Feasible Application of PCLake Model to Predict Water Quality in Tropical Reservoirs

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ABSTRACT

The PCLake model has not previously been used for tropical reservoirs. This study attempted to apply the PCLake model to predict the chlorophyll a concentrations (Chl-a) in a tropical reservoir in Thailand. Sensitivity analyses were performed for the constants affecting the prediction of Chl-a in the phytoplankton module. The model calibration was performed by using the adjusted value of the most sensitive constant with the observed data from July to December 2020. The effects of the initial trophic state of the reservoir on the simulated Chl-a were evaluated. The results showed that Chl-a were sensitive to six constants. Among these constants, the value of the specific extinction of detritus (cExtSpDet) was adjusted using the calculated values from the typical limnological parameters of the studied reservoir. Statistical analyses of the results of calibration and the subsequent validation with the observed data from February to September 2022 were listed as follows: NSE=0.55 and 0.37, RSR=0.67 and 0.79, and PBIAS=27% and 9%, respectively. The initial trophic state of the reservoir had no influence on the long-term prediction of Chl-a. This preliminary effort indicates that the PCLake model can be used to predict Chl-a, which is representative of algal biomass in tropical reservoirs and is essential to water quality models, without complex modifications.

1. INTRODUCTION

Eutrophication has many negative effects on aquatic ecosystems. Perhaps the most obvious consequence is the increased growth of algae and aquatic weeds that interfere with water use for fishing, recreational, industrial, agricultural and drinking purposes (Carpenter et al., 1998). Therefore, predictive model of eutrophication, such as the PCLake model, were used to predict and control eutrophication in various reservoirs. The model can estimate the temporal impacts of different reservoir operating policies, point/nonpoint sources of pollution, and land use management planning.

PCLake used in this study is a freely distributed OSIRIS version released under the GNU Lesser General Public License (Mooij et al., 2010). PCLake was created for non-stratified temperate lakes in Northwestern Europe and has been applied effectively to several temperate lakes (Kuzyaka, 2015; Rolighed et al., 2016; Zhao et al., 2020; Zhang et al., 2022) including those in the Mediterranean (Mellios et al., 2015; Laspidou et al., 2017; Coppens et al., 2020) and subtropical (Fragoso et al., 2011; Kong et al., 2017) regions. However, it has never been used in the tropical areas. Most parameter values have been taken from much earlier studies with the model on a phytoplankton-dominated lake (Janse and Aldenberg, 1990; Janse et al., 1992; Aldenberg et al., 1995), while other values were derived from experimental data and field research in a temperate Dutch lake and the remaining values were derived from literature reviews and from calibration based on the combined data of several lakes in the Netherlands (Janse et al., 1992; Janse et al., 1995).

Anthropogenic eutrophication is increasingly recognized as a major threat to inland and coastal water quality in Thailand, with frequent reports of increases in the frequency, duration and severity (Rayan et al., 2021; Thaipichitburapa and Mek-

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sumpun, 2021; Pinmongkhonkul et al., 2022; Saetang and Jakmunee, 2022).

Although the PCLake model was mainly applied for natural lakes (Kuzyaka, 2015; Rolighed et al., 2016; Coppens et al., 2020; Zhang et al., 2022), this model can also be applied to artificial reservoirs (Mellios et al., 2015; Kong et al., 2017; Laspidou et al., 2017), as it has flexibility regarding the input constants or time series for variables. This means that extreme fluctuations in the variable can be captured throughout the year, especially in reservoirs.

Algae play a key role in the eutrophication process and are essential for water quality modeling. In practice, total algal biomass is often represented by chlorophyll a (Chl-a), which is much easier to measure and provides a reasonable estimate of algal biomass (Zhen-Gang, 2017). This study attempted to demonstrate the potential application of the phytoplankton module of PCLake to predict the Chl-a in a tropical reservoir.

2. METHODOLOGY

Study area

The Khlong Luang Ratchalothorn (KLR) Reservoir is a reservoir providing water for agriculture, aquaculture, and water supply. The reservoir has a mean depth of 3.67 m, a surface area of 27 km^2 and a volume of 99 million m^3. The average water retention time is 355 days. The reservoir is in a sub-basin of the Bang Pakong basin, located at 13^{o}23’00” N and 101^{o}22’40” E in Ban Khlong sub-district, Tha Boon Mi district, Koh Chan, Chonburi province, Thailand at 35.5 m above sea level. The climate is tropical with annual mean precipitation of 1,302.3 mm (during 1993-2022), with the lowest mean monthly air temperature being in December (23^{o}C) and the highest in April (35^{o}C). The watershed areas (525 km^2) are mostly mountains. The potential wavelengths in this reservoir calculated from the reservoir fetch was 15.10 m, half of which was greater than the average water depth in the reservoir, indicating complete mixing of the water (Dodson, 2005; Blottiere, 2015).

Model set-up

From Figure 1, a monthly sampling campaign was conducted at the KLR Reservoir. Ten sampling stations were chosen, six in the reservoir (S1-S6) and four at the inlet (S7-S10). Surface water samples were collected based on grab sampling according to APHA et al. (1992). Originally, it was planned to collect samples once a month throughout the years 2020 until 2022, but due to the outbreak of the coronavirus (COVID-19), the locked down was declared for certain periods of those years. Therefore, samples could not be collected continuously. As a result, water quality data obtained from two time periods, July-December 2020 and February-September 2022, were used in the calibration and validation processes respectively. The analyzed water quality parameters were total phosphorus (TP), phosphate (PO_4), ammonium (NH_4), nitrate (NO_3), Kjeldahl nitrogen (TKN), chlorophyll a, and suspended solids (SS). The standard methods from APHA et al. (1992) were used to measure TP, PO_4, NH_4, NO_3, TKN, Chlorophyll a, and SS. A bulb thermometer was used to measure the water temperature. The clarity of the water was measured by Secchi disk.

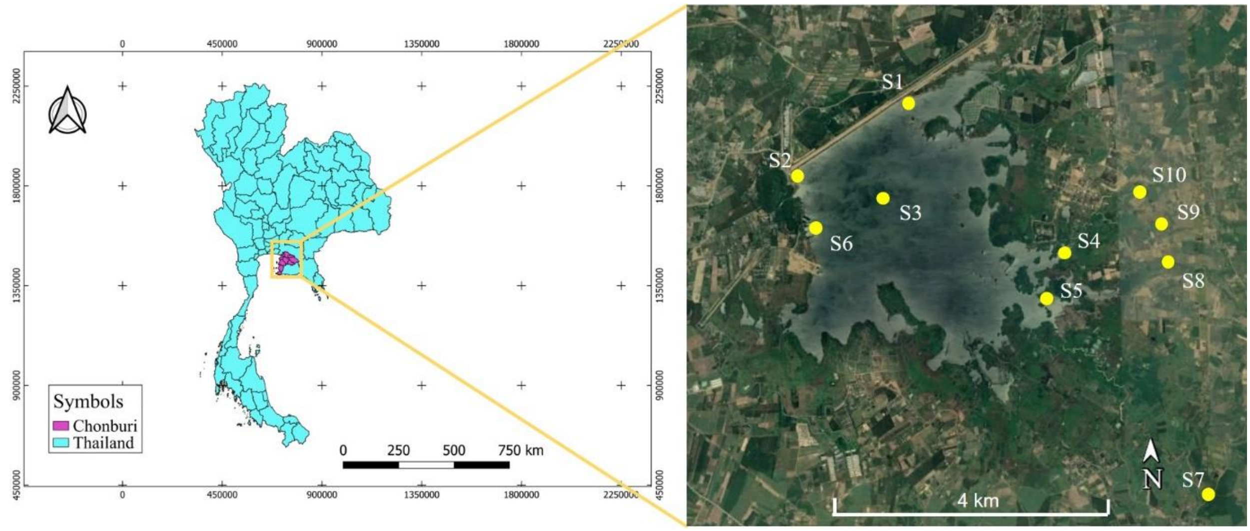

Figure 1. Location of sampling points (S1-S10) in Khlong Luang Ratchalothorn (KLR) Reservoir, Chonburi Province, Thailand.

The reservoir water level was recorded on a daily basis as part of the KLR Water Transmission and Maintenance Project of the Royal Irrigation Department. Meteorological data (mean daily wind speed and precipitation) was obtained from the Chonburi meteorological station of the Meteorological Department. The average daily global radiation was provided by the Department of Alternative Energy Development and Efficiency.

The average load of suspended solids leached from the soil surrounding the reservoir was calculated using the universal soil loss equation (Thitirojanawat and Chareonsuk, 1995). The nutrient load from the soil surface was determined by analyzing the soluble nutrients of different surface soils classified by land use types.

The PCLake model consists of seven comprehensive modules: phytoplankton (suspension), sedimentary phytoplankton, transport processes, vegetation, food webs, wetland zone (marsh zone), and seasonality. Current research requires the model to maintain mass balance of dissolved matter and particles in the water layer according to the amount of water flowing into and out of the reservoir. There is also a focus on simulating suspended phytoplankton in the form of Chl-a, therefore only the phytoplankton module and the transfer process module are used. Time step of calculation is 1 day.

2.1 Sensitivity and model performance testing

The constants affecting the Chl-a were identified in the phytoplankton module of the PCLake model. The sensitivity test determined the effect of changing the constant in the governing equation on the model output, based on the sensitivity coefficient (SC), as shown in Equation 1 (Rangel-Peraza et al., 2016):

$$SC = \frac{(\%\ \text{Change in output variables})}{(\%\ \text{Change in input constants})} \tag{1}$$

In the current study, the constant was doubled from the default value in the model (to represent extreme physical, chemical, or biological condition), except for maximum reduction factor of phosphorus adsorption affinity (fRedMax) that was increased only 1.2 times because the model could not be run with higher values. For each simulation run (365 days), only one constant was changed, while the other constants used the model defaults. The model default initial values, input factors, and time-series data of the variables were also used for model initialization in the sensitivity tests. Constant values accounting for the top-10% of the most significant change in Chl-a output were identified.

The Nash-Sutcliffe efficiency coefficient (NSE), the root-mean-square error (RMSE)-observations standard deviation ratio (RSR), and percentage bias (PBIAS) were used to evaluate model performance based on the general performance ratings (Table 1) (Moriasi et al., 2007).

NSE is a normalized measurement that assesses how much the residual variance differs from the measured data variance. NSE can be calculated using Equation 2:

$$NSE = 1 - \left[\frac{\sum_{i=1}^{n}(Yi^{obs} - Yi^{sim})^2}{\sum_{i=1}^{n}(Yi^{obs} - Y^{mean,obs})^2}\right] \tag{2}$$

Where; Yi^{obs} is the i^{th} observation for the constituent being evaluated, Yi^{sim} is the i^{th} simulated value for the constituent being evaluated, $Y^{mean,obs}$ is the mean of observed data for the constituent being evaluated and n is the total number of observations. NSE ranges from -∞ to 1.0. If the value is equal to or less than 0, it is considered unacceptable.

RSR is the RMSE normalized by the observed standard deviation. It is calculated as the ratio of the RMSE and the standard deviation of the measured data as shown in Equation 3:

$$RSR = \frac{RMSE}{STDEV_{obs}} = \frac{\left[\sqrt{\sum_{i=1}^{n}(Yi^{obs} - Yi^{sim})^2}\right]}{\left[\sqrt{\sum_{i=1}^{n}(Yi^{obs} - Y^{mean,obs})^2}\right]} \tag{3}$$

RSR is greater than or equal to zero. The lower the RSR (the lower the RMSE), the better the model simulation performance. If RSR is equal to 0, the model simulation is perfect.

PBIAS measures the average tendency of the simulated data to be larger or smaller than their observed counterparts. PBIAS is calculated with Equation 4:

$$PBIAS = \left[\frac{\sum_{i=1}^{n}(Yi^{obs} - Yi^{sim})}{\sum_{i=1}^{n}(Yi^{obs})} \times 100\right] \tag{4}$$

The optimal value of PBIAS is 0; positive values indicate a model bias toward underestimation, whereas negative values indicate a bias toward overestimation.

Table 1. General performance ratings for recommended statistics for monthly time step[1]

Performance Rating	NSE	RSR	PBIAS (%)
Very good	$0.75 < NSE \leq 1.00$	$0.00 \leq RSR \leq 0.50$	$PBIAS < \pm 25$
Good	$0.65 < NSE \leq 0.75$	$0.50 < RSR \leq 0.60$	$\pm 25 \leq PBIAS < \pm 40$
Satisfactory	$0.50 < NSE \leq 0.65$	$0.60 < RSR \leq 0.70$	$\pm 40 \leq PBIAS < \pm 70$
Acceptable/Unsatisfactory	$NSE \leq 0.50$	$RSR > 0.70$	$PBIAS \geq \pm 70$
Unacceptable	$NSE < 0$	–	–

NSE=Nash-Sutcliffe efficiency coefficient; RSR=RMSE-observations standard deviation ratio; PBIAS=Percentage bias.
[1]Moriasi et al. (2007)

2.2 The effect of using a field sensitive constant as a computational constant in the PCLake model

2.2.1 Calibration and validation

In the calibration process, values of the top-10% sensitive constants in the phytoplankton module were adjusted using either calculated or literature values. The default initial concentration of each phytoplankton species, which was set in eutrophic state, was used in the calibration since the observed Chl-a in the field from the beginning of July to December 2020 indicated that the reservoir was in eutrophic state.

The results (scenario 2) were compared with the simulation that used all constants as the model default (scenario 1). The validation of the model with the chosen constants in the calibration process was performed using the dataset of February to September 2022 (scenario 3). The initial concentrations of each phytoplankton species in model validation were obtained from the output of the calibration based on the Chl-a. The initial values, input factors and time-series data from actual field observations in calibration and validation are shown in Table 2.

2.2.2 Effect of initial concentrations of individual phytoplankton species

The effects of initial concentrations of diatoms, green algae, and blue-green algae were investigated. The concentration of each phytoplankton species varied with the trophic state of the reservoir. The studied reservoir, Khlong Luang Ratchalothorn (KLR) Reservoir (Figure 1) has the possibility to switch between 3 states: mesotrophic, eutrophic and hyper-eutrophic (Boondao et al., 2019). Because field data on the concentrations of individual phytoplankton species were not available, data from the literature were used for each state as shown in Table 3.

Table 2. Initial values, input factors and time-series data of variables used for calibration and validation in PCLake model

Description	Variable	Value (calibration step) from Jul to Dec 2020	Value (validation step) from Feb to Sep 2022	Unit
Initial value	Lake depth	2.25	2.97	m
	Initial concentration of diatoms in lake water	0.5 (default)	0.0171 (from calibration process)	g of dry-weight/m^3
	Initial concentration of green algae in lake water	0.5 (default)	0.0209 (from calibration process)	g of dry-weight/m^3
	Initial concentration of blue-green algae in lake water	3.0 (default)	0.4095 (from calibration process)	g of dry-weight/m^3
	Dry-weight fraction of solid in sediment	0.246	0.172	g of dry-weight/g of sediment
	Organic fraction of dry-weight sediment	0.102	0.073	g of dry-weight/g of dry-weight sediment
Input factors	Lake size, expressed as fetch	5,168	5,168	m
	Iron content of inorganic matter	0.032	0.016	g of iron/g of dry-weight
	Oxygen concentration in inflow	2.14	3.90	mg of oxygen/L
	Aluminum content of inorganic matter	0.021	0.019	g of aluminum/g of dry-weight

Table 2. Initial values, input factors and time-series data of variables used for calibration and validation in PCLake model (cont.)

Description	Variable	Value (calibration step) from Jul to Dec 2020	Value (validation step) from Feb to Sep 2022	Unit
Time-series	Water temperature	Monthly time-series; Values ranging from 24 to 30 (28±2)[1]	Monthly time-series; Values ranging from 28 to 32 (30±2)	°C
	Light	Daily time-series; Values ranging from 519.722 to 7,548.889 (4,719.991±1,493.247)	Daily time-series; Values ranging from 1,868.0711 to 7,590.625 (5,405.128±1,373.210)	W/m^2
	Wind	Daily time-series; Values ranging from 0.5631 to 3.3786 (1.4314±0.6489)	Daily time-series; Values ranging from 5.068 to 20.272 (8.762±2.881)	m/s
	Inflow	Daily time-series; Values ranging from 0.192 to 302.061 (30.084±44.477)	Daily time-series; Values ranging from 0.008 to 321.953 (33.586±43.908)	mm/d
	Outflow	Daily time-series; Values ranging from 0 to 22.688 (4.051±5.950)	Daily time-series; Values ranging from 1.685 to 74.654 (22.408±20.187)	mm/d
Time-series	Phosphorus loading	Monthly time-series; Values ranging from 0 to 0.225 (0.036±0.084)	Monthly time-series; Values ranging from 0 to 0.096 (0.032±0.038)	g of phosphorus/ $m^2 \cdot d$
	Phosphate loading	Monthly time-series; Values ranging from 0 to 0.089 (0.014±0.033)	Monthly time-series; Values ranging from 0 to 0.046 (0.015±0.019)	g of phosphorus/ $m^2 \cdot d$
	Phosphorus bound to organic matter	Monthly time-series; Values ranging from 0 to 0.062 (0.010±0.023)	Monthly time-series; Values ranging from 0 to 0.050 (0.017±0.019)	g of phosphorus/ $m^2 \cdot d$
	Nitrogen loading	Monthly time-series; Values ranging from 0 to 0.706 (0.113±0.262)	Monthly time-series; Values ranging from 0 to 0.357 (0.116±0.141)	g of nitrogen/$m^2 \cdot d$
	Ammonium loading	Monthly time-series; Values ranging from 0 to 0.09 (0.02±0.03)	Monthly time-series; Values ranging from 0 to 0.01 (0.01±0.01)	g of nitrogen/$m^2 \cdot d$
Time-series	Nitrate loading	Monthly time-series; Values ranging from 0 to 0.24 (0.04±0.09)	Monthly time-series; Values ranging from 0 to 0.14 (0.05±0.06)	g of nitrogen/ $m^2 \cdot d$
	Nitrogen bound to organic matter	Monthly time-series; Values ranging from 0 to 0.147 (0.023±0.055)	Monthly time-series; Values ranging from 0 to 0.213 (0.065±0.085)	g of nitrogen/ $m^2 \cdot d$
	Inorganic matter loading	Monthly time-series; Values ranging from 0.002 to 11.733 (1.745±4.406)	Monthly time-series; Values ranging from 0.002 to 8.186 (2.245±3.390)	g of dry-weight/ $m^2 \cdot d$

[1]mean±SD

Table 3. Initial concentration scenarios for each species of phytoplankton

Scenario	Initial concentration of phytoplankton in lake water (gDW/m^3)			Sources
	Diatoms	Green algae	Blue-green algae	
4 (eutrophic)	0.50	0.50	3.00	PCLake model's default values
5 (mesotrophic)	1.47	0.09	0.81	Napiórkowska-Krzebietke et al. (2013)
6 (hyper-eutrophic)	4.29	0.95	39.81	Dantas et al. (2008)

3. RESULTS AND DISCUSSION

3.1 Sensitivity and model performance testing

In total, there are 59 constants related to the Chl-a in the phytoplankton module of the PCLake model (except those in the Arrhenius equation and an optimum function). Only the sensitivity coefficients results of the top-10% sensitive constants are listed in Table 4.

The sensitivity coefficients indicated that the top-10% sensitive constants of variation in the Chl-a output were: cChDBlueMax (maximum chlorophyll-to-carbon ratio of blue-green algae), cTmOptBlue (optimum temperature of blue-green algae), cExtSpBlue (specific extinction of blue-green algae), kMortBlueW (mortality constant of blue-green algae in water), fPAR (fraction of photosynthetically active radiation), and cExtSpDet (specific extinction of detritus).

Because the composition of phytoplankton in tropical lakes is generally similar to that of temperate lakes (Nilssen, 1984; Sarmento, 2012), default values were given to the following model constants: cChDBlueMax, cTmOptBlue, cExtSpBlue and kMortBlueW. The value of fPAR was also given by default because it corresponded to those measured in tropical regions (Noriega et al., 2021).

The value of cExtSpDet is measured in m^2/gDW. This constant may vary depending on the size and on the light-absorption and light-scattering properties of the detritus. The value is the reciprocal of the amount of detritus per square meter in the water column above the Secchi disk and can be calculated using Equation 5 (Carlson, 1977):

$$\mathrm{cExtSpDet} = \frac{K_{det}}{(\mathrm{SS} - \mathrm{Chla})} \tag{5}$$

Where; SS is suspended solids, defined as organic solids (in g/m^3). Chla is the chlorophyll a concentration (in g/m^3). K_{det} is light extinction from detritus (in m^{-1}), calculated from Equation 6:

$$K_{det} = K - K_{pure} - K_{phyt} \tag{6}$$

Where; K is total light extinction (in m^{-1}), calculated from Equation 7, K_{pure} and K_{phyt} are light extinctions from pure water and phytoplankton, respectively. K_{pure} was set to be 0.1 m^{-1} (Lewis, 1987). K_{phyt} can be calculated according to Equations 8:

$$K = -1 \times \frac{\ln(SD_{light})}{SD} \tag{7}$$

Where; SD_{light} is the fraction of surface light penetration at the SD and is generally reported as 0.1 of SD (Huszar et al., 2006). SD is Secchi disk (in m).

$$K_{phyt} = \left(\frac{\mathrm{cExtSpDiat} + \mathrm{cExtSpGren} + \mathrm{cExtSpBlue}}{3}\right) \times \mathrm{Chla} \tag{8}$$

Where; cExtSpDiat, cExtSpGren, and cExtSpBlue are the specific extinction of diatoms, green algae, and blue-green algae, respectively (Huszar et al., 2006).

The values of SD, SS, and Chla were known from field surveys on November 26, 2020 (Table 5), while cExtSpDiat, cExtSpGren, and cExtSpBlue were obtained from the literatures (Riemann et al., 1989; Lee et al., 2000; Fujiki and Taguchi, 2002; Reynolds, 2006; Zhang et al., 2012; Vendruscolo et al., 2019). From Equations 5-8, the value of cExtSpDet would be 2.538 m^2/gDW.

3.2 The effect of using a calculated constant as a computational constant in the PCLake model

The simulated Chl-a from scenario 1 (all default constants) and scenario 2 (cExtSpDet, calculated from field data with a value of 2.538 m^2/gDW and other constants as model default values) were compared with the observed data in the period from July to December 2020 are shown in Figure 2.

The results show that scenario 2 (NSE=0.55, RSR=0.67, PBIAS=27%) is more consistent with the observed data than scenario 1 (NSE=-0.005, RSR=1.00, PBIAS=-75%). That is, the PCLake model satisfactorily predicted the Chl-a in the KLR Reservoir with only the cExtSpDet being changed from the model default (other constants were default values in the model) (NSE=0.55, RSR=0.67), but good and bias toward underestimated (PBIAS=27%). In the validation (scenario 3) with the observed data between February and September 2022, the performance was found to be acceptable (Figure 3, with NSE=0.37, RSR=0.79), but very good and bias toward underestimated (PBIAS=9%).

3.3 Effect of initial concentrations of individual phytoplankton species

The results of the simulation in reservoir with different initial trophic state are shown in Figure 4.

Table 4. The top 10% sensitivity constants relate to the chlorophyll a concentrations in the phytoplankton module of the PCLake model

Constant	Unit	Description	Default constant	Increased constant	Simulated mean chlorophyll a concentrations calculated from the default constant simulation (mg/m^3)	Simulated mean chlorophyll a concentrations calculated from the increased constant simulation (mg/m^3)	Sensitivity coefficient
cChDBlueMax	mg Chl/ mg DW	Maximum chlorophyll-to-carbon ratio of blue-green algae	0.015	0.030	51.599	92.321	-0.790
cTmOptBlue	ºC	Optimum temperature of blue-green algae	25	50	51.599	11.693	0.770
cExtSpBlue	m^2/g DW	Specific extinction of blue-green algae	0.35	0.70	51.599	34.524	0.330
kMortBlueW	d^{-1}	Mortality constant of blue-green algae in water	0.01	0.02	51.599	37.278	0.280
fPAR	–	Fraction of photosynthetically active radiation (PAR)	0.48	0.96	51.599	39.304	0.238
cExtSpDet	m^2/g DW	Specific extinction of detritus	0.15	0.30	51.599	39.423	0.236

Table 5. Secchi disk (SD), suspended solid (SS) and chlorophyll a concentration from field surveys on November 26, 2020

Variable	Value	Unit
Secchi disk	0.22	m
Suspended solid	6.8	g/m^3
Chlorophyll a concentration	0.0034	g/m^3

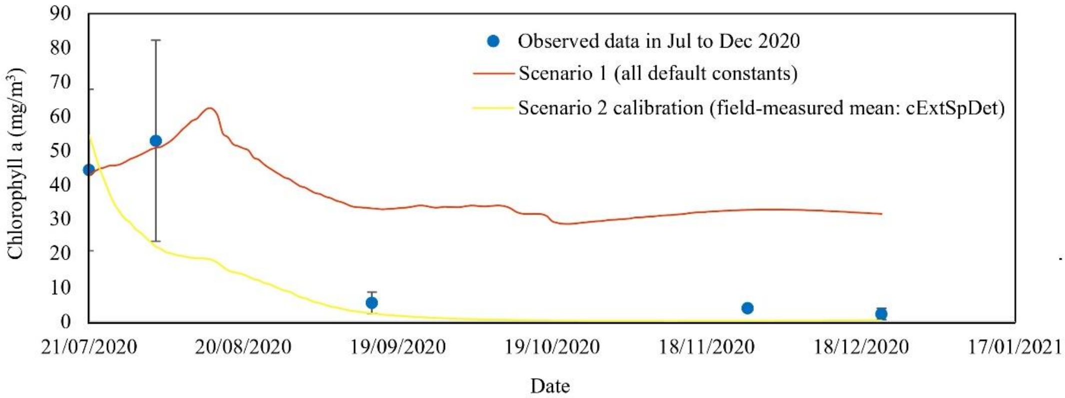

Figure 2. Simulated time-series of chlorophyll a concentrations using default and calculated cExtSpDet and observed chlorophyll a concentrations data in Jul to Dec 2020

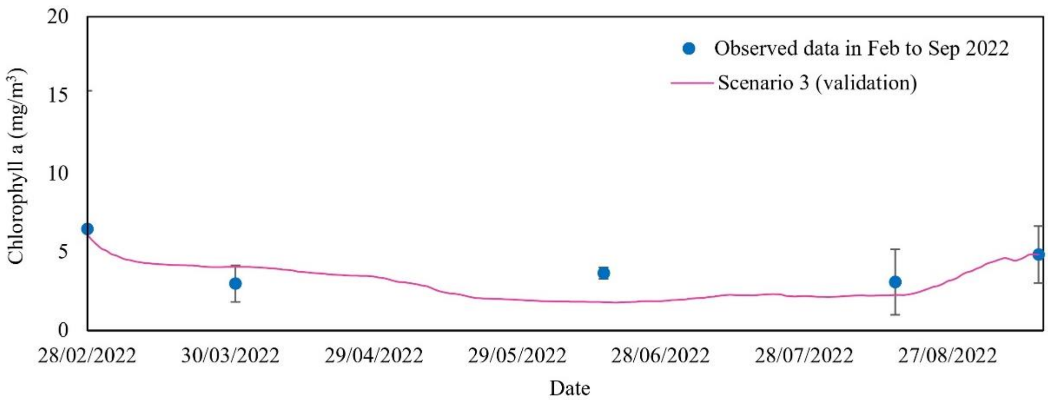

Figure 3. Simulated time-series of chlorophyll a concentrations against the observed data in the validation

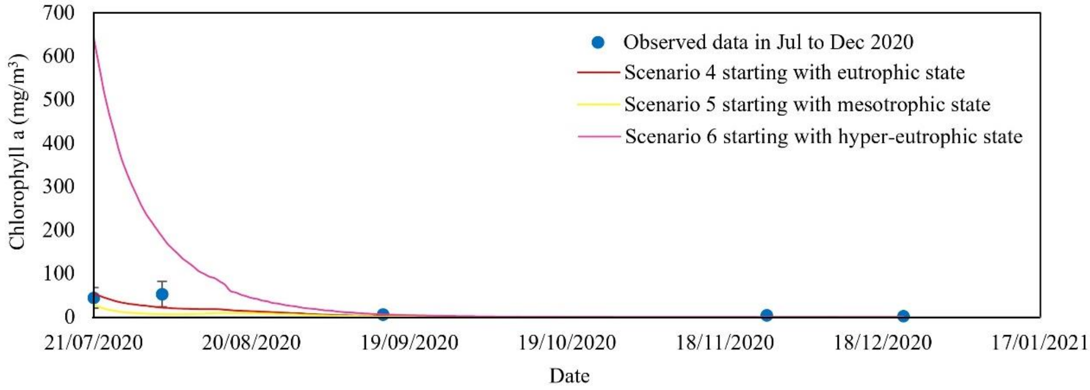

Figure 4. Simulated time-series of chlorophyll a concentrations with different initial trophic status

The results indicated that regardless of the initial trophic status of the KLR Reservoir, the simulated Chl-a were similar from day 60 onwards. In other words, the initial concentrations of diatoms, green algae, and blue-green algae in the reservoir had no influence on the long-term prediction of Chl-a.

Thus far, the PCLake model has been successful in simulating Chl-a and phytoplankton biomass in natural lakes located in the Mediterranean region (Coppens et al., 2020) and temperate regions (Zhao et al., 2020; Zhang et al., 2022), but has never been used in tropical areas. Therefore, the present research is the first attempt to apply such a model to a tropical area. The findings from this preliminary study indicated that the PCLake model could be applied to predict the Chl-a in this reservoir. The modification on one of the most sensitive constant, cExtSpDet, was made based on typical limnological parameters of the studied reservoir. Therefore, this model could potentially be applied to the tropical reservoir without complicated modifications. The potential usage of this model provides crucial support to the prospective water quality management programs for the existing reservoirs in Thailand. There is also an opportunity to apply for additional budget to extend the study period for more accurate simulation results.

4. CONCLUSION

The performance of the phytoplankton module in the PCLake model was examined for its application in tropical reservoir (i.e., the KLR Reservoir), in terms of its ability to predict Chl-a. The results show that six constants were sensitive to Chl-a: cChDBlueMax, cTmOptBlue, cExtSpBlue, kMortBlueW, fPAR, and cExtSpDet. To Apply the PCLake model to the KLR Reservoir, only the cExtSpDet was selected for calibration to best fit the observed Chl-a for the period July-December 2020 by using the calculated value from the typical limnological parameters of this reservoir. The performance results of the model were satisfactory to good and acceptable to very good in the calibration and validation process, respectively. The initial trophic status of the reservoir had no influence on the long-term prediction of Chl-a. The results demonstrated the potential usage of PCLake model to predict Chl-a in tropical reservoir with uncomplicated modification.

Until now, long-term field data related to the sensitive parameters in the calculation of Chl-a as well as the concentration of each species of phytoplankton were not available in the Khlong Luang Ratchalothorn Reservoir. It is suggested that monitoring plan for water quality simulation is necessary for water quality management in this and other reservoirs.

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