Consideration of phytoplankton diversity and water quality of Anamur (Dragon) Stream, Turkey

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Abstract

In this study, water pollution of Anamur Stream, 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 Stream were investigated. Samples were collected at five sampling sites in the course of the stream in April and June 2010. A total of 15 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 charactersitics. Anamur Creek is used for agriculture, fish farms and river sports. In recent years, it is planning to supply water requirements of the Turkish Republic of Northern Cyprus (TRNC) by a big project from this water source (Maden, 2013). For this reason, designation of the usage areas and amounts of this creek's water again, has an important role on it's trophic status. It is required that, Anamur Stream 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 datasets used to investigate and monitor the water quality in the designated study area. Therefore detailed studies on phytoplankton including physicochemical parameters, have to be carried out for controlling the water quality in Anamur Stream.

Keywords: Water pollution; phytoplankton; physicochemical parameters; statistical analyses; Anamur Stream.

INTRODUCTION

It is known that water is the essential substantial 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 (De, 2003). Day after day provide to usable freshwater is getting more hard. Due to exessive population growth, over urbanisation, integrated industry and uncontrolled use of natural resources lead to water pollution problems in Turkey, as well as the rest of the world (Fedra, 2005).

Artificial Neural Network analysis was basically founded by McCulloch and Pitta (1943). Back-propagation method was the conceptual development of ANN to be implemented extensively after Rumelhart et al. (1986) neural network training 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 work of Lek et al. (1996); Suen et al. (2003); Raghuwanshi et al. (2006); Kuo et al. (2007); Dogan et al. (2009); Singh et al. (2009); Ay and Kisi (2012); Chebud et al. (2012); Wen et al. (2013).

Phytoplankton, which are the primary producers in the food chain in waters, may be used as indicator organisms of water pollution. (Reynolds, 1998). 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 (Padisak et al., 2006; Katsiapi et al., 2011). Taxonomic studies on algal flora are very important in re-evaluation of the uses and stability of aquatic systems.

Nowadays, only few studies have been conducted to investigate the Anamur Creek and most of them are on it's geomorphological, hydrographical and climatological characteristics (Sunkar and Uysal,2014; Siler and Sengun, 2014). 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 activties with trout farms which are established since 1990. Furhermore, it is suitable for rafting, canoeing and kayaking river sports (Sunkar and Uysal, 2014).

A large number of ponds and dams have been constructed on the stream in order to meet 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 (Sunkar and Uysal, 2014). It is planning 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/sec. The flow rate which increases with the rainfalls in winter reaches to the maximum level with the snow melt 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 (Sunkar and Uysal, 2014). The goal of the study is to determine the relation between diversity of the phytoplanktonic algal flora and some water quality parameters of Anamur Creek.

MATERIAL AND METHODS

Phytoplankton Composition and Density

The study was carried out on April 2010 and June 2010 at 5 different sampling stations (Table 1). Samples were taken from the surface into Nansen bottles and fixed with Lugol's iodine. Phytoplankton were counted with an inverted microscope according to Lund et al. (1958). Phytoplanktonic organisms were identified in reference to the literature, including several comprehensive reviews on the subject.

Table 1. Locations of sampling stations.

Station 1	36º 19' 58.05" N	32º 47' 17.38" E
Station 2	36º 18' 46.45" N	32º 46' 41.99" E
Station 3	36º 17' 11.52" N	32º 46' 45.08" E
Station 4	36º 5' 14.74" N	32º 51' 42.49" E
Station 5	36º 4' 26.73" N	32º 52' 48 23" E

Physicochemical Parameters of Samples

Chlorophyll-*a* measurements of the phytoplankton were estimated according to Parsons and Strickland (1963). Dissolved O_2, pH, temperature, conductivity, salinity, TDS and resistance values were measured with the WTW Multi 340i /set made multiparameter in the field.

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 standing of the problem. In this study the Neural Analysis (Hsu, 1984) and Multivariate analysis (Anderson, 1958), PCA correlation (Gabriel, 1982) and Pairwise Comparison (Gabriel, 1982) were applied to examine the relationship between phytoplankton density, chlorophyll-a, dissolved oxygen, pH, temperature, salinity, electrical conductivity, TDS and resistance by using the SPPS 20.0 database program.

The neural network regression model is written as:

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

Where

$Y = E(Y|\boldsymbol{X})$. 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's used for logistic activation for the hidden layers.

$$\phi(z) = \tanh(z) = \frac{1 - e^{-2z}}{1 + e^{-2z}}$$

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 Figure 1.

The equation for the skip-layer neural network for regression is shown below.

$$Y = \alpha + \sum_{i=1}^{p} \beta_i X_i + \sum_{h} w_h \phi_h(\alpha_h + \sum_{i=1}^{p} w_{ih} X_i))$$

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.

Recall the skip-layer neural network regression model looks like this:

$$Y = \alpha + \sum_{i=1}^{p} \beta_i X_i + \sum_{h} w_h \phi_h(\alpha_h + \sum_{i=1}^{p} w_{ih} X_i))$$

However, this model most likely over fits the training data. Consequently, determination of the adequate performance of the ANNs 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:

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

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

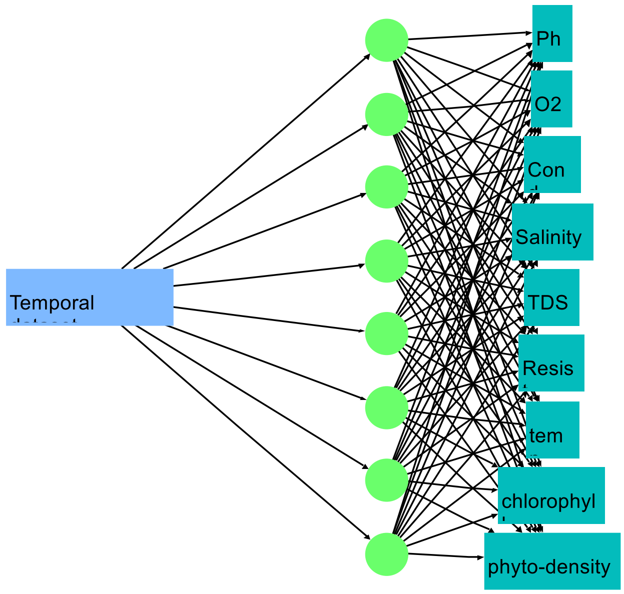

Figure 1. Artificial Neural Network scheme with 1 hidden layer and 8 nodes.

RESULTS AND DISCUSSION

In this study, a total of 15 taxa were identified belonging to 4 divisions: Bacillariophyta (11), Cryptophyta (1), Euglenozoa (1) and Miozoa (1). Distribution of phytoplankton groups was given in Figure 2. and list of recorded taxa was 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 ind/cm^3 and 181 ind/cm^3.

During the study period, measured chlorophyll-*a* contents varied between 4.04 and 26.23 mg/m^3, salinity varied from 0.1‰ to 40.1‰, electrical conductivity changed between 60 µS/cm and 44 mS/cm, pH ranged from 7.18 to 8.62, TDS measured 38.1 mg/L - 26.9 g/L and temperature varied from 15.3 to 22.4 ºC (Table 3).

Pollution degree of streams can be defined by observing the numbers and groups of existing relative organisms. For this purpose, blue-green algae, diatoms and green algae are used as available taxonomic groups for measurement of biological conditions of streams (Reynolds et al., 2002; Egemen, 2006). Phytoplankton of Anamur Stream consist of diatoms, cryptophytes and euglenophytes. The algal flora of Anamur Stream did not show rich species variation as a result of inflows causing very low numbers of phytoplankton taxa and biomass in running waters (Altuner, 1984). 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 (Egemen, 2006). In the present study, chlorophyll-*a* concentrations were estimated between 4.04- 26.23 mg/m^3 and it shows eutrophic charactersitics. Due to feeding on karstic sources, fairly high concentrations of salinity were measured both at station 1 (28.1‰) and station 3 (40.1‰) in the stream. Electrical conductivity was measured higher than normal values. According to the measured pH values, Anamur Stream is slightly alkaline (close to neutral values pH=7) and within normal limits.

Around the stream there are not so much settlement areas and population because of karstic geological characteristics. Only in summer the population increased permanently due to transhumance activities. Nowadays, great amount of Anamur Stream'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 (Sezgin and Unuvar, 2009).

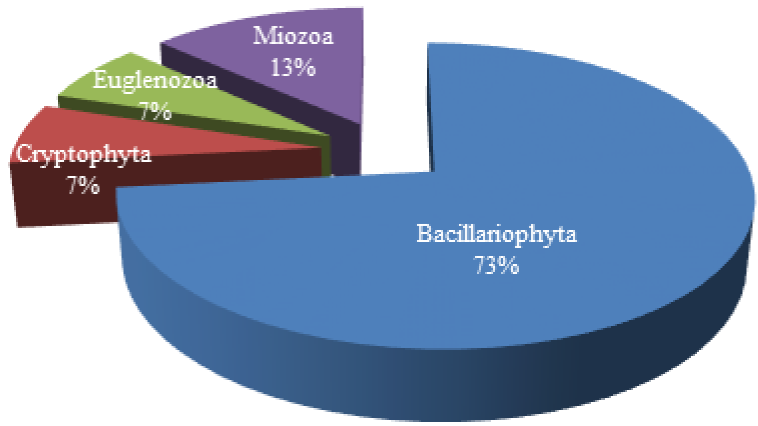

Figure 2. Percentage distribution of phytoplankton groups in Anamur Stream.

Table 2. Recorded taxa in Anamur Stream.

	St. 1	St. 2	St. 3	St. 4	St. 5
Divisio: Bacillariophyta					
Achnanthes lanceolata (Breb.) Grunow	+	-	-	+	-
Cocconeis placentula Ehrenberg	-	-	-	+	-
Cyclotella atomus Husted	+	+	-	+	+
Cyclotella ocellata Pantocsek	+	+	-	+	+
Cymbella affinis Kützing	-	+	+	+	-
Gomphonema olivaceum (Hornemann) Brebisson	+	+	-	-	-
Navicula cryptocephala Kützing	+	+	+	+	+
Navicula cuspidata (Kütz.) Kützing	+	+	+	+	+
Nitzschia acicularis (Kütz.) Wm. Smith	-	-	+	-	-
Ulnaria ulna (Nitzsch) P. Compere	+	+	+	+	-
Ulnaria acus (Kütz.) M. Aboal	-	+	-	-	
Divisio: Cryptophyta					
Cryptomonas erosa Ehrenberg	+	-	+	+	+
Divisio: Euglenozoa					
Euglena gracilis Klebs	-	-	-	+	+
Divisio: Miozoa					
Peridinium bipes Stein	-	+	+	-	-
Prorocentrum micans Ehrenberg	-	-	+	-	-

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

Based on RMSE and –log likelihood, April dataset showed that pH followed by Temperature were exercised 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 (Jiang, 2013). O_2 and Chlorophyll 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 (Jones and Marshall, 1992; Jiapaer et al., 2011) as it demonstrated in Figure 3a. where input variability were mapped against its mean.
June dataset showed different pattern of input parameters significance. Temperature was ranked the 1st 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 ^oC higher). Correspondingly to April dataset, O_2 and Chlorophyll concentration came in second in the significance order but with opposite importance due to temperature variation (Ay and Kisi, 2012). Phytoplankton density expressed the least significant variable expressed the lowest RMSE which indicates that Phytoplankton density statistically failed to show significant importance as it's illustrated in Figure 3b (Albergaria et al., 2014; Chen and Liu, 2014).

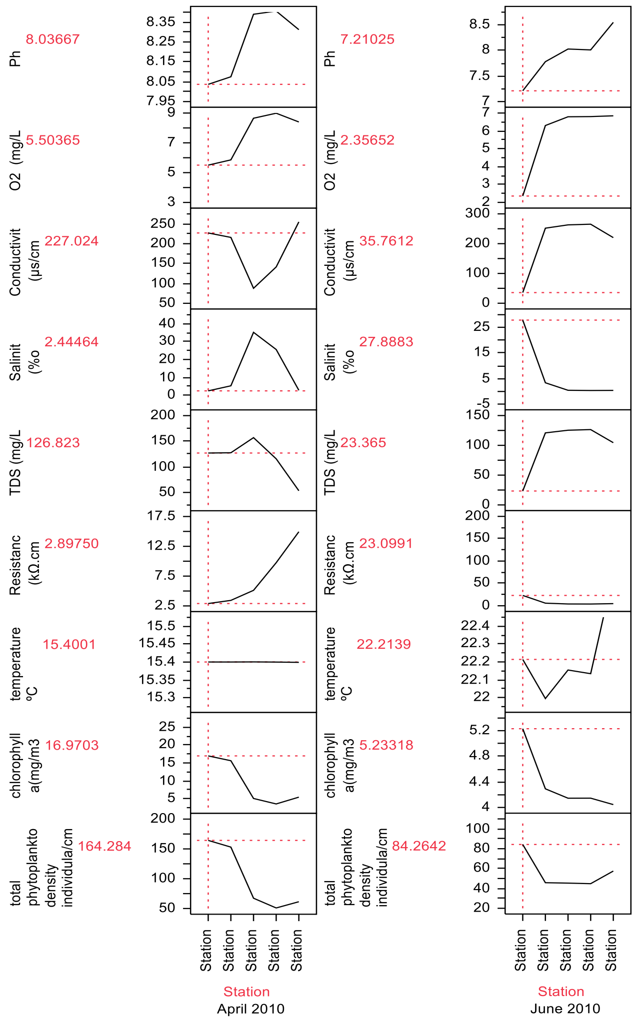

Figure 3a,b. Artificial Neural Network profiler

Table 3. Measured values of some physicochemical parameters and clorophyll-*a* concentrations of Anamur Stream.

		St. 1	St. 2	St. 3	St. 4	St. 5
Chlorophyll-*a*	April	7.00	15.40	5.83	26.23	4.53
(mg/cm^3)	June	5.24	4.38	4.14	4.14	4.04
Dissolved O_2	April	6.20	3.20	8.47	4.96	8.63
(mg/L)	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	April	15.3	15.4	15.4	15.5	15.4
(ºC)	June	22.4	22.0	22.4	22.4	22.3
Conductivity	April	219	253	60	261	271
(µs/cm)	June	44×10^{12}	571×10^{10}	271	244	221
Salinity	April	0.10	0.11	40.10	0.12	0.18
(%o)	June	28.10	3.05	0.13	0.11	0.10
TDS	April	112.90	116.80	178.50	120.90	38.10
(mg/L)	June	26900	3089	128.90	116.50	105.00
Resistance	April	4060	4080	2680	3940	16.8
(Ω.cm)	June	23.1	174.3	3710	4100	4540

Table 4. Neura l Network Analysis

	April 2010 dataset		June 2010 dataset	
	Training Measures	Validation Measures	Training Measures	Validation Measures
Ph				
RSquare	0.9989494	-3.451053	-0.693484	-4.837628
RMSE	0.0048583	0.0843901	0.4178269	0.5436266
Mean Abs Dev	0.0045111	0.0774765	0.2946722	0.4965023
-LogLikelihood	-11.72438	-2.106734	1.6387516	1.6188919
SSE	0.0000708	0.0142434	0.523738	0.5910598
Sum Freq	3	2	3	2
O^2 (mg/L)				
RSquare	-0.662772	-2.161361	-0.076464	-160.8821
RMSE	1.4309734	1.5646591	2.1175791	0.9542466
Mean Abs Dev	1.089994	1.5296715	1.7321706	0.951422
-LogLikelihood	5.3318802	3.7332131	6.5076361	2.7442108
SSE	6.1430542	4.8963165	13.452424	1.8211733
Sum Freq	3	2	3	2
Conductivity (µs/cm)				
RSquare	-0.120997	-117.1163	-0.184142	-42.94533
RMSE	95.031595	43.472528	127.40672	76.234964
Mean Abs Dev	73.380551	43.274112	126.14555	75.363443
-LogLikelihood	17.919444	10.382135	18.798969	11.505517
SSE	27093.012	3779.7215	48697.42	11623.54
Sum Freq	3	2	3	2
Salinity (%)				
RSquare	-0.112207	-2619569	-0.107732	-1536526
RMSE	19.866101	8.0925433	13.212585	6.1978357
Mean Abs Dev	16.240784	8.0822537	10.407508	6.1978344
-LogLikelihood	13.22386	7.0197632	12.000325	6.4862774
SSE	1183.9859	130.97852	523.71723	76.826335
Sum Freq	3	2	3	2
TDS (mg/L)				
RSquare	-0.012745	-6.871626	-0.179367	-36.36432
RMSE	57.72343	5.7515656	59.260196	35.147659
Mean Abs Dev	47.272136	5.3794496	58.32781	34.673944
-LogLikelihood	16.423805	6.3368213	16.502629	9.9569931
SSE	9995.9833	66.161014	10535.312	2470.7158
Sum Freq	3	2	3	2
Resistance (kΩ.cm)				
RSquare	0.1433464	-720.3255	-0.108213	-29254.68
RMSE	5.8828148	1.8800253	80.278714	37.629444
Mean Abs Dev	5.0119568	1.8678232	63.148441	37.628785
-LogLikelihood	9.5729217	4.1004475	17.413329	10.093451
SSE	103.82253	7.0689902	19334.016	2831.9501
Sum Freq	3	2	3	2
Temperature ºC				
RSquare	-7.169754	0.789648	-0.121635	-0.087474
RMSE	0.1347405	0.0229321	0.1997007	0.052141
Mean Abs Dev	0.1103005	0.0171173	0.1547368	0.0492303
-LogLikelihood	-1.756398	-4.712561	-0.575991	-3.06973
SSE	0.054465	0.0010518	0.1196411	0.0054374
Sum Freq	3	2	3	2
Chlorophyll- a(mg/m^3)				
RSquare	-24.23405	-2.42301	-0.543088	-9.277949
RMSE	5.0677508	10.018497	0.586637	0.1602962
Mean Abs Dev	4.9993495	8.6262833	0.413866	0.1518495
-LogLikelihood	9.1255068	7.4467432	2.6567682	-0.823587
SSE	77.046293	200.74055	1.0324288	0.0513897
Sum Freq	3	2	3	2
Total phytoplankton density individula/cm^3				
RSquare	-0.655997	-10.96934	-0.2	-4.077129
RMSE	47.796857	48.435433	29.3215	20.065178
Mean Abs Dev	43.514967	46.147418	20.921932	17.980215
-LogLikelihood	15.857695	10.59834	14.391779	8.8358488
SSE	6853.6188	4691.9824	2579.2512	805.22275
Sum Freq	3	2	3	2

CONCLUSION

Artificial Neural Network analysis succeeds to envisage the significance importance of input datasets used to investigate and monitor the water quality in the designated study area. Temperature and pH are significant parameters must be considered and 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 Stream 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 has an important role on it's trophic status because of the big project which is planning to supply water requirements of the Turkish Republic of Northern Cyprus (Maden, 2013).

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