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Forecasting algal bloom (chl-a) on the basis of coupled wavelet transform and artificial neural networks at a large lake

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ABSTRACT

Water quality control is affected by several factors such as climate change or the creation of an ecological park for human convenience. The Four-River restoration project of Korea is a government enterprise to solve a variety of problems, such as preventing floods, securing water resources, water quality management, and encouraging re-creation of land. It is evidence that technical developments and the concern of the government have sharply increased for water quality management. In particular, the phenomenon of eutrophication can cause various difficulties in drinking water treatment and water use. Accurate and reliable algal bloom forecasting models will prove very useful in ensuring sustainable water supply and proper water management in the near future. In this paper, a new method based on wavelet transforms and artificial neural networks was adopted for chlorophyll-a concentration forecasting 1, 3 and 7 days ahead. First, 12 models for forecasting chlorophyll-a concentration by combining water quality and hydrological factors from different models as input data were established by using an original ANN with a back-propagation algorithm. The best model, as evaluated by its performance functions, was selected and applied to the new method as a coupled wavelet analysis-artificial neural network (WA-ANN) to forecast chlorophyll-a concentration for 1, 3 and 7 days. Finally, the results of WA-ANN in the study were compared to those of a regular ANN with a back-propagation algorithm. The results showed that WA-ANN models constitute a promising new method for short-term chlorophyll-a concentration forecasting in large lakes.

Keywords: Wavelet transform; Artificial neural network; Forecasting; Chlorophyll-a; WA-ANN

1. Introduction

Climate change and alteration of the environment around rivers for human convenience cause various problems in water quality control. Therefore, short-term and long-term forecasting of water quality are important components of water resource management for a variety of reasons, such as helping optimize water resources as well as planning for the prevention

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of future pollution in a sustainable and effective manner. Highly accurate and reliable flow forecasting is particularly important in watersheds because of increasing environmental concerns directly related to human life and rapidly changing circumstances. Data collected on various water quality factors have been used to forecast changes in river water quality by using black box models or physical models in many studies worldwide. In particular, artificial neural network (ANN) may offer an effective and promising method for streamflow forecasts, as well as for water quality forecasting and water treatment [1]. Beginning with the Streeter–Phelps model, various ANN models have been developed to quantitatively simulate the phenomenon of water quality change. The ANN model has been widely used abroad for the purpose of effective control through water quality prediction. Studies on algal bloom forecasting using ANN have been widely implemented in various countries since 1990. Generally, these studies focus on predicting water quality components for 1–5 days, or even a month, using ANN models. Friedrich et al. [2] used water quality data that had been measured for 12 years, including orthophosphate, nitrate, Secchi depth, water depth, dissolved oxygen (DO), water temperature (Tw), and chlorophyll-a concentration (chl-a), as the input data for an ANN. The models were used to predict algal species abundance. Karul et al. [3] studied non-linear behavior in eutrophication processes with Levenberg—Marquardt (tangent-sigmoid) analysis to predict chl-a using a variety of water quality factors in the river reservoir as input factors. Palani et al. [4] forecasted chl-a a week ahead using general regression neural networks (NNs) to forecast eutrophication based on DO, Tw, and chl-a with a lag time of 2 weeks as input data. These previous studies included many forecasting methods for each component of water quality such as biochemical oxygen demand and DO, but studies on the prediction for chl-a, as well as models that chiefly predict chl-a a week or a month in advance, are rare. The chl-a is the main factor that causes eutrophication. If short-term forecasting of this element is implemented, water quality management will be much more efficient and would facilitate the prevention of water pollution. However, despite these studies, there are some problems with ANNs and other linear and non-linear methods, i.e. they have limitations when used with non-stationary data. Many methods such as NNs may not be able to handle non-stationary data if preprocessing of the input data is not done. The methods for dealing with non-stationary data are not as advanced as those for stationary data. Wavelet analysis has been investigated in a number of disciplines outside water resources engineering and hydrology, and has been found to be very effective with non-stationary data. Wavelet transforms provide useful decompositions of original time series, and the wavelet-transformed data improves the ability of a forecasting model by capturing useful information at various levels of resolution. Further, wavelet analysis can be a useful tool to analyze detailed temporal patterns of non-stationary hydrological and water quality signals over different temporal scales. Nakken [5] used continuous wavelet transforms to identify the temporal variability of rainfall and runoff and their relationships; in another study, Kang et al. [6] studied temporal patterns of three hydrological signals (precipitation, streamflow, and water level) for three periods (15 years, three years, and the hydrological year), as well as water quality signals (nitrate, chloride, and sodium), with the weighted wavelet Z-transform method. This study found that wavelet analysis of hydrological signals was more advantageous than classical Fourier analysis in detecting detailed temporal patterns. Hanbay et al. [7] predicted chemical oxygen demand (COD) based on wavelet decomposition, entropy, and a NN for rapid COD analysis. In particular, in the domain of hydrology, wavelet analysis has been actively used to describe the variability of streamflow [8] and to enable streamflow forecasting using discrete wavelet transform (DWT) [9,10]. In another study, Adamowski et al. [11] studied a method based on coupling DWT and ANN for flow forecasting applications in non-perennial rivers. The wavelet coefficients were then used as inputs into Levenberg—Marquardt ANN models to forecast flow. The relative performance of the coupled wavelet-neural network models (WA-ANN) was compared to regular ANN models for flow forecasting at lead times of one and three days for two different rivers. In other words, wavelet transform can be used in diverse fields to offset the disadvantages of ANNs.

In this study, wavelet transform was applied to decompose the signals of chl-a in an original time series directly related to the eutrophication process; these decomposed signals were used to improve the ability of algal bloom forecasting models. The research area was selected on the basis of a current pending issue which is concerned about water quality pollution under the conditions of water quality in Korea. Water quality management is needed in Daecheong reservoir because of the sudden increase of algal blooms in Geum River. This study uses wavelet transform and ANN to improve the accuracy of developed algal bloom models in previous studies [12] using ANN with back-propagation algorithm (BP-ANN).

2. Materials and methods

2.1. Study area and data description

The selected study area, Daecheong reservoir in Geum River, is one of the major sources of water supply in Korea. The length of the dam is 495 m, volume is 1,234,000 m^3, and height is 72 m. Its watershed area is 3,204 km^2 excluding the Yongdam reservoir basin. The dam has multiple uses, including domestic and industrial water supply. Daecheong reservoir stores 1,649 m^2 of water for supply, and 1,300 m^2 of the water is used for domestic and industrial purposes. Furthermore, the reservoir is very important because it offers space for leisure activities. Rainfall in this watershed occurs mostly from June to August, with the maximum rainfallfrom July to August. During the dry season, which lasts from January to April and from November to December, the reservoir receives only 15% of the annual rainfall. These patterns are typical Korean weather in which the rainfall is concentrated during the summer. This type of rainfall increases the possibility of risks in water quality management. Accordingly, an automatic water quality observation system has been installed by the Korean government to monitor changes in water quality in real time. However, there have been several occurrences of algal blooms in the same year because of decreased water levels and the effects of climate change in the area. The main reason for this is the unexpected eutrophication in summer with the effect that air temperature and rainfall frequency both increase. In light of this, the Korean government has established standards for algal bloom forecasting based on water quality parameters such as Tw, pH, DO, total organic carbon (TOC), chl-a, total nitrogen (TN), and total phosphorous (TP) in the area. For this study, we selected this area as a suitable site to establish an effective and promising model for short-term algal bloom forecasting (Fig. 1).

The data used in this study have been obtained from the automatic water quality observation system in Daecheong reservoir. This includes various water quality variables (Tw, pH, DO, TOC, TN, TP, and chl-a) from 2009 to 2010, and hydrological variables (inflow quantity (If) of Daecheong reservoir, outflow quantity (Of), and air temperature).

2.2. Theory of ANN

A BP-ANN is very useful because of its broad applicability in solving and managing many problems such as principal prediction and modeling for various purposes. According to a supervised learning method in the process, this NN requires a set of training data

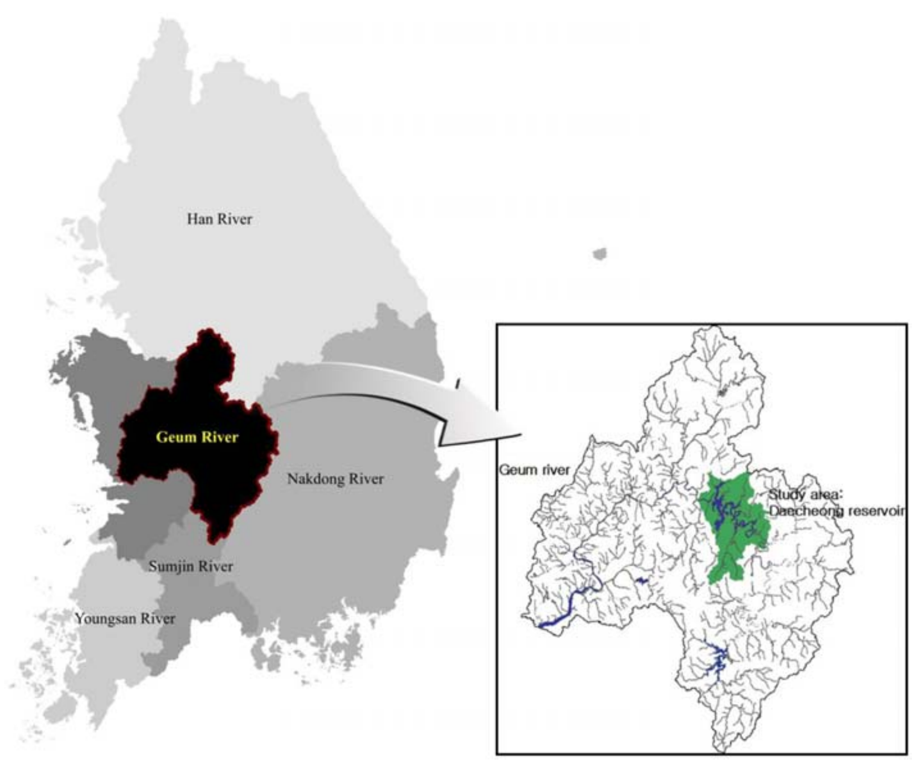


Fig. 1. Study area on Geum River watershed in South Korea.

in order to learn the relationships among several factors and testing data for validation. The architecture of BP-ANN consists of three nodes: input, hidden, and output nodes. The node-to-node connections, such as input-hidden and hidden-output are connected by weights and biases. In establishing a BP-ANN model, one must select an appropriate activation function, determine the number of hidden nodes, and estimate the corresponding parameters using an approximate computational scheme. The objective is to find a reasonable BP-ANN that will give an approximation to true output within a specified error. Approximating functions are needed for the superposition of the hyperbolic tangent as follows:

Hyperbolic tangent:

$$\varphi(v) = \frac{1-\exp(-v)}{1+\exp(-v)} \tag{1}$$

A description of the BP-ANN system based on the hyperbolic tangent activation function can be derived as follows:

$$\hat{y}_{t}^{(k)}(x) = \gamma_k + \sum_{h}^{j=1} \alpha_{jk} \tanh\left[\beta_j + \sum_{i=1}^{n} w_j^{(i)} x_t^{(i)}\right] \tag{2}$$

where the coefficients γ, α, β and ω are parameters of the ANN model. The coefficient γ_k is associated with the output node k, the coefficient α_{jk} is associated with the hidden node j and output node k, the coefficient β_j is associated with the hidden node j only, and the coefficient $\omega_j^{(i)}$ is associated with the input i and the hidden node j. Each output node receives data through each weighted value for all the hidden nodes. Each node produces the values by changing data added up that has been used with a non-linear function for producing values.

2.3. Theory of wavelet transform

Wavelet analysis method is mathematical tools, which has proven quite useful for time scale-based signal analysis in physics and engineering. The wavelet transform is a tool for decomposing a signal into components at different resolutions and time scales. The wavelet transform can be used to analyze a time series which contains non-stationary data at many different frequencies [13]. Wavelet transform produces a few significant coefficients and reconstructs the signal using significant coefficients from the signals with discontinuities. Wavelet analysis allows the use of long time intervals for low-frequency information and shorter intervals for high-frequency information, and it reveals aspects of data like trends, breakdown points, and discontinuities that other signal analysis techniques might miss. Another advantage of wavelet analysis is the flexible choice of the mother wavelet according to the characteristics of the investigated time series.

DWT of various wavelet transform methods involves the use of digital filtering techniques by decomposing the time series signal. DWT scales and positions are usually based on the powers of 2—the so-called dyadic scales and positions. Mathematically, it can be expressed as:

$$\Psi_{a,b}(t) = \mid a \mid^{\frac{1}{2}} \Psi\left(\frac{1-b}{a}\right) \tag{3}$$

where $\Psi_{a,b}(t)$ is the successive wavelet, and a and b are the scale and translation factor, respectively. The successive wavelet transform of $f(t)$ is defined as:

$$W_{\Psi}f(a,b) = \mid a \mid^{1/2} \int_{R} f(t)\bar{\Psi}\left(\frac{t-b}{a}\right)dt \tag{4}$$

where $\bar{\Psi}(t)$ is a complex conjugate function of $\Psi(t)$ The equation indicates that the wavelet transform is the decomposition of $f(t)$ under different resolution levels (scales). The DWT operates two sets of functions viewed as high-pass and low-pass filters. The original time series are passed through high-pass and low-pass filters, and detailed coefficients and approximation sub time series are obtained.

2.4. Methods

This study makes steady progress in the order shown in (Fig. 2).

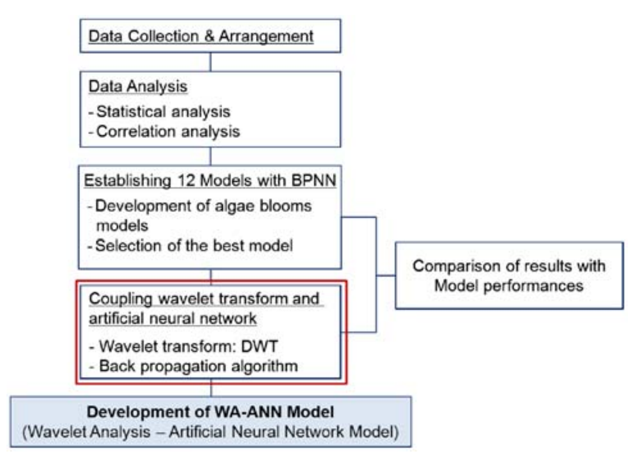


Fig. 2. Process of this study for establishing WA-ANN model.

There are two key points in this research: to select the best model for algal bloom forecasting by establishing 12 models with BP-ANN, and to develop the coupling WA-ANN. The optimal model was selected for water quality forecasting by establishing a variety of algal bloom real-time forecasting neural network models (AB-RF-NN models) based on water quality and hydrological components.

2.4.1. Developed AB-RF-NN models

Data analysis was implemented for basic statistical and correlation analyses between elements of hydrology and water quality which directly affect algal blooms. As already mentioned [12], this study used serial-correlation and cross-correlation analyses to define the relationship among the elements. To check the seasonal change and cyclical repeatability of the time series data, serial-correlation analysis r_k was used to derive the following Eq. (5).

$$r_k = \frac{\sqrt{\sum_{i=1}^{n-k}(x_i - \bar{x})(x_{i+k} - \bar{x})}}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \quad (5)$$

In this formula, $(\bar{x})$ is the average, and n is the number of the analyzed data.

Cross-correlation analysis used to correlate water quality and hydrologic elements yielded the following Eq. (6).

$$r_{xy}(\mathrm{k}) = \frac{C_{xy}(\mathrm{k})}{S_x S_y} \quad (6)$$

In this formula, C_{xy} is the covariance of x and y, and S_x and S_y are the standard deviations of x and y respectively. Using the abovementioned methods, the AB-RF-NN models for short-term algal bloom forecasting with ANN were built using the parameters If, Of, Tw, pH, DO, TOC, TP, TN, and chl-a, as shown in (Table 1), on the basis of the results of the correlation analysis. However, one disadvantage of the AB-RF-NN models is that it rarely sets a peak value for training data. Therefore, a set of training data were used in 2010, and a set of testing data were collected in 2009. For calibration/validation activity on the models, the following performance functions between the observed values and the calculated output were used: relative volume (RV), relative peak (RP), root mean square error (RMSE), and correlation coefficient (R^2), as shown in (Table 2).

Table 2
Description of model performance methods

Methods	Basic equations
Relative peak error (RP)	$\mathrm{RP} = \frac{[\hat{Q}-Q]}{Q}$, $\hat{Q}$ & Q: forecasted & observed peak value
Relative volume error (RV)	$\mathrm{RV} = \frac{[\hat{Q}_v - Q_v]}{Q_v}$, $\hat{Q}_v$ Q_v: forecasted & observed total volume
Root mean square error (RMSE)	$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum^{N}(\hat{Q}(t) - Q(t))^2}$, t: time, N: the number of data
Correlation coefficient	$R^2 = \frac{\sum^{N}(\hat{Q}-\bar{Q})^2}{\sum^{N}(Q-\bar{Q})^2}$, $\bar{Q}$: average of observed data

Table 1
Structure of AB-NN models used for reasonable estimation of output in this study

Output	Model	Factors of input data for neural network								
		If	Of	Tw	pH	DO	TOC	TN	TP	chl-a
Chl-a	Model 1		•	•	•	•	•			•
	Model 2		•	•	•	•	•			
	Model 3			•	•		•			
	Model 4			•			•			
	Model 5			•	•		•			•
	Model 6	•		•	•	•	•	•	•	•
	Model 7			•	•	•	•	•	•	•
	Model 8			•			•		•	
	Model 9		•	•			•		•	
	Model 10		•	•	•	•	•		•	•
	Model 11		•	•			•		•	
	Model 12			•					•	

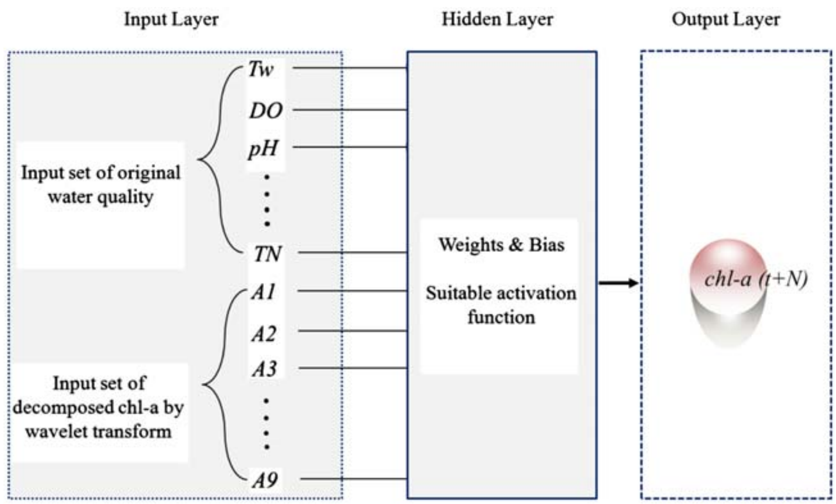


Fig. 3. Architecture of WA-ANN model.

2.4.2. Coupled WA-ANN models

The WA-ANN model is based on a BP-ANN, which uses sub-series components that are derived from the use of the DWT on the original flow time series data as inputs data. Each sub-series component plays a different role in the original time series, and the behavior of each sub-series is distinct. The ANN models are built such that the decomposition and details of the original time series are the inputs to the ANN and the original time series are the outputs of the ANN [11].

As shown in (Fig. 3), a WA-ANN was established to increase accuracy. The chl-a, the most important of the various water quality factors, was decomposed into sub-series of approximations and details. The process of decomposition was successively iterated, with approximation signals being decomposed in turn, so that the original observed chl-a was broken down into many lower resolution components.

The performance of developed models was evaluated in terms of statistical measures of the goodness of fit. In order to provide an indication of the goodness of fit between the observed and predicted values, RP, RV, RMSE, and R^2 were used, as shown in (Table 2). In general, the smaller the RMSE, the better the performance of the model. Similarly, the closer the value of R^2 to 1, the better the result of the model.

3. Results and discussion

3.1. AB-RF-NN forecasting models

As already analyzed in a previous study [12], the correlation analysis has been conducted to identify the relationship between water quality and hydrological factors, with chl-a directly taken as the standard with regard to the occurrence of eutrophication. We found that chl-a had highly correlated with Tw, pH, DO, TOC, TN, and TP. On the basis of these results, AB-RF-NN models, which were 12 models with input data consisting of each other factors from each of the models, were developed. The results of these models are shown in scatter plots (Fig. 4): Model 6, Model 7, and Model 10 were selected as the best models for chl-a forecasting based on the results of model performance parameters such as RMSE and R^2. Of these models, Model 6 showed RMSE and R^2 values of 1.65 and 0.98, respectively, for 1 day ahead; 3.34 and 0.93, respectively, for 3 days ahead; and 4.92 and 0.847, respectively, for 7 days ahead. Model 7 showed RMSE and R^2 values of 1.0 and 0.996, respectively, for 1 day; 2.9 and 0.953, respectively, for 3 days; and 3.95 and 0.918, respectively, for 7 days ahead, thereby rendering it the best algal bloom forecasting model for three periods. Lastly, the RMSE and R^2 values in Model 10 were 1.88 and 0.956, respectively, for 1 day; 2.95 and 0.948, respectively, for 3 days; and 5.86 and 0.81, respectively, for 7 days ahead. Model 7 was the best AB-RF-NN model for comparing the improvements in WA-ANN. Fig. 5 showed the results from selected AB-RF-NN models with high performance based on RMSE and R^2 values. The results of performance models were shown at (Table 3).

3.2. Coupled WA-ANN models

In this study, coupled WA-ANN models were developed for improving the high performance of the AB-RF-NN models, as well as to increase accuracy for the purpose of water quality management, and not

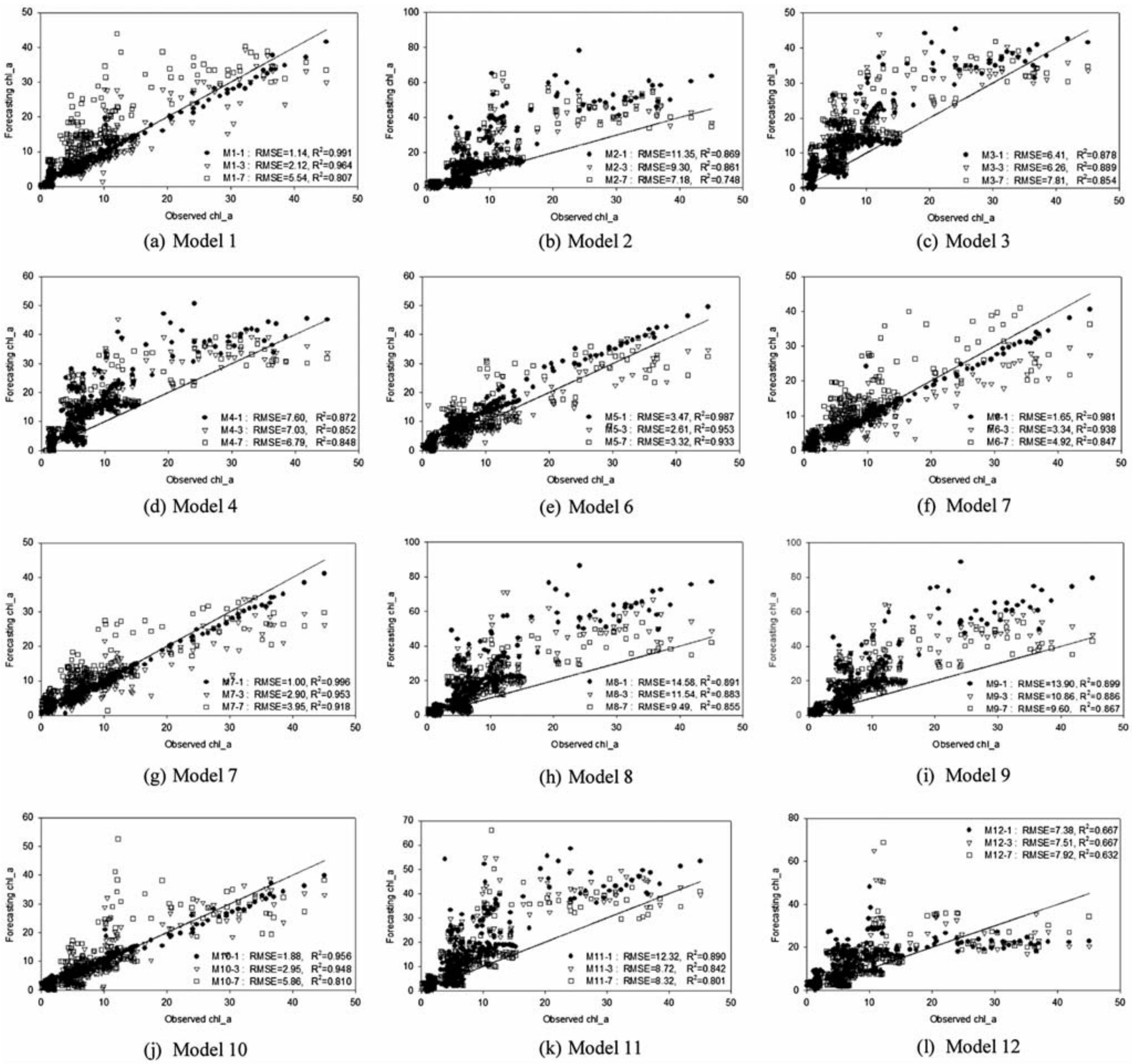
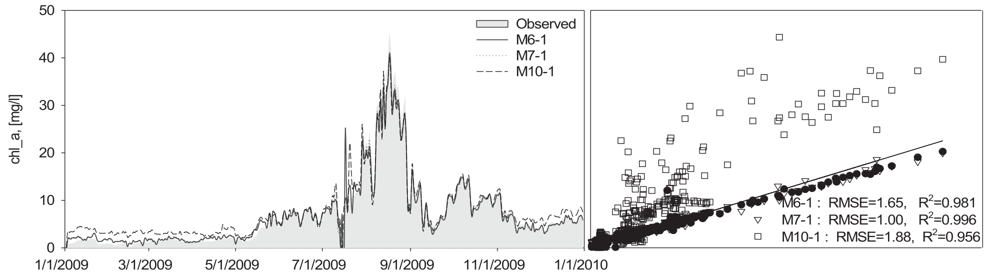
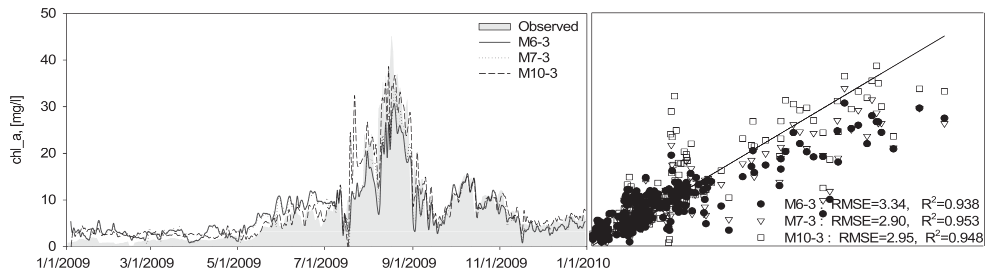


Fig. 4. Results of chl-a forecasting by AB-RF-NN models: scatter plots between observed and forecasted data.

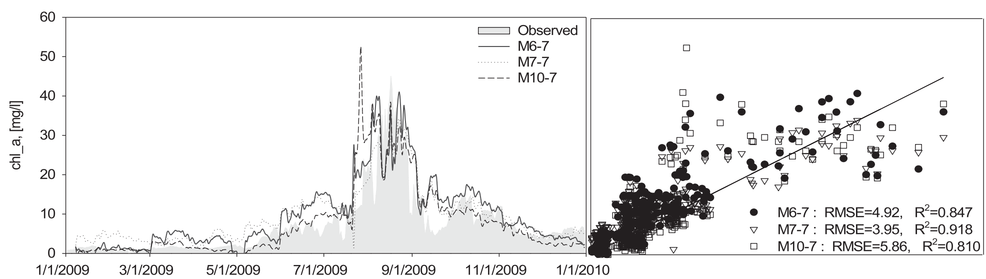
just as a precaution. WA-ANN models were coupled with DWT and AB-RF-NN. The chl-a of a variety of water quality factors was decomposed by a DWT into level 9 using the Daubechies-3 function. The WA-ANN models consisted of 5 components of water quality (the same as the input factors of AB-RF-NN models, except for chl-a) and decomposed approximations of low frequencies as input data. The WA-ANN models were same as Model 7-1-1, Model 7-1-3, Model 7-1-7, Model 7-3-1, Model 7-3-3, Model 7-3-7, Model 7-4-1, Model 7-4-3, and Model 7-4-7, in each case, the numbers indicate the best AB-RF-NN model, case, and lead time, in that order. New model combining Model 7 of the AB-RF-NN models and the DWT was established for short-term forecasting. From these models, reasonable models were selected on the basis of the model performance results such as the RMSE and R^2. Table 4 indicated the architecture of the WA-ANN models in forecasting chl-a by training and testing. Subsequently, the WA-ANN models were compared to AB-RF-NN models at a large lake. The model performance results between these 2 models in the case of 1-day forecasting appeared to be similar. The model performance results in the case of the



(a) 1 day



(b) 3 days



(c) 7 days

Fig. 5. Results from selected AB-RF-NN models with high performance based on R^2 and RMSE criteria.

3-day forecasting showed that the optimal WA-ANN model, Model 7-1, had a positive capacity for improvement. In contrast, in the case of the 7-day forecasting, the results of the WA-ANN were higher

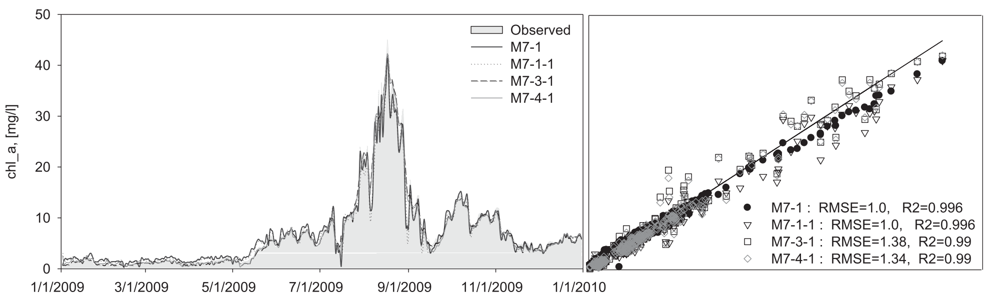
Table 3
Results of model performance for optimal AB-NN model and WA-NN model results

	Model	Lead time	Results of model performance			
			RP	RV	RMSE	R^2
Optimal AB-NN model	7	1	8.85	0.34	1.0	0.99
		3	24.96	2.57	2.90	0.95
		7	24.12	32.98	3.95	0.91
Optimal WA-NN models	7-1	1	9.28	3.0	1.0	0.99
		3	16.83	5.91	2.17	0.97
		7	19.02	32.71	3.98	0.92
	7-3	1	6.77	1.80	1.38	0.99
		3	24.59	7.17	2.80	0.95
		7	16.15	43.48	4.34	0.92
	7-4	1	6.44	3.12	1.34	0.98
		3	22.95	4.23	2.70	0.95
		7	22.66	7.77	2.97	0.93

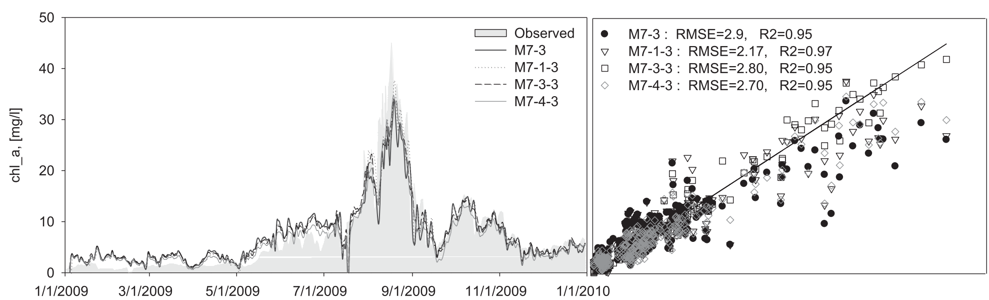
Table 4
Architecture of WA-NN models for chlorophyll-a forecasting by training

Model	Lead time	Factors of input data	Structure
Model 7-1	$t+1$	Tw, pH, TOC, TN, TP, (A1 of chl-a)	12-16-1
	$t+3$		14-18-1
	$t+7$		8-14-1
Model 7-3	$t+1$	Tw, pH, TOC, TN, TP, (A1, A2, and A3 of chl-a)	12-16-1
	$t+3$		14-18-1
	$t+7$		14-18-1
Model 7-4	$t+1$	Tw, pH, TOC, TN, TP, (A1, A2, A3, and A4 of chl-a)	14-18-1
	$t+3$		14-18-1
	$t+7$		15-18-1

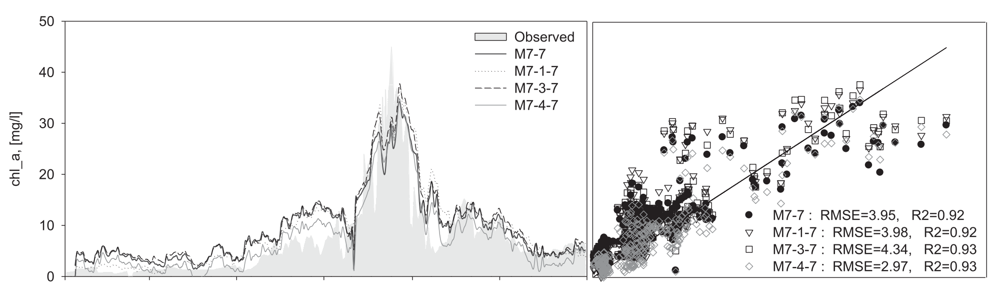
than those of the Model 7 among the AB-RF-NN models. (Fig. 6) showed the results of testing using linear graphs and scatter plots from selected WA-ANN models out of the nine models with high performance results based on RMSE and R^2. In particular, Fig. 7 shown as above, residuals were explored by



(a) 1 day

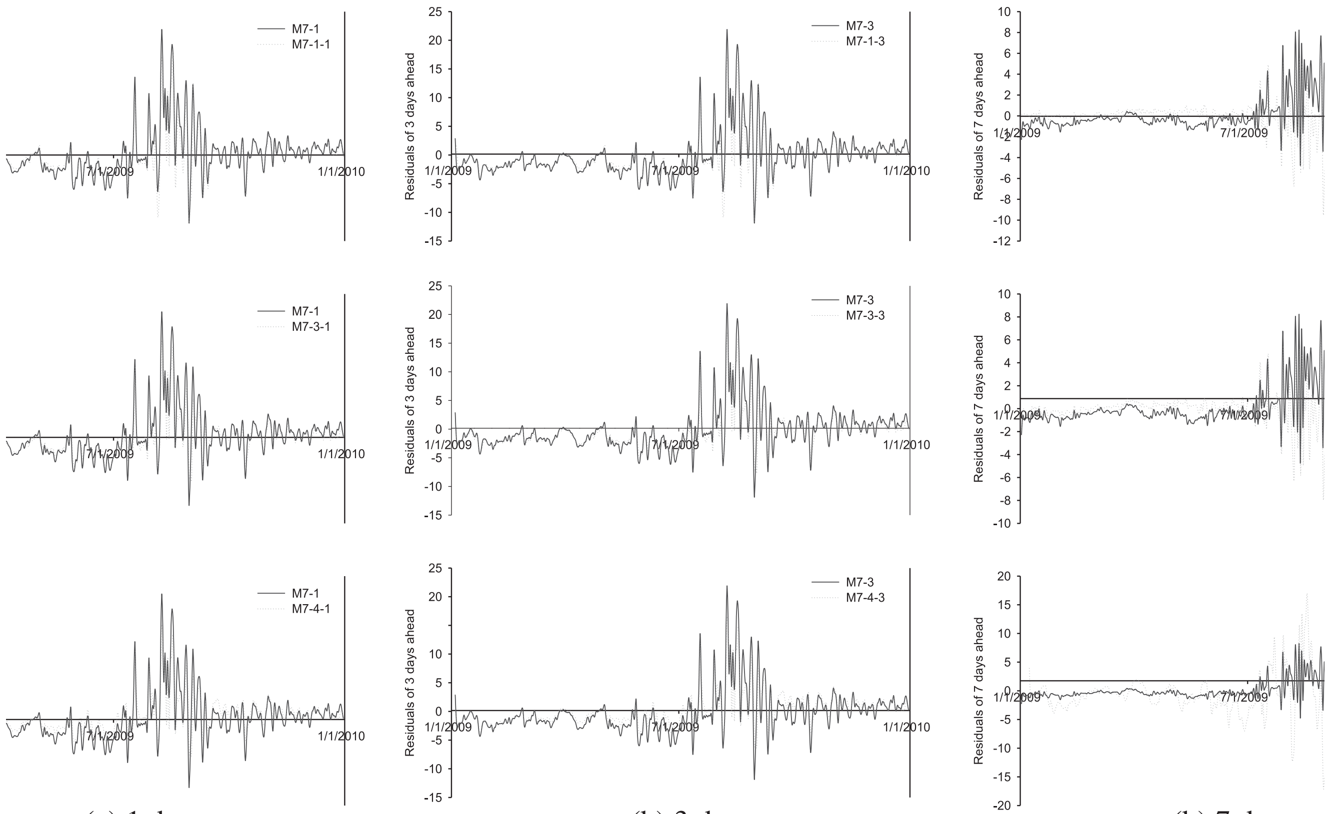


(b) 3 days



(c) 7 days

Fig. 6. Results from selected WA-NN models with high performance based on R^2 and RMSE criteria.



(a) 1 day (b) 3 days (b) 7 days

Fig. 7. Residuals of comparisons between AB-NN and WA-NN models for chl-a forecasting result.

comparing results between AB-RF-NN and WA-NN models for forecasting chl-a for 1, 3 and 7 days ahead.

4. Conclusions

The WA-ANN model is a new and promising method to forecast chl-a over the short term; this model includes a DWT and an ANN. In particular, in this study, the model is proposed to increase the effectiveness of water quality management and manage clear water use in a sustainable manner. The accurate forecasting results on a large lake indicate that the WA-ANN model is a potentially useful method for chl-a forecasting. As mentioned above, the model was compared to AB-RF-NN models for chl-a forecasting on a large lake with a lead time of 1, 3 or 7 days. Results in this study using ANN for chl-a forecasting were excellent in the short term, but were considerably improved using the WA-ANN model under the same conditions. This study demonstrated the effectiveness of wavelet analysis in forecasting water quality by using the model that yielded the best AB-RF-NN results. Also, in case of having various hydrological or water quality characteristics on each watershed, the WA-ANN models could be widely utilized to forecast. Salerno et al. [8] said that WA can potentially be applied to help define the nature and behavior of the karst contribution to river flows and improve the future performance of surface hydrological modeling.

With reference to purposes in this study, the results with comparison could be explored: (1) WA-ANN models were improved for water quality forecasting, (2) the models showed the accuracy higher than AB-RF-NN models, (3) the models showed higher possibility to forecast chl-a for 3 days and 7 days, as well as 1 day. Comparison with a similar study, but differing the unit of used input data, results of correlation coefficient was better than others.

It is recommended that future studies explore the use of the WA-ANN model in forecasting chl-a for other watersheds and a variety of lead times (such as weekly and monthly) and compare the forecasting performance of the wavelet-based noise removal method to other filtering methods. In further research, WA-ANN models on the basis of other AB-RF-NN models, not with the best model, would better establish a forecasting model for water quality management. And then this might support the level of accuracy and applicability in WA-ANN model.

This would make water quality management easier in various large lakes or many rivers. Furthermore, an attempt could be made to obtain information regarding the water quality characteristics of each river by applying the validated WA-ANN to various rivers. Finally, this study can be applied directly to maintain reasonable water quality in the reservoir and to prevent deterioration of water quality in future incidents.

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