Desalination and Water Treatment
www.deswater.com

doi: 10.1080/19443994.2016.1190107

57 (2016) 26783–26791
November

Taylor & Francis
Taylor & Francis Group

Monthly chlorophyll-a prediction using neuro-genetic algorithm for water quality management in Lakes

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Received 16 December 2015; Accepted 29 December 2015

ABSTRACT

A genetic algorithm (GA) was combined with artificial neural networks (ANN), designated as neuro-genetic algorithm (NGA) in this study, to determine the effective number of nodes and optimal activated functions (FAs) in an ANN structure. Developed NGA was applied to predict Chlorophyll-a (Chl-a) concentrations in one-month increments in Lakes used as drinking water sources. Correlation analysis was used to setup input parameters. A simulation was conducted for four study sites with the most serious Chl-a problems in South Korea. Results from correlation analysis have indicated that phosphate phosphorus (PO_4-P) and electrical conductivity showed high correlation with Chl-a, a factor not often considered in other studies. As the results of prediction of one-month forward Chl-a concentration, NGA showed high accuracy, with averaged determination coefficients of 0.89 and 0.84 in training and testing period, respectively. Double hidden layers showed better performance than a single hidden layer, while a logistic sigmoid function was frequently selected by the genetic algorithm in hidden layers in comparison with linear and hyperbolic tangent function. Practical uses for NGA in proactive water quality management are also discussed in this study.

Keywords: Chlorophyll-a; Neural networks; Neuro-genetic algorithm; Proactive water-quality management

1. Introduction

Lakes are important water sources worldwide. However, significant water quality problems such as algal blooms happened every year, and are certain to gradually increase globally due to climate change effects. There are generally two categories of methods, namely prevention and post-treatment, used to solve water quality problems. Prevention technology includes precautionary strategies to cope with environmental events in advance and minimize risk by predicting damages that may occur in the future. Post-treatment technology includes methods to eliminate or lessen the impact of environmental damages after an

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Presented at the 8th International Desalination Workshop (IDW) 2015, November 18–21, 2015, Jeju Island, Korea

incident. Technologies such as algae fences, water treatment, and algae removal boats are considered post-treatment technologies to address algal bloom problems.

An algae early warning system, a kind of prevention technology, is operated in many countries such as the United States of America, Australia, and Canada. An algae early warning system has also been implemented in South Korea, but the current system only considers current algae concentration without predicting for the future. Prediction of algae concentration at least 2–4 weeks prior is necessary for a proper warning system and to prevent algae blooms [1,2]. In addition, it is desirable to set up proactive management solutions, considering the Korean weather conditions, as the average temperature is over 20℃ in summer and algae grows very quickly in the summer season.

Based on the literature, Chl-a concentration can represent population of algae [3–5]. There are several programs using governing equations, e.g. WEAP (Water Evaluation and Planning System developed by the Stockholm Environment Institute), EFDC (Environment Fluid Dynamics Code developed by US EPA), and HEC-RAS (Hydrologic Engineering Centers River Analysis System developed by US Army), for the simulation of water quality. Generally, these types of simulation programs show splendid performance if geological and hydrogel data are sufficient [6,7]. However, black-box models such as artificial neural network (ANN) and Fuzzy may be adopted without geological information, with high applicability for real-time simulation [8–10]. Among the black-box models, ANN has received more attention due to its benefits, which are fast calculating speed and low data requirements.

However, there are several issues which must be addressed for the use ANN. For one thing, input data are generally selected through a trial-error method based on the modeler's experience with less consideration of statistical analysis [11,12]. Secondly, big personal differences may happen in composing nodes and activated functions of ANN, and these differences affect accuracy of ANN [13]. Lastly, it is difficult to adopt ANN in practical way because prediction is targeted to the near future (<1 week) which is almost not useful. For practical usage, Chl-a prediction of 2–4 weeks forward is necessary in order to set up proactive strategies. Therefore, in this study, prediction of one-month forward Chl-a concentration may be implemented by selecting input data based on statistical analysis, establishing ANN using genetic algorithm (GA), and selecting a study area where extreme water quality problems exist. Then, proactive water quality strategies through developed neuro-genetic algorithm (NGA) are able to be discussed.

2. Methodology

2.1. NGA development

Machine-learning technology was developed from computational learning theory and pattern recognition in artificial intelligence. As a kind of machine-learning technology, ANN imitates the human brain's connections of neurons, neural cells, and synapses [14,15]. Several ANN models have been developed since the 1980s. Among these models, multi-layer perceptrons (MLP), Hopfield networks, and Kohonen's self-organizing map may be considered representative models. Following several studies [8,16,17], the MLP networks (Fig. 1) show excellent performance for forecasting because of their inherent capability of arbitrary input–output mapping. However, construction factors such as activated function and number of nodes for MLP setup are still challenging. Lee et al. [13] suggested a hybrid genetic algorithm (GA) with ANN, called a NGA, to predict real-time water level in rivers, and the prediction results showed high model accuracy. Thus, the NGA was modified and applied to predict monthly Chl-a concentration in several lakes by selecting effective activated function and number of nodes. As activated functions, a Logistic function (Lo) (Eq. (1)), Hyperbolic tangent function (Tanh) (Eq. (2)), and Linear function (Li) (Eq. (3)) were used:

$$f(x) = \frac{1}{1 + e^{-x}} \tag{1}$$

$$f(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}} \tag{2}$$

$$f(x) = x \tag{3}$$

Pearson correlation analysis [18] was used to select model inputs, while back propagation algorithm [19,20] was used to adjust weights.

2.2. Case study sites

A total of 93 lakes exist in South Korea. Problematic lakes, which showed high Chl-a concentration (>15 mg/m^3) observed over 5 times in last 10 years, were selected as study sites. Among the 93 lakes in South Korea, four lakes (Gwangdong Lake, Yeongcheon Lake, Topjung Lake, and Daearm Lake) were chosen as study sites (Fig. 2). Water quality data were collected from Korea Nation Institute of Environmental Research, and water flow and rainfall data were provided by Korea Water Management Information System. Water quality data were measured monthly and opened to the public since 2005. Six years' data

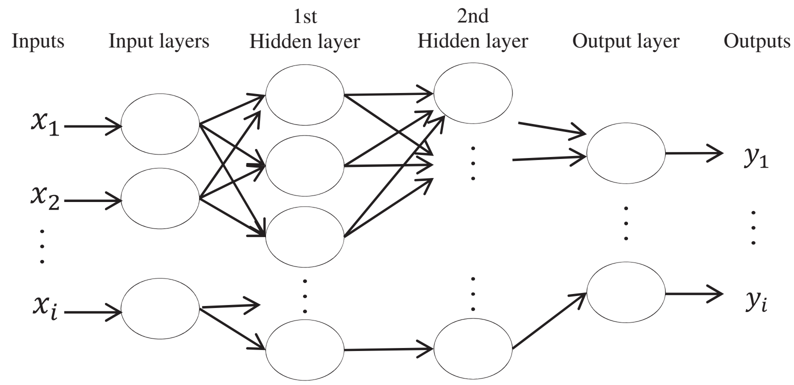

Fig. 1. Simple schematic of multi-layered perceptron.

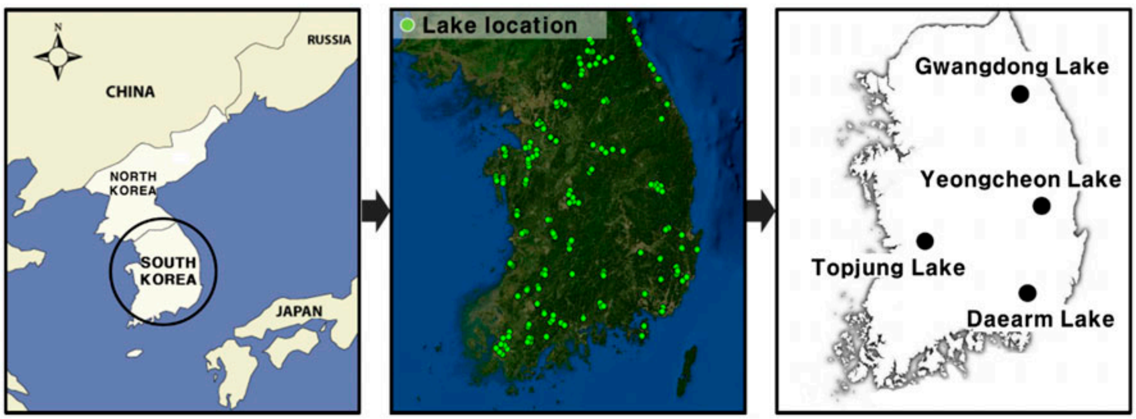

Fig. 2. Four study sites in South Korea.
Source: National Institute of Environmental Research (NIER), South Korea, http://water.nier.go.kr.

from 2006 to 2011 were used because this study was conducted from 2012 until 2013. The reason why data from 2005 were not used in this study is because of several missing data points. All data were subdivided into training-validation (four years) and testing period (two years). The four-year training-validation period (2006–2009) was divided into training and validation parts. Data were rearranged in order to observation date and numbered. Even numbers were used for training data while odd numbers were used for validation data. Data were adjusted on a scale ranging from 0 to 1, and then used for input parameters. Both the coefficient of determination (R^2) and mean-square error (MSE) were used as criteria.

3. Results and discussion

3.1. Specification and correlation analysis of water quality data

The specifications for 93 of domestic lakes were conducted in order to predict Chl-a concentration through NGA. As the results, Gwangdong Lake, Yeongcheon Lake, Topjung Lake, and Daearm Lake were selected. Fig. 3 shows trends of Chl-a concentration from 2006 to 2011.

Chl-a concentration of Gwangdong Lake reached to first warning level (15 mg/m^3) every year. Gwangdong Lake is one of main drinking water sources in Gangwon-province and its Chl-a concentration in every summer (July–September) showed problematic concentrations. In this area, water quality analysis is implemented once per month and reanalysis is implemented once per week when Chl-a concentration is close to minimum regulation lever (15 mg/m^3) according to algae early warning system. There are two upper streams named Bunchun and Goljichun in Gwangdong Lake. Fifteen types of water quality data such as temperature (temp), dissolved oxygen (DO), pH, biological oxygen demand (BOD), chemical oxygen demand (COD), suspended solid (SS), ammoniacal nitrogen (NH_3-N), nitrate (NO_3-N), dissolved total nitrogen (DTN), total nitrogen (TN), phosphate

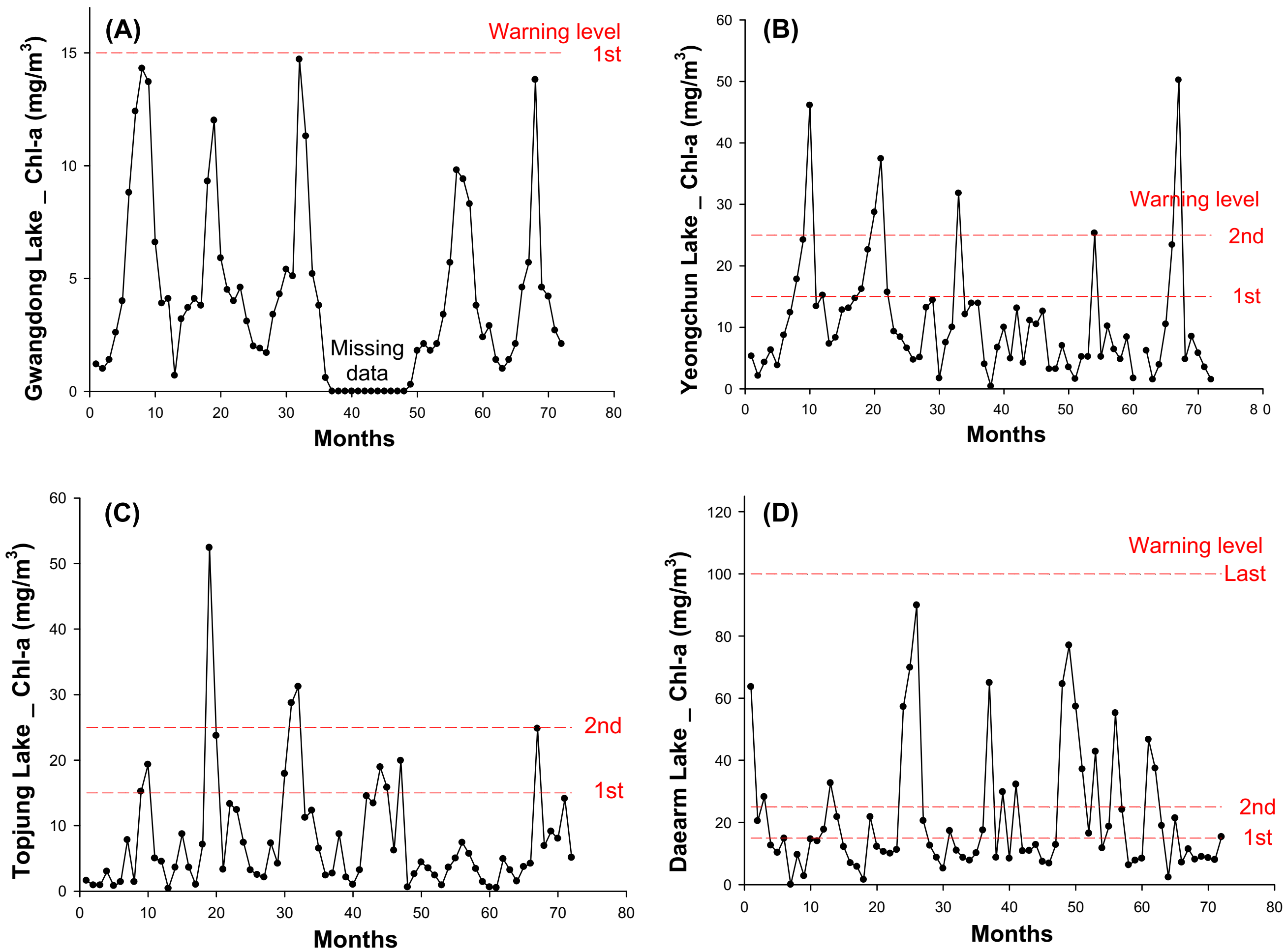

Fig. 3. Observed Chl-a data for 6 years, (A) Gwangdong Lake, (B) Yeongchun Lake, (C) Topjung Lake, and (D) Daearm Lake.

phosphorus (PO_3-P), dissolved total phosphorus (DTP), total phosphorus (TP), electrical conductivity (EC), and Chl-a have been measured monthly in the water intake station of Gwangdong Lake and the sampling point of two upper streams. As a result of correlation analysis between water quality data in upper streams and Chl-a data in Gwangdong Lake, a total of 7 types of observed data were highly correlated at under *p*-value 0.05 of significance level (Table 1), and the corresponding data were used as input data of NGA. PO_4-P and TP at the upper streams and Chl-a at downstream are highly correlated with Chl-a. This is a consistent finding with other studies [21–23]. The effects of high correlated data on Chl-a prediction will be discussed in prediction results part.

In the case of Yeongchun Lake, Chl-a concentration was close to the serious level every year. Fig. 3 shows that Chl-a concentration in Yeongchun Lake reached the second warning level nearly every year. Yeongchun Lake is also one of main drinking water sources and needed to be managed strictly. An upper stream named Jukjangchun existed in the catchment of Yeongchun Lake. Fifteen types of water quality data, as for Gwangdong Lake, have been measured, and seven types of water quality data were highly correlated with Chl-a under 0.05 of *p*-value as the result of correlation analysis. As a singularity, it was determined that PO_4-P, DTP, TN, and EC were highly correlated with Chl-a. Correlation between Chl-a and phosphorus is well known in others researches of course [3,22,24–27]. However, it worth noting that types of phosphorus or nitrogen are correlated higher than pH. The selected seven types of water quality data were used as input data for NGA.

Topjung Lake also has problems because of high Chl-a concentration in every summer. The singularity

Table 1
Selected parameters based on correlation analysis

Study site	Selected parameters based on correlation analysis ($p < 0.05$)
Gwangdong Lake	[a]Bunchun_temp, Bunchun_DO, Bunchun_PO_4, Bunchun_Chla, Goljichun_temp, Goljichun_DO, Goljichun_TP
Yeongcheon Lake	Jukjang_Temp, Jukjang_DO, Jukjang_SS, Jukjang_TN, Jukjang_PO_4, Jukjang_DTP, Jukjang_EC
Topjung Lake	Nonsan_Temp, Nonsan_pH, Nonsan_BOD, Nonsan_COD, Nonsan_DTN, Nonsan_TN
Daearm Lake	Hazam_Temp, Hazam_DO, Hazam_pH, Hazam_PO_3-P, Jakdong_Temp, Jakdong_DO, Jakdong_PO_3-P, Jakdong_TP, Jakdong_EC

[a]Parameters are listed as "name of sampling point_data". For example, "Bunchun_temp" means the temperature data at Bunchun sampling point.

in this area is that high Chl-a concentration lasts in summer time (from July to September). Especially, in this area, high Chl-a concentration had been observed for five months from June to September in 2009 (Fig. 3(C)). Topjung Lake is one of water protection areas in Chungcheong-province. The main reason why Chl-a concentration was high for the long-term is that the upstream flow from Sunya Mountain runs through 22 km of rural areas. Nonsanchun is the only one upstream of Topjung Lake and 15 types of water quality data were measured as same as Gwangdong Lakes. Following the water quality data of upstream, nitrogen concentration increased from April to May every year and Chl-a concentration in the downstream of Topjung Lake area increase as soon as nitrogen concentration increased. It is noteworthy that fertilizers contained nitrogen are spread in the spring time (from March to May) in South Korea. Six types of water quality data were highly correlated with Chl-a at $p < 0.05$ significant level as the result of correlation analysis (Table 1). As we expected, nitrogen concentration in water is highly correlated with Chl-a concentration in this area. Six selected types of water quality data through correlation analysis were used as input data for Chl-a prediction.

Daearm Lake is located in southern part of Korea, and annual average temperature which effects on Chl-a concentration is the highest among the study sites. In Daearm Lake, over 60 mg/m^3 of Chl-a concentration was observed 5 times and first warning occurred 13 times from 2006 to 2011. Geological feature of six small streams at the upper stream makes the management difficult. Daearm Lake has two upper streams named Hazam and Jakdong. Fifteen types of water quality data were measured as above at each water quality measurement station and correlation analysis was conducted. As the result of correlation analysis, nine types of water quality data at the upper stream were highly correlated with Chl-a concentration and the nine types of water quality data were used as input data for ANN. The singularity of correlation analysis of Daearm Lake is that correlation with phosphorous at the upper stream is high compare to nitrogen.

Results of correlation analysis at each study sites were used to determinist input parameters of NGA. Water flow and rainfall data were not involved in input data-set because of retention time. Considering retention time may be a flaw, because retention time keeps changing according to wet-season, dry-season, and normal-season. Calculating retention time by each season absolutely increases model uncertainty. Even if calculating the exact retention time is possible, water quality data available for corresponding retention time is nonexistent or spotty because water quality data are measured once per month at all study sites. Therefore, several studies also simulate Chl-a concentration without consideration of flow and rainfall [1,28,29]. Therefore, if one model can predict one-month forward Chl-a concentrations effectively without geological and hydrological information [1], the model may be applied for algal early warning system. With this point of view, present (=t_0) water quality data at the upper streams and 1-month after (t_{0+1}) Chl-a data at the target sites were used as input data for NGA.

3.2. *Prediction of one-month forward Chl-a concentration*

The prediction results for one-month forward Chl-a concentration for each of the study sites are in Fig. 4 and ANN structure built by genetic algorithm are stated in Table 2. Final ANN structures built by GA are illustrated in Table 2. Except for Topjung Lake, double layer showed high model accuracy, which means high nonlinearity between input and output variables [30]. Logistic function was selected to compare to other activated function, which is similar to the results of Daliakopoulos et al. [31]. Tanh functions showed best performance in the output layers.

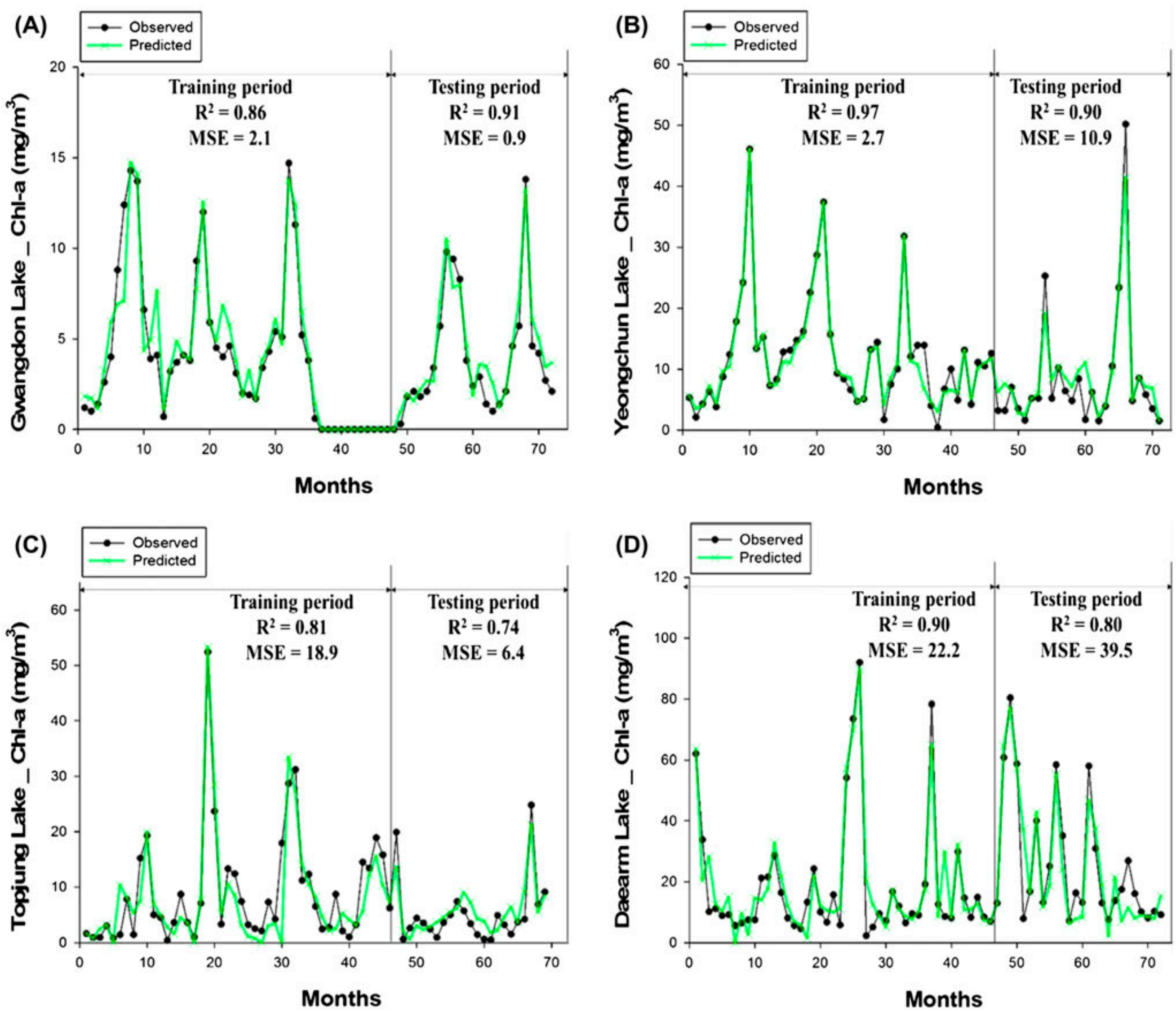

Fig. 4. Simulation results of one-month later Chl-a concentration, (A) Gwangdong Lake, (B) Yeongchun Lake, (C) Topjung Lake, and (D) Daearm Lake.

Table 2
Results of optimizing ANN structure by GA

Site	Number of inputs	Number of hidden layers	AFs at first hidden layer[a]	AFs at second hidden layer[a]	AF at output layer
Gwangdong Lake	7	2	11Lo, 13T, 9Li[a]	14Lo, 9T	T
Yeongcheon Lake	7	2	12Lo, 6T, 7Li	9Lo, 1Li	T
Topjung Lake	6	1	6Lo, 6T, 2Li	–	Li
Daearm Lake	9	2	8Lo, 6T, 1Li	5Lo	T

[a]The expression “aLo, bT, cLi” means that “a, b, c” is the number of each function and “Lo, T, Li” stand for logistic function, hyperbolic tangent function, and linear function in order. The sum of “a, b, and c” is the total number of nodes at each layer.

In Fig. 4, averaged R^2 of all study sites are 0.89 and 0.84 in training and testing period, respectively. Yeongchen Lake shows the highest accuracy ($R^2 = 0.97$) for training period, while Gwangdong Lake shows the highest accuracy ($R^2 = 0.91$) in testing period. Then, Yeongchen Lake showed high model accuracy with 0.90

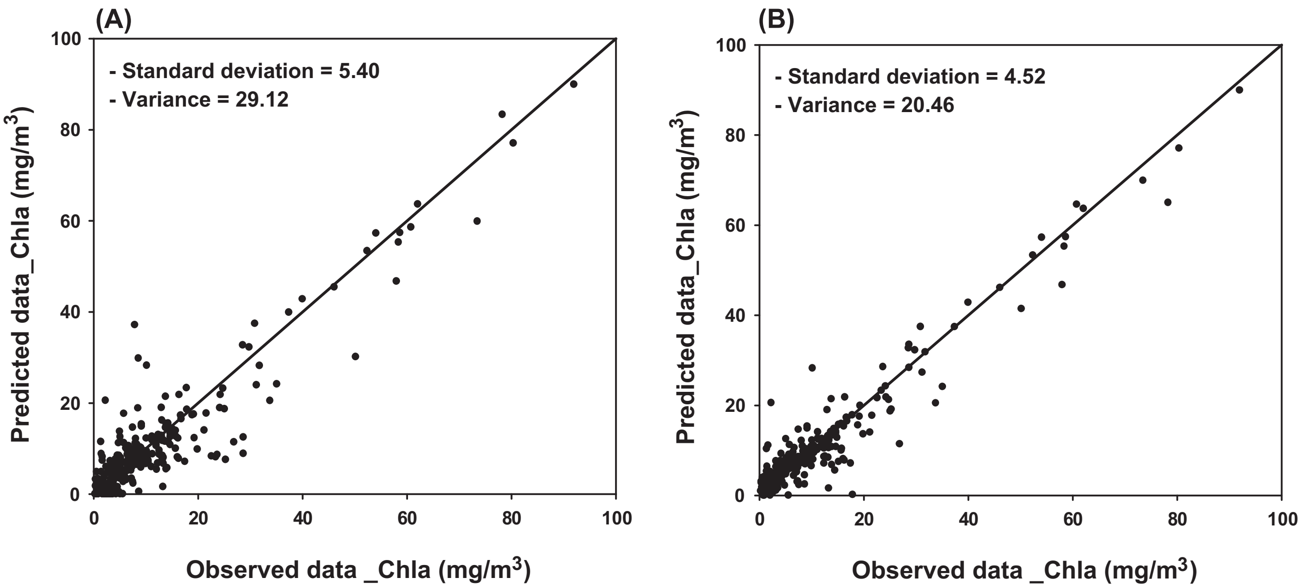

Fig. 5. Comparison of simulation results with (A) literature-based model-input and (B) correlation-analysis-based model-input.

R^2 for testing period, similar to Gwangdong Lake. The important point of the prediction results is that NGA simulated Chl-a concentration almost exactly at a high level (>15 mg/m^3). Normally, high peak data are difficult to predict because of both variously changeable effected by rainfall and non-point contaminant source from upstream. However, NGA showed strong potential to predict high peak of Chl-a concentration without consideration of water flow and rainfall. In Fig. 4, Chl-a concentration is obviously different at each site and period. However, high concentration of Chl-a lasts no longer than a month except Daearm Lake, so it is difficult to cope with rapid changes in Chl-a concentration with the present algae alert system. Analyzing water quality once per week may be the most effective method, but is not proper in terms of cost and manpower utilization. Therefore, if a model can predict one-month after Chl-a concentration, activities to reduce Chl-a concentration should be implemented in advance. This is known as the proactive water quality management. An accurate prediction model is needed to be developed for the proactive strategies, and the NGA developed in this research is regarded as a proper candidate. When the ability to predict water quality is ready through an optimal model, available prevention strategies should be investigated. For example, in the case of high nitrogen problem, prevention strategies such as reorganizing waterfront areas, preparing facilities to reduce biologically nitrogen, and reducing use of fertilizers at the upper stream area should be planned and carried out in order of effectiveness.

Comparison of simulation results with literature-based model-input and correlation-analysis-based model-input were illustrated in Fig. 5. Based on the results, it is obvious that the model using correlation-analysis-based model-input showed high accuracy than using general model inputs.

On those terms, in this study, Chl-a concentration was predicted in a month forward through NGA in order to support algae early warning system and the proactive management process of lakes. Correlation analysis was conducted to select input data and it was analyzed that PO_3-P and EC are highly correlated with Chl-a, unlike previous studies. Prediction of water quality using the selected input data in this research shows more accurate results than when the data of existing research such as temperature, pH, DO, NH_3-N, and TP was used as input data (Fig. 5). The results of this research are regarded as a method to support proactive water quality management.

4. Conclusion

NGA was developed to predict one-month forward Chl-a concentration in lakes. GA was used to select optimal numbers of layers and nodes, and activated functions were selected also by GA. Four study sites with serious Chl-a problems were selected among 93 lakes in South Korea. Water quality parameters were screened via correlation analysis and used as input parameters for NGA. Among 15 kinds of water quality data, PO_4-P and EC are highly correlated with

Chl-a, which are not often preferred in other studies. In the results of one-month forward prediction of Chl-a concentration in four study sites, NGA was shown to simulate Chl-a concentration properly with high R^2 (=0.9). For optimal ANN structure, single and double layer were tested and double hidden layers showed better performance than single hidden layer. A logistic function was mainly selected as an activated function in hidden layers, whereas hyperbolic tangent functions were mostly selected in output layer. Finally, developed NGA showed a high possibility to simulate one-month forward Chl-a concentration in lakes. The results of these predictions may support a water quality management system with proactive strategies.

Acknowledgments

This research was supported by Fundamental Research Grands funded by the Ministry of Higher Education in Malaysia (Grant no. FP016-2014A).

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