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Determination of Turbidity in Filyos Stream Water by Artificial Neural Network

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Abstract

Water is in an endless cycle, which is source of life for human beings. During this cycle, substances that are contaminated in water cause physical, chemical or biological alteration of the water's natural features, that leads to water pollution and therefore causes the environmental balance to deteriorate over time. This quality changes cause deteriorations in ecosystem. For this reason, it is important to investigate the water quality in rivers and water reservoirs which are close to settlement areas. In this study, surface water quality measurements were carried out at downstream of the Filyos stream, which forms the largest sub-basin in the Western Karadeniz Basin, at intervals of thirty days in one year period between September 2015 and August 2016. In the scope of the study, zinc, chromium, calcium, aluminium, manganese and turbidity parameters measured in the laboratory and estimation of the turbidity parameter basaed on parameters of zinc, chromium, calcium, aluminium, manganese was performed by artificial neural networks

Key words

Filyos Stream, Heavy Metal, Turbidity, Artificial Neural Networks, Western Blacksea Basin

1. INTRODUCTION

Rivers and streams are used in many parts of the world for drinking water, agricultural irrigation and industrial purposes. Today, rapidly growing population, developing infrastructural deficiencies resulting from the expansion of industrial and residential areas and the inadequacy of treatment plants cause pollution of rivers and freshwater resources. The increasing rate of pollution destroys the balance of nature and reaches the dimensions that threaten human life.

Water quality changes cause the animal and plant species that exist in nature to change, thus causing the ecosystem to change. Therefore, investigations of water quality in rivers and water reservoirs close to their habitat are important.

Make observations and measurements over the river, prodives information to researchers and planner. When these researches are planned on a basin basis, sustainable management of water resources has considerable precaution.

A better understanding of the hydrodynamic properties of reservoirs has also gained momentum with advances in computer technology in recent years. Measurements in water quality models, such as mathematical and artificial neural network, can also be analyzed with methods. In this study, artificial neural networks were used and data obtained from water quality studies were estimated in this method.

In this study, surface water quality measurements were made at the observation station selected at the Filyos Stream (228 km), the largest sub-basin of the Western Black Sea Basin, at intervals of thirty days in one year period. Water quality parameters (turbidity, calcium, aluminium, manganese, chromium and zinc) measured and analysis were performed in the laboratory according to standart methods, After, estimation of the turbidity parameter based on parameters of calcium, aluminium, manganese, chromium and zinc was performed by artificial neural networks.

Figure 1. Subbasin of Western Blacksea Basin (URL-6)

2. MATERIALS AND METHODS

Surface water quality measurements were carried out at downstream of the Filyos stream, which forms the largest sub-basin in the western Karadeniz Basin, at intervals of thirty days (September 2015- August 2016) in one year period. (Figure 2).

Figure 2. Filyos downstream satellite image (Google Earth, 2017)

The collection, storage and delivery of water samples in accordance with standard methods has been carried out. During sampling, the sample containers of the water samples to be taken were rinsed with water, filled with no gaps and tightly closed. +4 °C prodected samples brought to the laboratory in six hours. Turbidity and ion analysis were performed in the laboratory according to the standart methods. Nexion 300D model ICP-MS was used in the analysis.

Figure 3. Nexion 300D model ICP-MS

An artificial neural network (AAN) model was prepaered for the samples which taken from downstream to estimate the turbidity according to month. MATLAB-based artifical neural network (ANN) toolbox was used for model analysis. AAN topology analysis was performed to determine the number of AAN hidden layer neurons in the preparation phase. AAN performances for different hidden layer neuron numbers, R^2 (Determination coefficient) and MSE (Mean Squared Error) statistical performance analysis criteria were used. The hidden layer neuron counts were taken as 3, 4, 6, 8 and 10, respectively, and the AAN topologies were trained and tested.

The AAN analysis method used for estimating the turbidity parameter in the water is the multi-layered sensor (MDA) model; input layer, intermediate layers and output layer. In the models, Ca^{+2} Al^{+3} Mn^{+2} Cr^{+3} Zn^{+2} parameters are input and turbidity is used as output parameter.

3. RESULTS AND DISCUSSION

The results of the parameters analyzed in the laboratory according to standard methods are given in Table 1.

Table 1.Laboratory Analysis Results

Months	Turbidity	Ca^{+2}	Al^{+3}	Mn^{+2}	Cr^{+3}	Zn^{+2}
1	98.6	52.31	7.65	0.217	0.087	0.246
2	86.4	50.68	10.96	0.147	0.135	0.547
3	95.6	51.64	12.8	0.351	0.426	0.372
4	78.4	52.31	17.5	0.438	0.258	0.254
5	68.3	54.86	25.4	0.372	0.324	0.212
6	69.1	55.16	15.24	0.371	0.355	0.127
7	46.7	55.13	4.327	0.326	0.132	0.59
8	28.12	55.23	4.641	0.108	0.033	0.658
9	63.25	55.25	2.142	0.642	0.284	0.392
10	35.72	55.31	5.526	0.02	0.114	0.587
11	17.09	53.48	4.434	0.093	0.05	0.286
12	64.12	51.68	8.61	0.154	0.074	0.097

According to the obtained analysis results, the models in Table 2 for different input layers in AAN have been established. Weights, number of hidden layers and number of nodes were found by trial and error to obtain the most appropriate result between 1 input and 1 output while the model was being created.

Table 2. Models created for different input layers

Model No	Input Layer Variables	Output Layer
1	Ca^{+2}	Turbidity
2	Al^{+3}	Turbidity
3	Mn^{+2}	Turbidity
4	Cr^{+3}	Turbidity
5	Zn^{+2}	Turbidity

In this study, each parameter was tried as an input data value, and the turbidity as the output value was estimated.. The data were normalized between 0-1 before being given to the network. Accordingly, the YSA results will remain between 0-1. The model results are shown in tables for each parameter separately and the topologies with the best performance is charted.

Table 3. Zn^{+2} topology analysis for parameter

Model No	Number of Hidden Layer Neurons	R^2	MSE
1	3	0.9667	0.0021
2	4	0.9264	0.0047
3	6	0.9900	0.0006431
4	8	0.9030	0.0062
5	10	0.9821	0.0008031

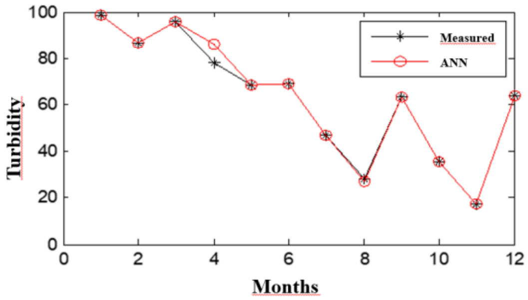

Figure 4. Zn^{+2} *parameter AAN performance*

Table 4. Cr^{+3} *topology analysis for parameter*

Model No	Number of Hidden Layer Neurons	R^2	MSE
1	3	0.9409	0.0038
2	4	0.9115	0.0057
3	6	0.9643	0.0023
4	8	0.9759	0.0016
5	10	0.9874	0.0008133

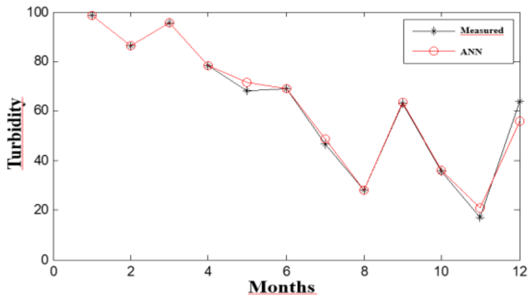

Figure 5. Cr^{+3} *parameter AAN performance*

Table 5. Ca^{+2} *topology analysis for parameter*

Model No	Number of Hidden Layer Neurons	R^2	MSE
1	3	0.9563	0.0028
2	4	0.8747	0.0081
3	6	0.9776	0.0021
4	8	0.9231	0.0052
5	10	0.9570	0.0028

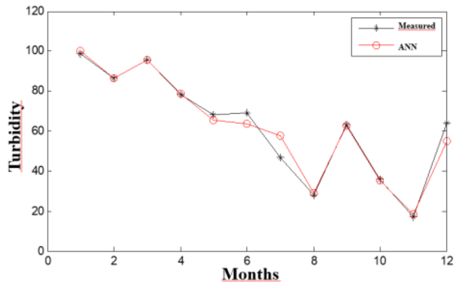

Figure 6. Ca^{+2} *parameter AAN performance*

Table 6. Al^{+3} topology analysis for parameter

Model No	Number of Hidden Layer Neurons	R^2	MSE
1	3	0.9426	0.0037
2	4	0.8761	0.0080
3	6	0.9722	0.0018
4	8	0.9473	0.0034
5	10	0.9608	0.0025

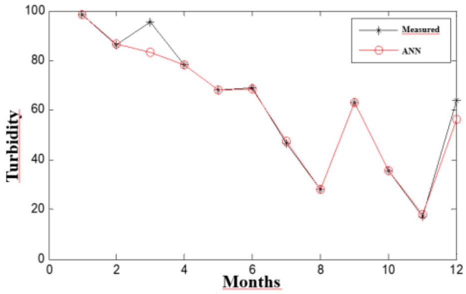

Figure 7. Al^{+3} parameter AAN performance

Table 7. Mn^{+2} topology analysis for parameter

Model No	Number of Hidden Layer Neurons	R^2	MSE
1	3	0.9642	0.0061
2	4	0.9198	0.0052
3	6	0.8762	0.0080
4	8	0.9642	0.0023
5	10	0.9335	0.0043

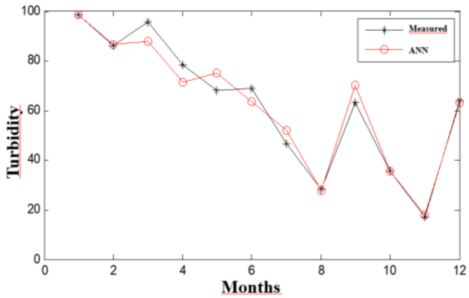

Figure 8. Mn^{+2} parameter AAN performance

4. CONCLUSIONS

Clarity is a magnitude that determines the natural structure of water Organic and inorganic materials etc. causes turbidity in the waterThe strength of the sulfur contaminant causes water turbidity. For this reason, the turbidity level of surface waters is measured as the degree of pollution. The measurement of the turbidity parameter in the surface water can be used to follow the pollution test in the water and the natural cleansing of the river. For this reason, the studies in which the pollution dimension is searched are the investigations that should be done routinely.

However, since turbidity depends on many parameters changing over time, it is difficult to be formulated For this reason, artificial neural networks come into play here. In this study, considering the ions affecting the turbidity, AAN models were established and the parameters giving the best test performance were determined. As a result of the analyzes made, it has been observed that the Zn parameter has the best test performance. This is followed by the parameters Cr, Ca, Al, Mn, respectively. As it is clear from the graphs, it is determined that there are not very big differences between the results obtained from AAN and the measured values. It has been demonstrated that YSA can be successfully implemented and produces safe estimates.

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