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Consideration of phytoplankton composition and water quality of Anamur (Dragon) Creek, Turkey

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ABSTRACT

In this study, water pollution of Anamur Creek, one of the water resources of Mersin (Turkey), was determined. For this purpose, phytoplankton composition and some physicochemical parameters in the surface water of Anamur Creek were investigated. Samples were collected at five sampling sites in the course of the stream in April and June 2010. Fifteen taxa were identified belonging to Bacillariophyta (11), Cryptophyta (1), Euglenozoa (1) and Miozoa (2) divisions. In terms of chlorophyll-a concentrations (4.04–26.23 mg/m^3) the stream shows eutrophic characteristics. Anamur Creek is used for agriculture, fish farms and river sports. Nowadays, water has been started to be supplied from the Anamur Creek to the Geçitköy Dam, located in Turkish Republic of Northern Cyprus, with the project which began in 2011 and completed in 2015. For this reason, designation of the usage areas and amounts of this creek's water again has an important role on its trophic status. It is required that Anamur Creek should be taken under protection for improving its water quality by relevant authorities. Artificial neural network analysis succeeds to envisage the significance importance of input data sets used to investigate and monitor the water quality in the designated study area. April data set showed that pH followed by temperature was exercised to descend the neural network classification parameters. Dissolved oxygen and chlorophyll-a concentration came in second in the significance order, while conductivity ranked the last. June data set showed that temperature was ranked the most important variable followed by the pH. Correspondingly to April data set, dissolved oxygen and chlorophyll-a concentration came in second in the significance order but with opposite importance due to temperature variation. Therefore, detailed studies on phytoplankton including physicochemical parameters have to be carried out for controlling the water quality in Anamur Creek.

Keywords: Water pollution; Phytoplankton; Physicochemical parameters; Statistical analyses; Anamur Creek

1. Introduction

It is known that water is the essential substance for the survival of all organisms on the earth. Only 1% of earth's water is available in the form of freshwater, which is used for drinking and potable needs [1]. Day after day provide to usable freshwater is getting more hard. Due to excessive population growth, over urbanisation, integrated industry and uncontrolled use of natural resources lead to water pollution problems in Turkey, as well as in the rest of the world [2].

Artificial neural network (ANN) analysis was basically founded by McCulloch and Pitta [3]. Backpropagation method was the conceptual development of ANN to be implemented extensively after Rumelhart et al. [4] neural network training

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procedure. The uses of ANN are comprehensively and successfully applied in several field related to hydrology and water resources management. Related fields to water quality assessment and water resources management were discussed in several scholarly works of Lek et al. [5], Suen and Eheart [6], Raghuwanshi et al. [7], Kuo et al. [8], Dogan et al. [9], Singh et al. [10], Ay and Kisi [11], Chebud et al. [12] and Wen et al. [13].

Phytoplankton, which are the primary producers in the food chain in waters, may be used as indicator organisms of water pollution [14]. Phytoplankton are one of the four biological elements suggested for assessing the ecological status and potential of surface waters according to the EU Water Framework Directive introduced in 2000 [15,16]. Taxonomic studies on algal flora are very important in re-evaluation of the use and stability of aquatic systems.

Nowadays, only few studies have been conducted to investigate the Anamur Creek, and most of them are on its geomorphological, hydrographical and climatological characteristics [17,18]. To our knowledge, this is the first report on the phytoplankton composition of Anamur Creek, one of the most important streams of Taşeli Plateau (Mersin, Turkey), which is located on the southern most corner of Taşeli Peninsula. It is fed by karstic sources and poured into the Mediterranean Sea. It is used in agriculture as irrigation water and in fishing activities with trout farms, which are established since 1990. Furthermore, it is suitable for rafting, canoeing and kayaking river sports [17]. A large number of ponds and dams have been constructed on the stream in order to supply water requirements during the dry period. A major part of these ponds and dams are used in order to meet the water requirement of Anamur locality. In recent years, projects for meeting water requirements of the Turkish Republic of Northern Cyprus (TRNC) have been put into practice. For this purpose, Anamur Creek has been chosen due to its high potential and its closeness to the TRNC [17]. It is planned to transfer 75 million m^3 water per year from Alaköprü Dam, which is going to be constructed on Anamur Stream to Geçitköy Dam (Girne, TRNC). The monthly average flow rate of Anamur Creek, which has a non-uniform flow pattern, is 24.43 m^3/s. The flow rate, which increases with the rainfalls in winter, reaches to the maximum level with the snowmelt in winter. It decreases to the minimum level in summer depending on the drought. The fact that the flow is low during summer and high during winter and spring directly relates with the climatic characteristics [17]. The goal of the study is to determine the relation between composition of the phytoplanktonic algal flora and some water quality parameters of Anamur Creek.

2. Material and methods

2.1. Phytoplankton composition and density

The study was carried out in April 2010 and June 2010 at five different sampling stations (Table 1; Fig. 1). Samples were taken from the water surface, poured into Nansen bottles and fixed with Lugol's iodine solution. Phytoplankton were counted with an inverted microscope according to Lund et al. [19]. Phytoplanktonic organisms were identified in reference to the literature, including several comprehensive reviews on the subject [20–29].

2.2. Physicochemical parameters of samples

Chlorophyll-a measurements of the phytoplankton were estimated according to Parsons and Strickland [30]. Dissolved oxygen (DO), pH, temperature, conductivity, salinity, total dissolved solids (TDS) and resistance values were measured with the WTW Multi 340i. The multiparameters were set in the field.

2.3. Statistical analysis

Several statistical methods will be implemented in the current research study to decompose the interconnected relationships of the input parameters for the better comprehensive understanding of the problem. In this study the neural analysis [31] and multivariate analysis [32], principal component analysis

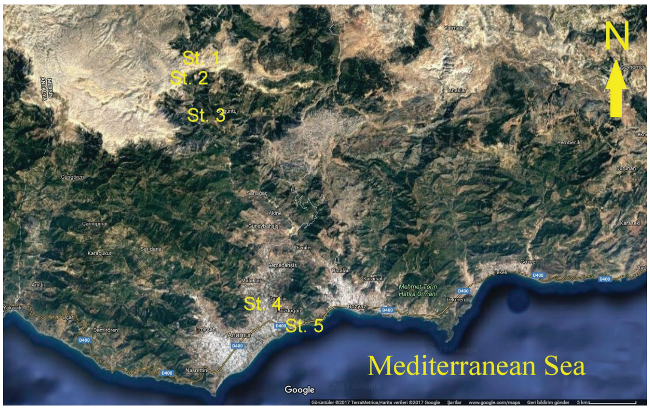

Fig. 1. The map of the study area and sampling stations.

Table 1
Characteristics and locations of sampling stations

St.	Coordinates		Characteristics
St. 1	36°19′8.05″ N	32°47′17.38″ E	St. 1 is the beginning of the creek that includes livestock areas and dry agriculture.
St. 2	36°18′46.45″ N	32° 46′41.99″ E	St. 2 contains settlements and livestock areas with dry agriculture.
St. 3	36°17′11.52″ N	32°46′45.08″ E	There are livestock areas including fish farms in st. 3.
St. 4	36°5′14.74″ N	32°51′42.49″ E	Irrigated agriculture and livestock are carried out in st. 4 where settlements and Alaköprü Dam are located.
St. 5	36°4′26.73″ N	32°52′48 23″ E	St. 5 is the point where the creek flows into the Mediterranean Sea and includes settlements and irrigated agriculture areas.

Note: St. – Sampling stations.

correlation [33] and pairwise comparison [33] were applied to examine the relationship between phytoplankton density, chlorophyll-a, DO, pH, temperature, salinity, electrical conductivity, TDS and resistance by using the SPPS 20.0 database program.

The neural network regression model is written as Eq. (1):

$$Y = \alpha + \sum_h w_h \phi_h \left(\alpha_h + \sum_{i=1}^{p} w_{ih} X_i \right) \quad (1)$$

where Eq. (2):

$$Y = E(Y \mid X) \quad (2)$$

This neural network model has 1 hidden layer but it is possible to have additional hidden layers.

The $\phi(z)$ function used is hyperbolic tangent activation function. It is used for logistic activation for the hidden layers (Eq. (3)):

$$\phi(z) = \tan h(z) = \left(\frac{1 - e^{-2z}}{1 + e^{-2z}} \right) \quad (3)$$

It is significant that the final outputs to be linear not to constrain the predictions to be between 0 and 1. Simple diagram of a skip-layer neural network is illustrated in Fig. 2.

The equation for the skip-layer neural network for regression is shown below (Eq. (4)):

$$Y = \alpha + \sum_{i=1}^{p} \beta_i X_i + \sum_h w_h \phi_h \left(\alpha_h + \sum_{i=1}^{p} w_{ih} X_i \right) \quad (4)$$

It should be clear that these models are highly parameterized and thus will tend to over fit the training data. Cross-validation is therefore critical to make sure that the predictive performance of the neural network model is adequate.

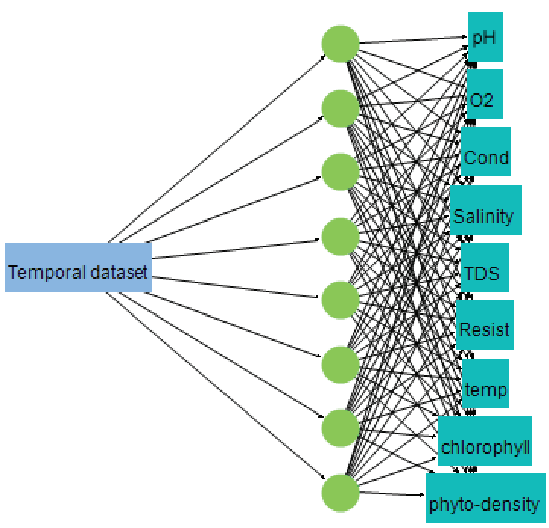

Fig. 2. Artificial neural network scheme with 1 hidden layer and 8 nodes.

Recall the skip-layer neural network regression model looks like this (Eq. (5)):

$$Y = \alpha + \sum_{i=1}^{p} \beta_i X_i + \sum_h w_h \phi_h \left(\alpha_h + \sum_{i=1}^{p} w_{ih} X_i \right) \quad (5)$$

However, this model most likely over fits the training data. Consequently, determination of the adequate performance of the ANN model is a must. Five different criteria are used: the Pearson coefficient of correlation (*R*), the root mean square error (RMSE), the mean absolute deviation (MAD), the negative log-likelihood and the unconditional sum of squares (SSE). Basically, RMSE is the examined parameter for comparability reasons. RMSE can be computed as Eq. (6):

$$\text{RMSE} = \sqrt{\frac{1}{T_0} \sum_{t=1}^{T_0} (y_1 - \acute{y}_1)^2} \quad (6)$$

where t is the time index, and $\hat{y}_t$ and y_t are the simulated and measured values, respectively. Principally, the higher value of R and smaller values of RMSE ensure the better performance of model.

3. Result and discussion

In this study, 15 taxa were identified belonging to 4 divisions: Bacillariophyta (11), Cryptophyta (1), Euglenophyta (1) and Miozoa (2). The list of recorded taxa is given in Table 2. The Bacillariophyta division was found to be dominant in terms of species number and density. The phytoplankton density varied between 52 and 181 ind/cm^3.

It is stated that using phytoplankton functional groups is very efficient for determining the trophic structure of aquatic systems [34]. The phytoplankton functional groups comprised more than 45 assemblages that were identified by alphanumerical codes according to their sensitivity and tolerance levels [35,36]. In terms of functional groups, the phytoplankton of Anamur Creek formed in 6 groups: B, D, Lo, MP, W1 and Y. These groups' members are characteristics of mesotrophic and eutrophic waters, having tolerance to light and nutrient deficiencies and sensitivity to nutrient depletion and increased pH.

According to earlier studies carried out in the freshwaters in Turkey, Bacillariophyta members were recorded to be the dominant group in terms of species number like in Anamur Creek [37–39]. Bacillariophyta was represented by 11 species. *Cyclotella atomus* and *C. ocellata* were recorded at all stations except station 3. *Cyclotella* species indicate mesotrophic lakes with species sensitive to the onset of stratification [40,41]. Codon B was represented by *C. atomus* and *C. ocellata.* This group is tolerant to light deficiency and sensitive to an increase in pH. *Ulnaria ulna* was found at all sampling points except station 5. It is a characteristic inhabitant of eutrophic lakes and prefers inorganically turbid, shallow lakes [35,40]. *Ulnaria acus* was only found at station 2 and *Nitzschia acicularis* only at station 3. Codon D was represented by *U. acus* and *U. ulna* and *N. acicularis*. They usually occur in shallow, enriched turbid waters and are sensitive to nutrient depletion [35,36]. Codon MP, indicated inorganically turbid shallow

Table 2
Recorded taxa in Anamur Creek

	St. 1	St. 2	St. 3	St. 4	St. 5
DIVISIO: BACILLARIOPHYTA					
Order: Bacillariales					
Nitzschia acicularis (Kütz.) Wm. Smith	–	–	+	–	–
Order: Cocconeidales					
Cocconeis placentula Ehrenberg	–	–	–	+	–
Order: Cymbellales					
Cymbella affinis Kützing	–	+	+	+	–
Gomphonema olivaceum (Hornemann) Brébisson	+	+	–	–	–
Order: Licmophorales					
Ulnaria ulna (Nitzsch) Compère	+	+	+	+	–
Ulnaria acus (Kütz.) Aboal	–	+	–	–	–
Order: Mastogloiales					
Achnanthes lanceolata (Bréb. ex Kütz.) Grunow	+	–	–	+	–
Order: Naviculales					
Navicula cryptocephala Kützing	+	+	+	+	+
Navicula cuspidata (Kütz.) Kützing	+	+	+	+	+
Order: Stephanodiscales					
Cyclotella atomus Husted	+	+	–	+	+
Cyclotella ocellata Pantocsek	+	+	–	+	+
DIVISIO: CRYPTOPHYTA					
Order: Cryptomonadales					
Cryptomonas erosa Ehrenberg	+	–	+	+	+
DIVISIO: EUGLENOPHYTA (=Euglenozoa)					
Order: Euglenales					
Euglena gracilis G.A.Klebs	–	–	–	+	+
DIVISIO: MIOZOA					
Order: Peridiniales					
Peridinium bipes Stein	–	+	+	–	–
Order: Prorocentrales					
Prorocentrum micans Ehrenberg	–	–	+	–	–

lakes, was represented by *Navicula cuspidata, N. cryptocephala* and *Cymbella affinis. N. cuspidata* and *N. cryptocephala* were recorded at all stations; *C. affinis* at stations 2, 3 and 4.

The Lo assemblage, mostly found in summer epilimnia in mesotrophic lakes, was represented by *Peridinium bipes* and *Prorocentrum micans*. It is tolerant to segregated nutrients and sensitive to prolonged or deep mixing. *P. bipes* a marine species of dinoflagellates was recorded only at station 3, which has the highest salinity concentration during the study. *P. micans* and *P. bipes* of Miozoa are considered harmful phytoplankters, which may cause red tides under appropriate conditions [42]. Assembladge W1 shows small organic ponds and is represented by *Euglena gracilis*. The presence of *E. gracilis* at stations 4 and 5, pointed out organic pollution as comparison with other stations. Due to there are residential areas near to this sampling sites. Codon Y, which indicated small enriched waters, was represented by the Cryptophyta division member *Cryptomonas erosa,* recorded except station 2 at all sampling points.

Pollution degree of streams can be defined by observing the numbers and groups of existing relative organisms [37]. For this purpose, blue-green algae, diatoms and green algae are used as available taxonomic groups for measurement of biological conditions of streams [35]. Phytoplankton of Anamur Creek consist of diatoms, cryptophytes and euglenophytes. The algal flora of Anamur Creek did not show rich species variation because of inflows causing very low numbers of phytoplankton taxa and biomass in running waters [37]. Chlorophyll-a distribution is an important indicator of pollution and primary production in surface waters. It was known that chlorophyll-a was used for determining the algal biomass in many investigations. In the present study, chlorophyll-a concentrations were estimated between 4.04 and 26.23 mg/m^3, and they showed eutrophic characteristics. When comparing the sampling stations, station 4, which is selected from the Alaköprü Dam, was found the richest station in terms of species numbers. Also the maximum phytoplankton density and the highest chlorophyll-a concentrations were determined in station 4.

During the study period, measured dissolved oxygen concentrations varied between 2.42 and 8.47 mg/L, salinity varied from 0.1‰ to 40.1‰, electrical conductivity changed between 60 μS/cm and 44 ×10^{12} mS/cm, pH ranged from 7.18 to 8.62, TDS fluctuated between 38.1 mg/L and 26.9 g/L and temperature varied from 15.3°C to 22.4°C (Table 3). Due to feeding on karstic sources, high concentrations of salinity were measured both at station 1 (28.1‰) and station 3 (40.1‰) in the stream. In Anamur Creek, electrical conductivity values were in standard limits (150–500 μS/cm) at stations 3,4 and 5 and higher than the standard limits at stations 1 and 2 in June 2010 according to the protocols assigned for protection of surface water sources against pollution [43]. In terms of the measured pH values, Anamur Creek is slightly alkaline (close to neutral values pH = 7) and within normal limits.

Around the creek, there are not many settlement areas and population because of the karstic geological characteristics. Only in summer, the population increased permanently due to transhumance activities. Nowadays, great amount of Anamur Creek's water is used for agricultural lands, strawberry and banana greenhouses and fish farms. Moreover, the stream bank is used for river sports like rafting, canoeing and kayaking [44].

The ANN analysis was carried out under 1 hidden layer, 8 nodes, and hyperbolic tangent activation function conditions for each temporal data set, respectively. These conditions were carefully exercised to prevent the algorithm overfitting; ANN analysis is demonstrated in Table 4.

Based on RMSE and negative log-likelihood, April data set showed that pH followed by temperature were exercised

Table 3
Measured values of some physicochemical parameters and chlorophyll-a concentrations of Anamur Creek

		St. 1	St. 2	St. 3	St. 4	St. 5
Chlorophyll-a (mg/m^3)	April	7.00	15.40	5.83	26.23	4.53
	June	5.24	4.38	4.14	4.14	4.04
Dissolved O_2 (mg/L)	April	6.20	3.20	8.47	4.96	8.63
	June	2.42	6.63	6.86	6.75	6.90
pH	April	8.04	7.96	8.38	8.04	8.33
	June	7.18	7.76	7.93	8.17	8.62
Temperature (°C)	April	15.3	15.4	15.4	15.5	15.4
	June	22.4	22.0	22.4	22.4	22.3
Conductivity (μS/cm)	April	219	253	60	261	271
	June	44×10^{12}	571×10^{10}	271	244	221
Salinity (‰)	April	0.10	0.11	40.10	0.12	0.18
	June	28.10	3.05	0.13	0.11	0.10
TDS (mg/L)	April	112.90	116.80	178.50	120.90	38.10
	June	26,900	3,089	128.90	116.50	105.00
Resistance (Ω.cm)	April	4,060	4,080	2,680	3,940	16.8
	June	23.1	174.3	3,710	4,100	4540

Table 4
Neural network analysis

	April 2010 data set		June 2010 data set	
	Training measures	Validation measures	Training measures	Validation measures
pH				
R^2	0.9989494	–3.451053	–0.693484	–4.837628
RMSE	0.0048583	0.0843901	0.4178269	0.5436266
Mean absolute deviation	0.0045111	0.0774765	0.2946722	0.4965023
–log likelihood	–11.72438	–2.106734	1.6387516	1.6188919
SSE	0.0000708	0.0142434	0.523738	0.5910598
Sum frequency	3	2	3	2
DO (mg/L)				
R^2	–0.662772	–2.161361	–0.076464	–160.8821
RMSE	1.4309734	1.5646591	2.1175791	0.9542466
Mean absolute deviation	1.089994	1.5296715	1.7321706	0.951422
–log likelihood	5.3318802	3.7332131	6.5076361	2.7442108
SSE	6.1430542	4.8963165	13.452424	1.8211733
Sum frequency	3	2	3	2
Conductivity (μS/cm)				
R^2	–0.120997	–117.1163	–0.184142	–42.94533
RMSE	95.031595	43.472528	127.40672	76.234964
Mean absolute deviation	73.380551	43.274112	126.14555	75.363443
–log likelihood	17.919444	10.382135	18.798969	11.505517
SSE	27093.012	3779.7215	48697.42	11623.54
Sum frequency	3	2	3	2
Salinity (‰)				
R^2	–0.112207	–2619569	–0.107732	–1536526
RMSE	19.866101	8.0925433	13.212585	6.1978357
Mean absolute deviation	16.240784	8.0822537	10.407508	6.1978344

(Continued)

Table 4 *(Continued)*

	April 2010 data set		June 2010 data set	
	Training measures	Validation measures	Training measures	Validation measures
–log likelihood	13.22386	7.0197632	12.000325	6.4862774
SSE	1183.9859	130.97852	523.71723	76.826335
Sum frequency	3	2	3	2
TDS (mg/L)				
R^2	–0.012745	–6.871626	–0.179367	–36.36432
RMSE	57.72343	5.7515656	59.260196	35.147659
Mean absolute deviation	47.272136	5.3794496	58.32781	34.673944
–log likelihood	16.423805	6.3368213	16.502629	9.9569931
SSE	9995.9833	66.161014	10535.312	2470.7158
Sum frequency	3	2	3	2
Resistance (kΩ.cm)				
R^2	0.1433464	–720.3255	–0.108213	–29254.68
RMSE	5.8828148	1.8800253	80.278714	37.629444
Mean absolute deviation	5.0119568	1.8678232	63.148441	37.628785
–log likelihood	9.5729217	4.1004475	17.413329	10.093451
SSE	103.82253	7.0689902	19334.016	2831.9501
Sum frequency	3	2	3	2
Temperature (°C)				
R^2	–7.169754	0.789648	–0.121635	–0.087474
RMSE	0.1347405	0.0229321	0.1997007	0.052141
Mean absolute deviation	0.1103005	0.0171173	0.1547368	0.0492303
–log likelihood	–1.756398	–4.712561	–0.575991	–3.06973
SSE	0.054465	0.0010518	0.1196411	0.0054374
Sum frequency	3	2	3	2
Chlorophyll-a (mg/m^3)				
R^2	–24.23405	–2.42301	–0.543088	–9.277949
RMSE	5.0677508	10.018497	0.586637	0.1602962
Mean absolute deviation	4.9993495	8.6262833	0.413866	0.1518495
–log likelihood	9.1255068	7.4467432	2.6567682	–0.823587
SSE	77.046293	200.74055	1.0324288	0.0513897
Sum frequency	3	2	3	2
Total phytoplankton density individual/cm^3				
R^2	–0.655997	–10.96934	–0.2	–4.077129
RMSE	47.796857	48.435433	29.3215	20.065178
Mean absolute deviation	43.514967	46.147418	20.921932	17.980215
–log likelihood	15.857695	10.59834	14.391779	8.8358488
SSE	6853.6188	4691.9824	2579.2512	805.22275
Sum frequency	3	2	3	2

to descend the neural network classification parameters. The significant variables obtained from the analysis imply their importance to determine the water quality in the Creek [45]. DO and chlorophyll-a concentration came in second in the significance order, while conductivity ranked the last. This could be explained due to the close range of pH and temperature variations within the collected data from the different five stations. In contrary, conductivity showed the highest range of input data variability as it demonstrated in Fig. 3(a) where input variability were mapped against its mean [46,47].

June data set showed different pattern of input parameters significance. Temperature was ranked the first important variable followed by the pH. Basically, this could be explained due to the higher mean temperature recorded in June rather than April (closely to 7°C higher). Correspondingly to April data set, DO and chlorophyll-a concentration came in second in the

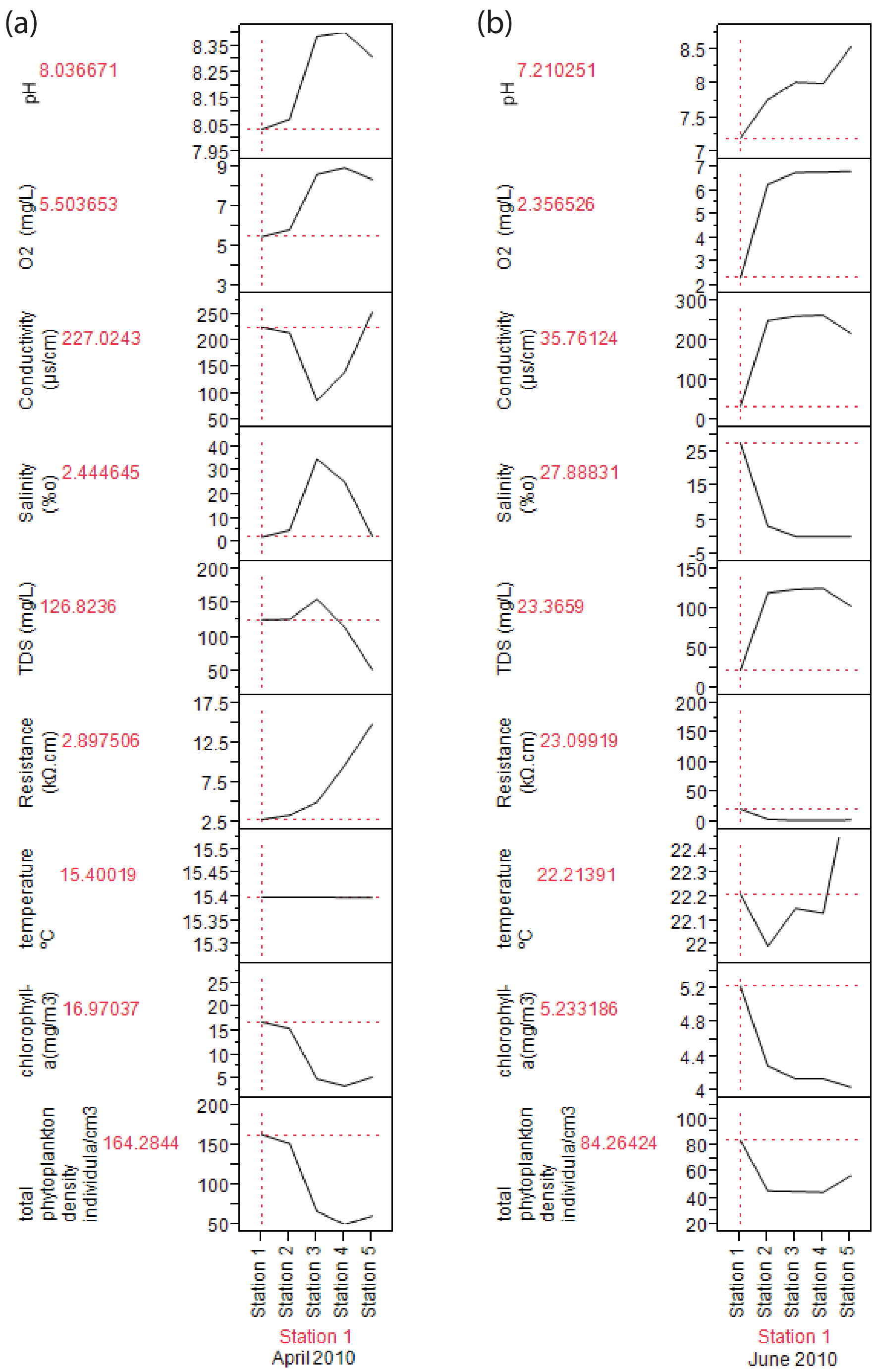

Fig. 3(a) and (b). Artificial neural network profiler.

significance order but with opposite importance due to temperature variation [11]. Phytoplankton density expressed the least significant variable expressed the lowest RMSE, which indicates that phytoplankton density statistically failed to show significant importance as it is illustrated in Fig. 3(b) [48,49].

4. Conclusion

ANN analysis succeeds to envisage the significance importance of input data sets used to investigate and monitor the water quality in the designated study area. Temperature and pH are significant parameters. It must be considered regularly monitored for water quality management plans in the Creek. Further temporal data analysis is required to identify the trends of the input parameters. In conclusion, Anamur Creek should be taken under protection as soon as possible for improving its water quality by relevant authorities. Therefore, detailed studies on phytoplankton including hydrological parameters have to be carried out for controlling its water quality. Inspect over the usage area and amounts of this creek's water have an important role on its trophic status because of the big project which is used to supply water requirements of the TRNC [50].

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