index values is not normal, it needs to be transformed to a normal distribution so that a random number can be generated and used with the probability distribution of clearness index to obtain a clearness value, K_t. The transformation can be expressed as follows (Graham et al., 1988)(see previous page).

The hourly solar radiation estimates are obtained using an empirical equation proposed by Graham and Hollands (1990) (see previous page).

Oxygen Consumption by Nitrification

Nitrification is a major factor in determining DO concentration. In previous models, nitrification was considered as a component of water column respiration. Water column respiration also includes the oxygen consumed in the oxidation of organic matter, phytoplankton dark respiration, and zooplankton respiration (Losordo, 1988; Culberson, 1993). For short term simulations, water column oxygen consumption rate has been considered to be a function of temperature only. However, for long term simulation, the rates of nitrification and oxidation of organic matter are different, and they cannot be considered as functions of water temperature only. In separating nitrification rate from other water column oxygen consumption processes, its rate is assumed to follow a first order model as a function of temperature and total ammonia nitrogen concentration. The inclusion of nitrification as a separate oxygen consumption term is also associated with the addition of ammonia nitrogen as a state variable to the pond model. In addition to nitrification, other processes affecting ammonia concentration, such as fertilization, fish feeding, and phytoplankton growth, need to be considered in the model. Oxygen consumption by nitrification is expressed as follows (Lee, et al. 1991):

$$MOnitr = 4.57\ K_N \theta^{(T-20)} N \qquad (7)$$

where,

K_N = nitrification rate, 1/hr;

q = water temperature dependence coefficient of nitrification;

T = temperature, ˚C; and

N = ammonia concentration, mg/l.

Results and Discussion

The model has been verified using PD/A CRSP data collected in Thailand. The model was run (for twenty simulations) using stochastically generated weather inputs to obtain maximum, minimum, and average values for output variables. The simulations were run for an 83 day period, from Julian day 40 to 123. Because observed hourly values are available for only six days during this period in 1988 (Julian day 40, 54, 68, 82, 96, and 110), the simulation hourly results are compared to the observed data for these six days. The simulated results are compared to the observed data including the cumulative probability curves of daily solar radiation, hourly solar radiation, temperature, DO, and fish weight (Figures 1 through 9).

The cumulative probability distributions of daily solar radiation values generated are compared to the measured data in Figure 1, showing good agreement. The hourly solar radiation values are compared to the observed data in Figure 2. The measured values fall within the range of generated values for most cases—only a few data points fall below the minimum simulate value obtained after twenty simulations, especially on Julian day 68. The cumulated probability functions were obtained using the data from 1990 to 1995. The generated data are compared with the data collected from Thailand in 1988. It was noted that the measured data in 1988 were much lower than the data measured from 1990 to 1995.

The simulated temperatures at three depths are shown in Figures 3 through 5. The observed data are not always within the range of simulated values. Although this is evident at the three depths, the differences are more pronounced for the surface water layer than for the middle and bottom layers. On Julian day 40, 54, and 82, the measured values are underestimated, while on Julian day 68 the values are overestimated. The maximum difference between the average simulated temperature and the observed value is 2.5˚C at the top layer on Julian day 40, the initial day of the simulation.

The comparison of hourly DO values at the three layers are shown in Figures 6 through 8. Most of the measured values available fall within the range of simulated values. The maximum DO difference between the observed and simulated values is 6.8 mg/l on Julian day 110 at bottom layer. The differences are caused, in part, by the lack of stratification evident in the measured

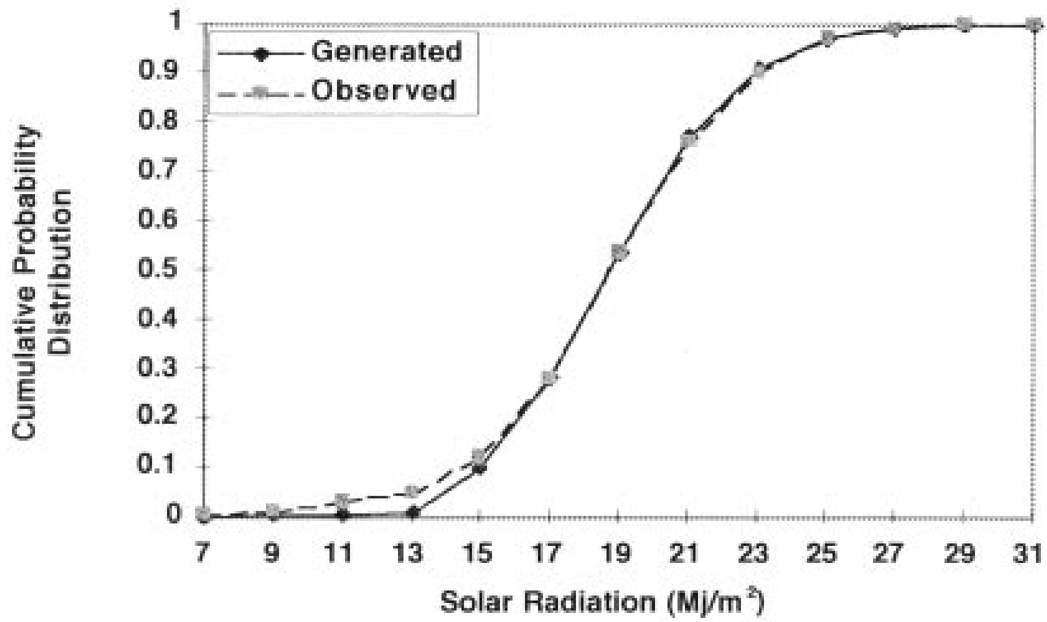

Figure 1. Comparison of the cumulative probability distribution curves between the generated and measured data.

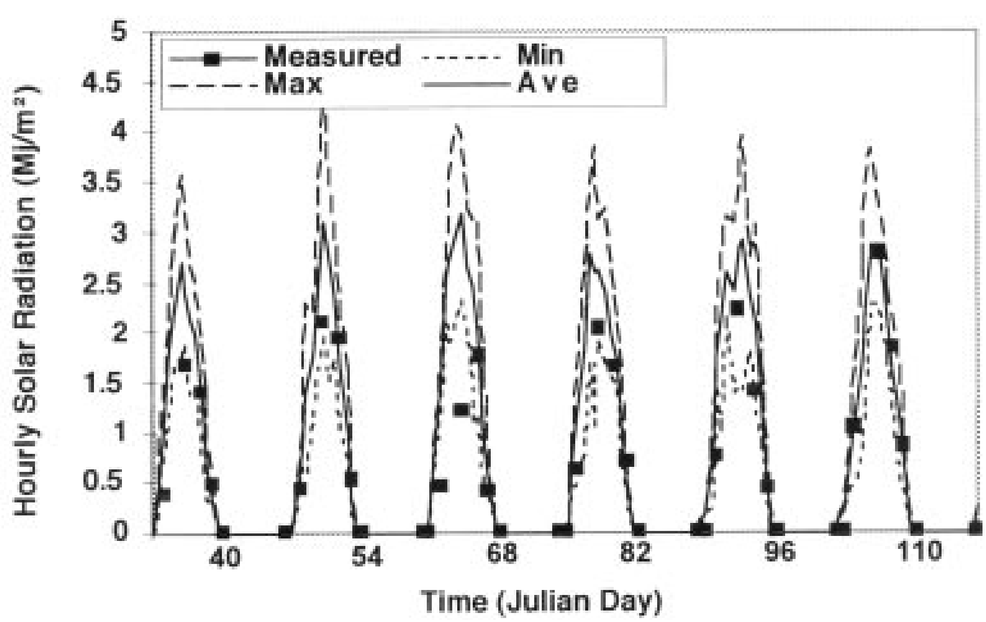

Figure 2. The generated hourly solar radiation values are compared to the measured hourly values on Julian day 40, 54, 68, 82, 96, and 110.

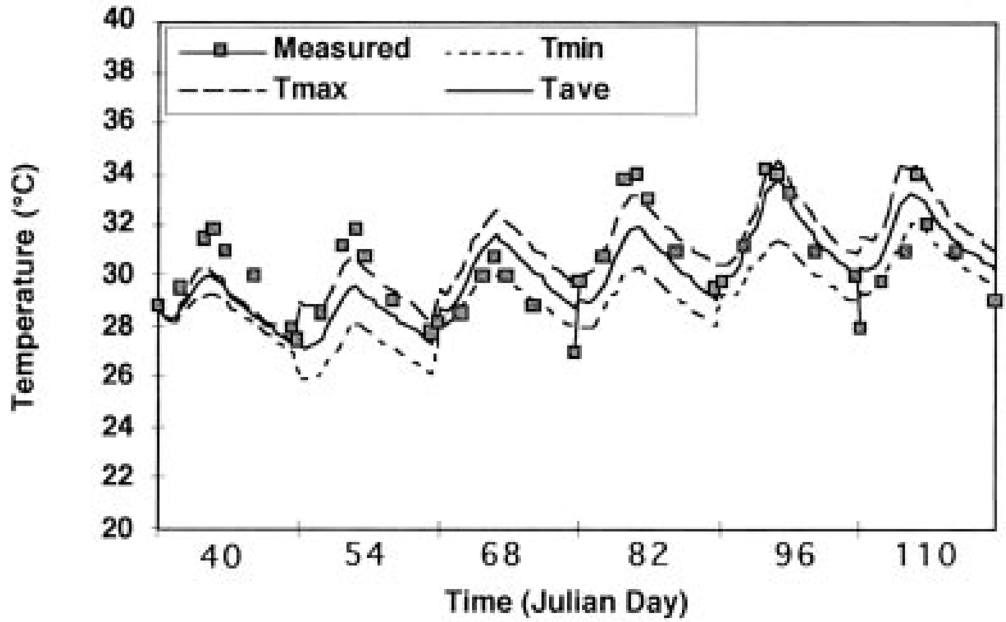

Figure 3. The generated maximum, minimum, and mean temperatures for the top pond layer are compared to the measured hourly data on Julian day 40, 54, 68, 82, 96, and 110.

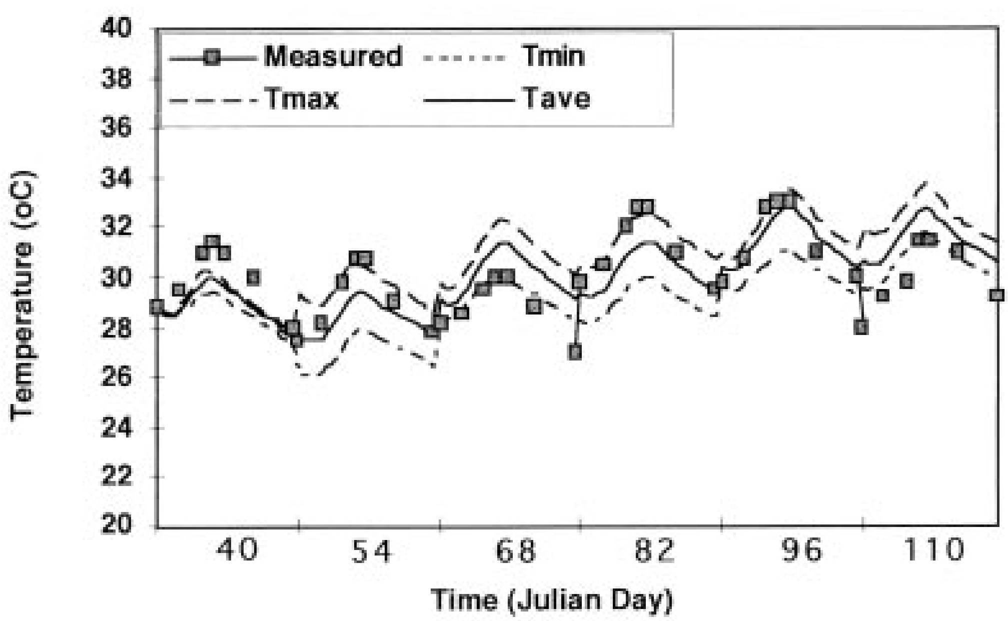

Figure 4. The generated maximum, minimum, and mean temperatures for the middle layer are compared to the measured hourly data on Julian day 40, 54, 68, 82, 96, and 110.

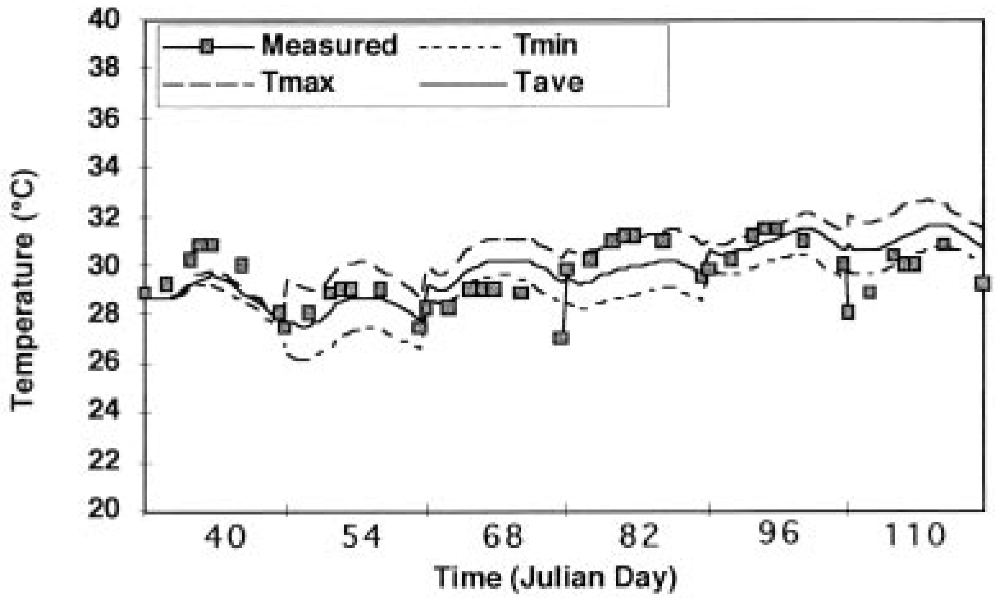

Figure 5. The generated maximum, minimum, and mean temperatures for the bottom layer are compared to the measured hourly data on Julian day 40, 54, 68, 82, 96, and 110.

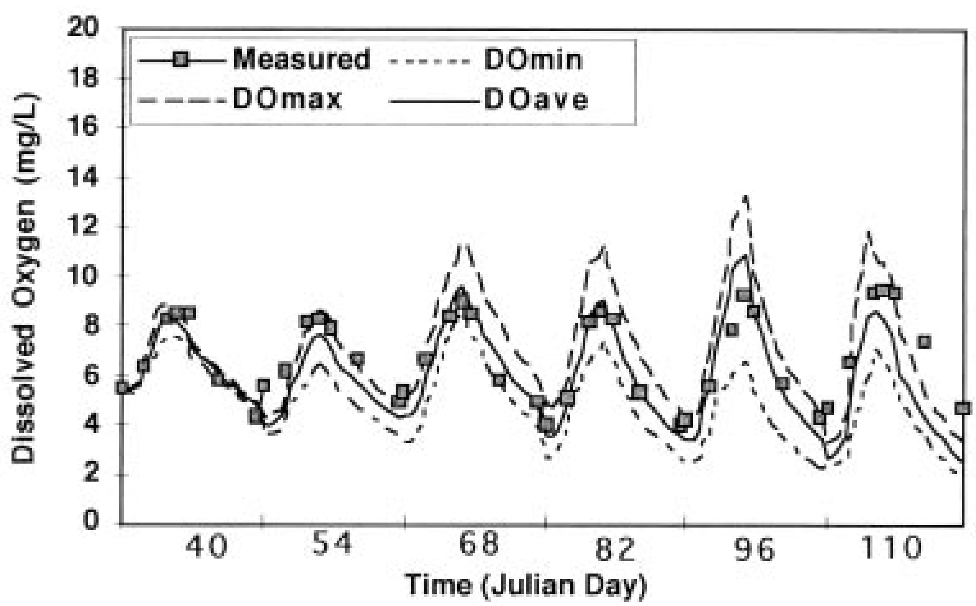

Figure 6. The generated maximum, minimum, and mean DO for the top layer are compared to the measured hourly data on Julian day 40, 54, 68, 82, 96, and 110.

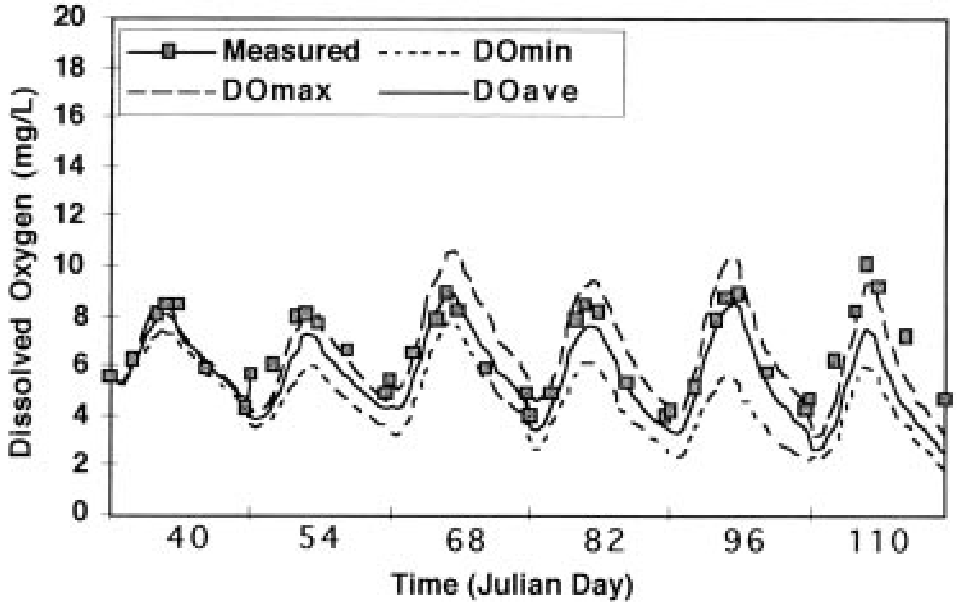

Figure 7. The generated maximum, minimum, and mean DO for the middle layer are compared to the measured hourly data on Julian day 40, 54, 68, 82, 96, and 110.

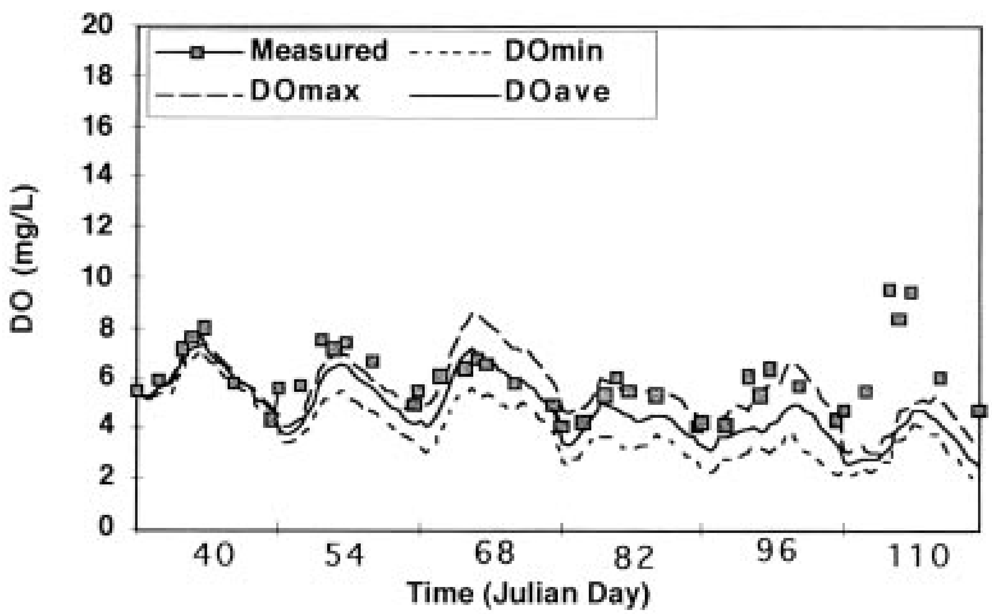

Figure 8. The generated maximum, minimum, and mean DO for the bottom layer are compared to the measured hourly data on Julian day 40, 54, 68, 82, 96, and 110.

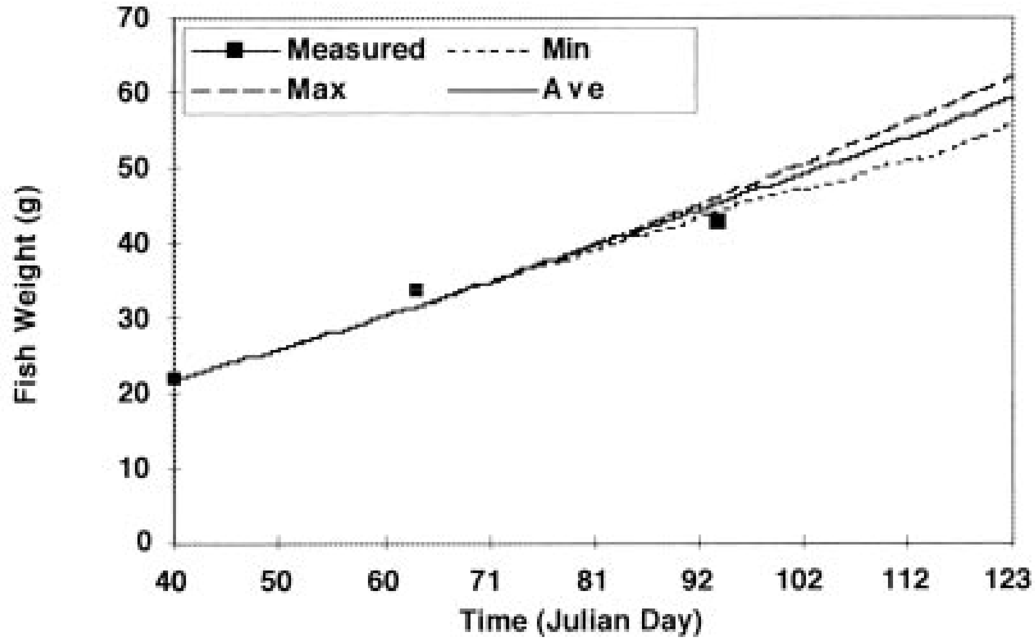

Figure 9. The generated maximum, minimum, and mean individual fish weight are compared to the measured data on Julian day 40, 64, and 97.

DO values while the simulations predicted stratified DO conditions. However, temperature stratification was predicted in the simulations (Figures 3 though 5). For this date, there appears to be a de-coupling of temperature and DO stratification which is not adequately considered in the model.

Although very limited fish growth data are available, measured values fall within the range of simulated values (Figure 9). The difference between maximum and minimum simulated values increases with time, indicating that the width of the probability distribution of the size of harvested fish increases with time.

Conclusions

The modified solar radiation sub-model provides an effective means of using limited data sets to estimate solar radiation values. The method is relatively simple and easy to couple with a water quality model. Temperature, DO, and fish growth simulation results follow measured values even for long term simulations of over 80 days. Although minor improvements to the model are still needed, very useful results can be obtained with the current version.

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