Original Article

Artificial Neural Network Approaches to the Prediction of Eutrophication and Algal Blooms in Aras Dam, Iran

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Abstract

Background and purpose: Eutrophication is one of the major environmental problems in waterways causing substantial adverse impact on domestic, livestock and recreational use of water resources. Aras Dam, Iran which provides Arasful city with drinking water, has chronic algal blooms since 1990. Levels of up to 900,000 cells/mL of toxic cyanobacteria (mainly Anabaena and Microcystis) have been recorded in the dam.

Materials and Methods: In this study, artificial neural network (ANN) model was investigated to predict the chlorophyll-a (Chl-a) concentration in water of dam reservoir. Water samples were collected from 5 stations and analyzed for physical quality parameters including; water temperature, total suspended solids, biochemical oxygen demands, orthophosphate, total phosphorous and nitrate concentrations using standard methods. Chl-a was also measured separately in order to investigate the accuracy of the predicted results by ANN.

Results: The results showed that a network was highly accurate in predicting the Chl-a concentration. The mean squared error and coefficient of correlation (R^2) between experimental data and model outputs were calculated. A good agreement between actual data and the ANN outputs for training was observed, indicating the validation of testing data sets. The initial results of the research indicate that the dam is enriched with nutrients (phosphorus and nitrogen) and is on the verge of being eutrophic.

Conclusion: The Chl-a concentration that was predicted by the model was beyond the standard levels; indication the possibility of eutrophication especially during fall season.

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Key words: Aras Dam, Eutrophication, Artificial Neural Network, Water Quality, Algal Bloom

1. Introduction

Algae are a wide-ranging group of aquatic plants including chlorophyll and other photosynthetic pigments. Many of these algea are microscopic while some of them are large. They grow as single cells or aggregations of colonies (1). Algae are surprisingly varied in size, shape, and color. They contain a variety of aquatic plants found in a broad spectrum from single-celled plants that are indistinct to the naked eye to gigantic kelps that can grow up to 45 m and weigh as much as a small tree (2). Exist on soil, beneath the polar ice and in snow, but greatest numbers are found in the waters that cover 70% of the earth’s surface (3). Chlorophyll and other photosynthetic pigments are responsible for algea’s colors. Piles of green or brownish weed stranded are the results of algea growth along an estuary or ocean shorelines. Algea also cause lake waters turn a murky “pea soup” green color (4). Photosynthesis is the conversion of carbon dioxide and water to carbohydrates using light energy. Oxygen is produced in the process. Eutrophication is the process whereby water bodies become enriched by nutrients (Phosphorus and Nitrogen) from both external and internal sources. Eutrophication is recognized as one of the most influential environmental problems in both the developed and the developing countries (5). Eutrophication and an inordinate amount of blue-green algal (cyanobacteria) growth are one of the prominent water-quality problems in waterways (6). Raised nutrient levels in aquatic ecosystems are normally originated from point sources (e.g., municipal and industrial effluent) and non-point (diffuse) source namely, agricultural runoff from fertilized top soils and livestock processing (7). Cyanobacteria contribute to many water-quality angst, including potential production of toxins and taste-and-odor compounds. When dense algae populations develop, they alter water a green or greenish brown color referred to as a “bloom” which can be defined as high concentrations of algal cells with “pea soup” appearance (8). Dense blooms near the surface may resemble a layer of green paint. Blooms’ trouble occurs in the summer months and are repeated in times of drought (1,9). Greatest number of algea growth, the chances for problems are also increased. World Health Organization (WHO) standard for problem blooms is when the population of algal cells exceeds 100,000 cells/mL, or the equivalent of 24 million algal cells in an 8-ounce cup of water (1). In Iran, this water quality setback is associated with land degradation rooting from poor land management practices over the past 200 years. Large agricultural areas in Iran are being inappropriately used, and many agricultural practices are simply inappropriate (10). Recent studies have shown that the phosphorus in some turbid waterways is derived from naturally phosphorus-rich soil. Quality deterioration of water resources is increasingly becoming a major concern due to the fact that it further complicates the problems associated with the water scarcity in Iran (10). Bloom density in pond water is often measured using a Secchi disk. Blooms are considered to be too dense when the Secchi depth is < 12 inches (11). The phenomenon of algal blooms within the dam ecosystem threatens both recreational and commercial pursuits. In general, algal blooms occur when a favorable set of environmental conditions exist. These blooms often lead to the discoloration of dam water and in some instances, dissolved oxygen depletion, fish kills and potential shellfish poisoning. Dam ecosystems are highly complex dynamic systems (1). The Aras dam, Iran has been experiencing algal problems since 1985. Levels of up to 450,000 cells/mL of cyanobacteria (mainly Anabaena and Microcystis) have been recorded in the dam (10). When the level of blue-green algae in the dam exceeds 25,000 cells/mL, the dam is closed to recreational users. Department of Public Works and Services reported that the existing dam storage is on the border of being eutrophic i.e. susceptible to blue-green algal growth with associated impacts on water quality. Outbreak of blue-green algae depends on the interaction of a wide range of biophysical processes and socio-economic factors such as nutrients, temperature, light, dissolved oxygen, aquatic ecosystem balance, land use, and catchment management. From a management point of view, prediction of eutrophication based on the available influencing factors is essential.

It is not the intent of this paper to provide an ecological model of algal bloom dynamics, rather it is to provide a framework for developing a predictive model which utilizes Artificial Neural Network (ANN) modeling. The main advantage of this approach is that ANNs are able to model non-linear, dynamic and noisy data, especially when the underlying physical/biological relationships are not fully understood (12). Prediction of Chlorophyll-a (Chl-a) within dams' environment is a suitable application of ANNs. This predictive tool provides opportunities for proactive rather than reactive management regimes with regard to mitigating the effects of dams' algal blooms. The main goal of this study was to predict Chl-a concentration by ANN model and compare the data obtained with its natural concentration measured by HPLC (Model 210D).

2. Materials and Methods

Aras Dam, which was built in 1963 to provide Azerbaijan town a secure water supply, is located downstream of Poldasht in West Azerbaijan Province, Iran and Nakhchivan City in Nakhchivan Autonomous Republic, Azerbaijan. The Aras Dam is 40 m (130 ft) tall from its foundation and 34 m (112 ft) tall from the riverbed. It is 1,026 m (3,366 ft) long and 8 m (26 ft) wide on its crest. At a normal water elevation of 777.5 m (2,551 ft) above sea level, the dam withholds a reservoir of 1.35 km^3 (1,090,000 acre·ft) with a surface area of 145 km^2. Since opening, the reservoir has provided irrigation water for 400,000 hectares (990,000 acres) of arable land in Azerbaijan and Iran, including about 60,000 hectares (150,000 acres) in Dasht-e Moghan area.

Totally, 6 stations were sampled in a year 2013 (Figure 1). Stations chose with navigate location and as regards water depth, macrophytes population and wind direction of the dam place. Samples were taken in three water depth (surface- middle-upper depth) for each season. Therefore, a total of 144 samples were taken from different stations and various water depth. At each station, salinity and temperature were measured with a conductivity, temperature, and depth probe. Samples were collected using Niskin bottles. Dissolved inorganic nutrients (NO_3, NO_2, NH_4), dissolved inorganic phosphorus were measured using automated colorimetric techniques after filtration through GF/F filters. Dissolved oxygen and pH were detected using (Horiba-U10). Chlorophyll a (Chl-a) concentrations were analyzed on GF/F filters that were stored frozen until extraction and analysis by high-performance liquid chromatography.

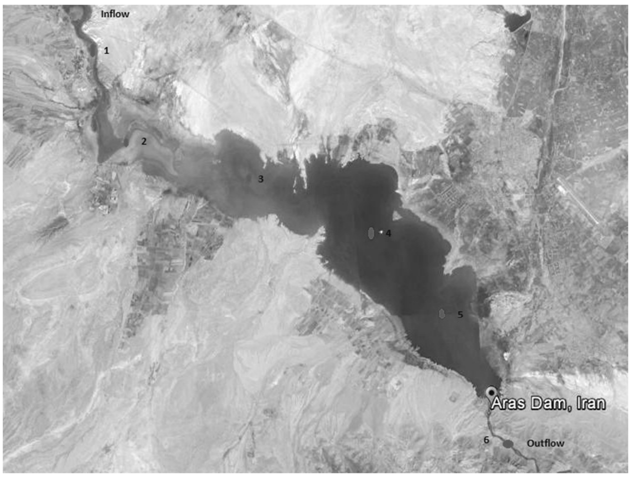


Figure 1. Map of the six sampling stations

Various input variables including nutrients, Chl-a, water temperature, alkalinity and salinity were selected for conducting different scenarios in ANN. Fourth scenarios defined. In each scenario PO_4, temperature, NO_3, DO, total suspended solids (TSS) in different season of year are chosen as inputs and Chl-a prediction as outputs. The aim of using ANN was to provide a robust model based on the lowest number of input variables, with a modest data requirement Water temperature is also known as a prominent variable regulating algal biomass and subsequent bloom conditions. Temperature is considered for the inputs of the model with consideration given to diurnal and seasonal patterns. These patterns showed that the warmest diurnal temperatures took place during the afternoon and that the warmest seasonal temperatures are associated with summer months. These warm periods are mostly associated with the highest Chl-a measurements. Therefore, variables considered to be most influential for the prediction of algal blooms included: time-lagged Chl-a, water temperature, TSS, Biochemical oxygen demands, orthophosphate, total phosphorous and nitrate concentrations.

Being conceptually based on biological nervous systems, ANNs consist of a large number of highly interconnected processing elements. ANNs contain artificial neurons which receive a number of inputs (either from original data or from the output of other neurons in the network). Each of these inputs comes via a connection that has a strength (or weight); these weights correspond to the synaptic efficiency. Each neuron also has a single threshold value. The weighted sum of the inputs is formed, and the threshold subtracted, to compose the activation of the neuron. The activation signal is passed through an activation function (also known as the sigmoid transfer function), to produce the output of the neuron. ANNs are mathematical models inspired by the neural architecture of the human brain. A neurone or node is a simple non-linear unit. Neurones collect inputs from single or multiple sources and produce an output. Interconnecting many of these single nodes in a known layer configuration creates an artificial neural model. Each node j receives incoming signals from every node i in the previous layer. Associated with each incoming signal (x_i) there is a weight (W_{ji}). The effective incoming signal (I_j) to node j is the weighted sum of all the incoming signals (13):

$$I_j = \sum_{i=1}^{q} XiWji \qquad (1)$$

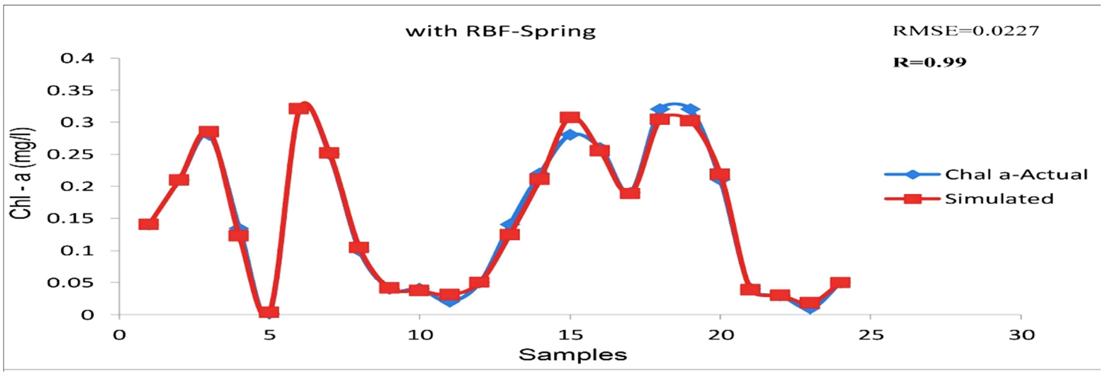
3. Results

The inputs to the model are directly connected to the quantity of information given to the neural network. The output corresponding to these inputs is Chl-a concentrations. The number of hidden layers and its neuron, learning rate (g), momentum term (l), learning algorithm and activation function, depend on the problem complexity and the number of training patterns and the amount of noise in the data. The performance of all the models has been evaluated using the statistical parameters including minimum root mean square error (RMSE) and maximum determination coefficient (R^2); based on the following equations (12)**:**

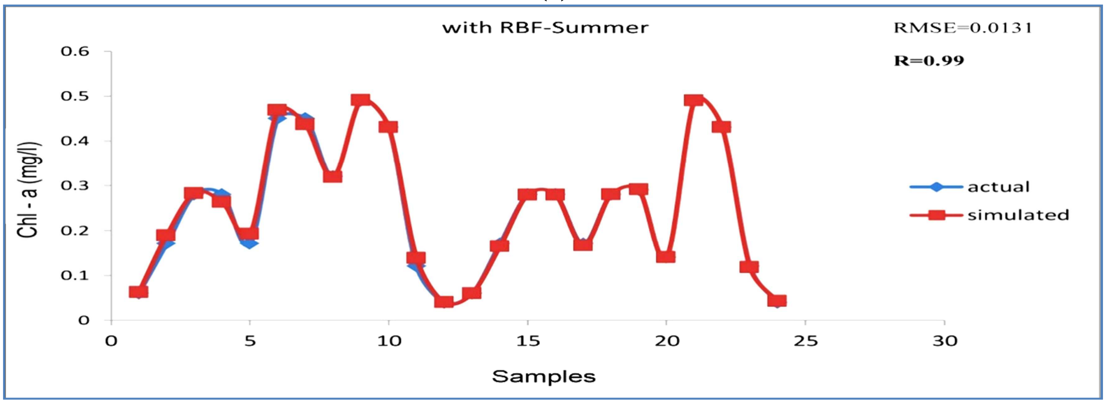
$$\mathrm{RMSE} = \sqrt{\sum_{i=1}^{n} (T_{actual} - T_{forcast}) \Big/ n} \qquad (2)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (T_{actual} - T_{forcast})^2}{\sum_{i=1}^{n} (T_{actual} - T_{forcast})^2} \qquad (3)$$

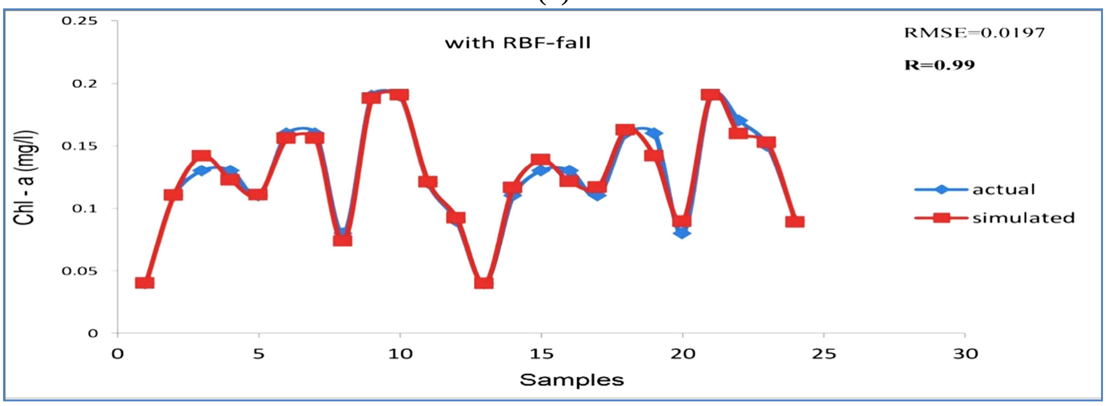
In which, actual T is the Target coming out after the tests, forecast T is the Target figured out via the neural network, average T is the mean Target resulting from the tests and n stands for the number of the parameters to be examined. Finally, in order to test the accuracy of ANN analyzer, the level of Chl-a simulated by the model was compared with the results obtained experimentally. Figures 2a-d show the actual and simulated



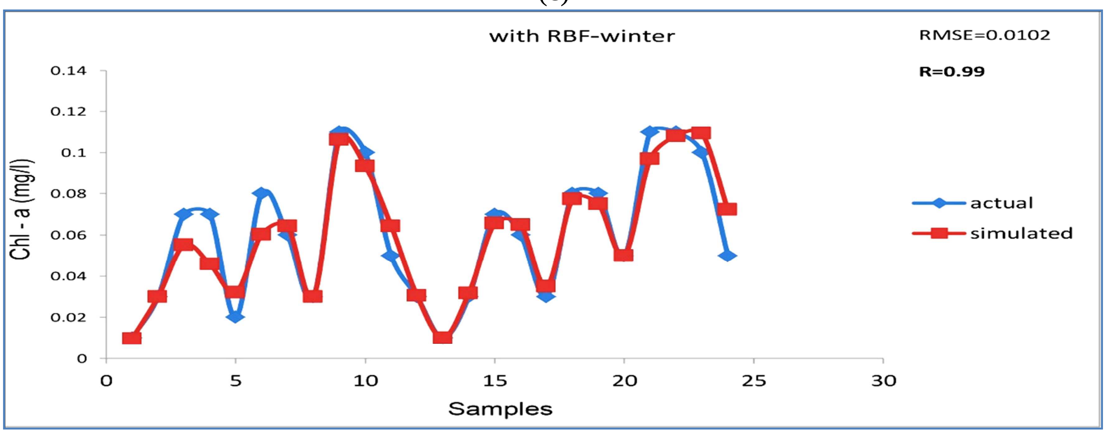
(a)



(b)



(c)



(d)

Figure 2. Comparing artificial neural network output and experimental data for chlorophyll-a concentration in spring (a), summer (b), fall (c), and winter (d)

Table 1. Maximum, minimum, average, and SD (Standard deviation) of each parameter measured in 1 year period

Variables	Dimension	Minimum	Maximum	Mean	SD
Temperature	C	18.20	36.50	31.58	3.90
pH	-	7.90	8.30	8.12	0.08
BOD_5	Mg/L	0.14	1.15	0.39	0.32
DO	Mg/L	6.30	10.46	7.04	0.84
TSS	Mg/L	1.80	1.00	1.14	10.53
NO_3	Mg/L	0.05	1.00	0.44	0.28
Alkalinity	Mg/L	44.00	68.00	51.25	5.62
PO_4	Mg/L	0.05	0.21	0.14	0.11
Chl-a	Mg/L	0.04	0.32	0.15	0.147

SD: Standard deviation; TSS: Total suspended solids; BOD: Biochemical oxygen demands

Table 2. Range of Chl-a (Chlorophyll-a) predicted with regarding error analysis of ANN (Artificial neural network) model

Scenario number	Chl-a (mg/L)	RMSE	R^2
1	0.21	0.0227	0.9902
2	0.33	0.0131	0.9903
3	0.11	0.0197	0.9917
4	0.05	0.0102	0.9901

ANN: Artificial neural network; Chl-a: Chlorophyll-a; RMSE: Root mean square error

concentration of Chl-a obtained by ANN model analysis in different seasons. The minimum, average, and maximum values of measured variables (PO_4, Temperature, NO_3, DO, Chl-a, Phosphate, TSS) are shown in table 1. The RMSE, and R^2 between actual and predicted Chl-a concentration obtained from training and testing data set of ANN models were averaged, and the results are provided in table 2.

4. Discussion

As shown in the figures, the Concentration of chlorophyll–a reduced as approaching toward the colder months due to the lower amount of sunlight available, the lower water temperature and limited nutrient concentration. A low RMSE values (Table 2) indicate that the ANN model predictions are closely matching with the actual observations when compared to the ANN model predictions. Further, the 'R^2' values for the ANN models are greater than (0.99). It shows that ANN model predictions are accurate. Maximum recorded chlorophyll a ranged among systems from 0.2 to 0.47 mg/L. The largest proportion of maxima occurred in the summer (60%), followed by spring, fall and winter. It is suggested that Chl-a concentrations should be kept below 5 ug/L in reservoirs used for drinking water and below 20 mg/L for recreational places (14,15). These maxima generally are in relation with the most stable flow conditions in dam streams. The findings of the current study are consistent with Ruya et al (2014) who found the maximum value of Chl-a was for the period of summer, and the minimum values were found in winter (16). Temporal and spatial variability in abundance of Chl-a were noticed in mid-summer when surface water nutrients were higher as verified in the figures. A number of studies supported that the bloom might occur during spring or fall or even winter (17-19). During the bloom period, the population of algae was above the drinking water protection level i.e. 1000-2000 cells/mL of toxic algae. Later Chl-a declined probably due to the cold water inflow to the dam. Differences in the seasonal distribution of Chl-a might be expected to introduce variability for maximum algae cells because seasonal variations in light levels and temperature can strongly influence growth rates. Indeed, higher growth rates did occur during the summer in a subset of the streams. Most of the sampling time, the values were beyond the standard range (0.005-0.025 mg/L) reported in the literature for productive waters (14). The present findings seem to be consistent with other research which found the predicted Chl-a by ANN (17).

5. Conclusion

In this research, ANN was used for prediction of Chl-a concentration in the water of the Aras dam (Iran). The identified models were trained, validated, and tested on Chl-a concentration measured in 2013. The network designs including 7 input variables and 1 output neuron were found to be suitable for this study. We propose the neural network as an effective tool for the computation of reservoir water quality, and it could also be used in other areas to improve the understanding of reservoir pollution indexes. Excellent agreement between experimental data and ANN results was indicated. The ANN can be seen as a powerful predictive alternative to traditional modeling techniques.

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