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Estimation of Stream Temperature in Degirmendere River (Trabzon-Turkey) Using Artificial Neural Network Model

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Abstract

Artificial Neural Networks (ANN) is a modeling technique with training which takes the working system of the brain as basis. Learning in ANNs is realized with the renewal of the connection gaps. ANNs make possible to solve the non-defined problems through the learning ability. In this study, we have estimated various environmental factors using an artificial model of the brain, known as Artificial Neural Network (ANN). Here, we has developed and tested an ANN model to predict stream temperature of Degirmendere in the Black Sea, using local water temperature, air temperature, and stream temperature. In the structure of the ANN used in the model, the number of the hidden neuron was determined as 16, Sum-Squared Error was determined as 0.005 and the number of the iteration was determined as 40,000. As a result of the regression analysis realized between the model outputs and measurement results obtained in the study, the value of r = 0.92 was calculated. When the other literature studies which had done before have been examined, in the light of the model outputs and statistical evaluations, and regarding the complex and nonlinear structure of the study environment, it was seen that the ANN modeling technique can be utilized in the timely prediction of the temperatures of the stream waters.

Keywords: Artificial Neural Networks (ANN), Degirmendere, Stream temperature, Eastern Black Sea.

Introduction

Water temperature is one of the most important abiotic factors determining the overall health of fish and other aquatic organisms in aquatic ecosystem studies. It is vital in relation to chemical processes as well as influencing many biological processes such as growth and mortality of aquatic organisms (Risley, 2000). At the surface and close to the shore, the water temperature varies with seasonal climate changes and geographic latitude zones. Temperature, like salinity, affects density of the seawater and also affects its viscosity (Duxbury and Duxbury, 1994). At polar latitudes, the surface water is cold, denser, and more viscous, and organisms float more easily. In tropic latitudes, the warm less dense, less viscous water is home for species with more appendages, larger surface areas and greater gas-bubble production, for the water is less buoyant and offers less resistance to sinking.

At the sea surface, the temperature changes with latitude much the same as the climate changes on land (Duxbury and Duxbury, 1994). Seasonal fluctuation in surface temperature at the middle latitudes is reflected in periods of spring and summer reproduction and growth and in water dormancy.

Variations in stream water temperatures are also significant in limnological studies. For example, water temperature determines the rate of decomposition of organic matter and the saturation concentration of dissolved oxygen (Nemerov, 1985). Perturbations of the thermal regime in a stream can significantly impact the utilization of fish habitats and stream water temperature can be one of the limiting factors in determining the habitat potential of a stream (Boyee, 1982; Sivri *et al*., 2007). At Degirmendere River, variables like oil, grease, COD etc. measured in river stations did not exhibit any temporal variations with the exception of temperature (Boran and Karacam, 1996; Sivri *et al*., 2006).

In this study, we has estimated various environmental factors using an artificial model of the brain, known as Artificial Neural Network (ANN). ANNs are particularly well suited for problems in which large datasets contain complicated nonlinear relations among many different inputs. ANNs are able to find and identify complex patterns in datasets that may not be well described by a set of known processes or simple mathematical formula (Rounds, 2002). Here, we has developed and tested an ANN model to predict stream temperature of Degirmendere in the Black Sea, using local water temperature, air temperature, and stream temperature.

Materials and Methods

Sampling Area

Degirmendere River, located in the Northeast of Turkey (41º00'03" N, 31º45'50" E) (Figure 1), flows through the Zigana Mountain to the Black Sea, which supplies the city of Trabzon's drinking water and springs from the south of Trabzon and flows to the Black Sea. It is 55 km long, from its source in the

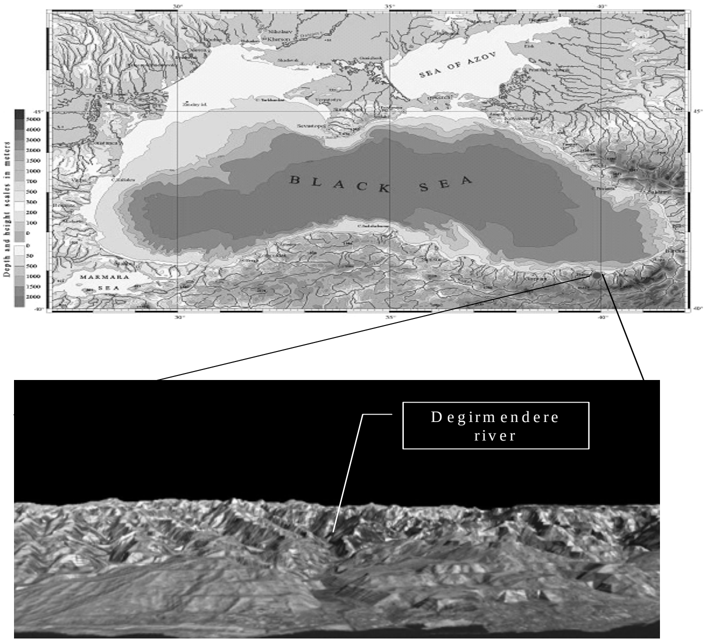

Figure 1. Location and 3D model of Degirmendere River.

Horos (2536 m) and Kalkanli mountains.

In this study, it is aimed that the water temperatures belonging to Degirmendere are modeled with the ANN technique. As input parameters, temperature of the sea surface waters (Eastern Black Sea), weather temperature and the water temperatures in Degirmendere were used. Output parameter is the water temperatures of Degirmendere. Training set in the ANN structure is composed of the data of the years of 1996, 1997, 1998 and 1999; whereas the test set is composed of the data of the years of 2000 and 2001. Back-propagation algorithm with adaptive learning rate was used in the training section. Statistical analyses and test of the data were studied through SPSS 12, whereas the model was studied by the use of Matlab 7.0® program.

Artificial Neural Networks

ANN is a multi-layered, nonlinear parallel processing structure, which can optimize various input-output parameters and find a path in these parameters. An important advantage of ANNs over traditional statistical models is that they impose fewer and more flexible constraints in their application. ANNs are particularly well suited for problems in which large dataset contain complicated nonlinear relations among many different inputs. ANNs are able to find and identify complex patterns in datasets that may not be well described by a set of known processes or simple mathematical formula (Saila and Cheeseman, 2004; Rounds, 2002; Soyupak *et al*., 2003).

In general, neuron could be modeled as a non-linear activated function of which the total potential inputs into synaptic weights are applied. The artificial model of neuron consists of the three elements (Sivri *et al*., 2006; Ozcan *et al*., 2006). These are:

1. A set of synapses or connection links, each of which is characterized by a weight or strength of its own.
2. An adder for summing the input signals, weighed by the synapses of the neuron.
3. An activation function or transfer functions for limiting the amplitude of the output of a neuron.

The neuron model could also include an externally applied bias, denoted by b_k. The bias b_k has the effect of increasing or lowering the net input of the activation function depending on whether it is positive or negative, respectively. Mathematically, the neuron k will be described by the following equations:

$$u_k = \sum_{j=1}^{m} w_{k,j} x_j \tag{1}$$

Where $\{x_1,....,x_m\}$ are the input signals; $\{w_{k,1},....,w_{k,m}\}$ are synaptic weights of neuron k. The activation function, denoted by $f(v)$, defines the output of a neuron which considerably influences the behavior of the network:

$$v_k = u_k+b_k \tag{2}$$

$$y_k = f(v_k) \tag{3}$$

Where threshold value and f activation function are generally used in ANN. These are:

Piecewise-linear function:

$$f(v_k) = \begin{cases} 1 & v_k \geq \frac{1}{2} \\ v & \frac{1}{2} > v_k > -\frac{1}{2} \\ 0 & v_k \leq -\frac{1}{2} \end{cases} \quad (4)$$

threshold function:

$$f(v_k) = \begin{cases} 1, & if\ v_k \geq 0 \\ 0, & if\ v_k < 0 \end{cases} \quad (5)$$

sigmoid function:

$$f(v_k) = \frac{1}{1+e^{av_k}} \quad (6)$$

Where is the slope of the activation function.

Results

In the study, the temperatures of weather, sea and stream water of the years of 1996-2004 were measured. With model study, the data regarding the monthly averages of the stream temperatures of Degirmendere are shown in Figure 2. Timely changes of measured values are shown in Figure 3. According to the Figure 2, for Degirmendere's water temperatures, the highest temperature value is 26.8ºC, the lowest temperature value is 4.2ºC, and average temperature value was calculated as 11.90ºC. In this process, the lowest temperature average of 6.10ºC was witnessed in February. The highest average belongs to July with 19.88ºC.

All of the data which were used in model are normalized into the range {-1.0, 1.0}. This was carried out by determining the maximum and minimum values of each variable over the whole data period and calculating normalized variables using equation (7) as below.

$$x_{norm} = 2 * \left[\frac{(x - x_{\min})}{(x_{\max} - x_{\min})} \right] - 1.0 \quad (7)$$

Statistical analyses of the values given in Figure 2 were realized with the Box-Whisker test. This test is a non- parametric test and approaching trend to theoretical normal distribution is defined with the values of which representation power is high. In this study carried out, values belonging to the monthly data of 9 years have been subjected to the test. Results are shown in Figure 4. The correlations between the values used in the model (temperatures of stream, sea and weather) were shown in Figure 5.

After the statistical evaluations, ANN algorithm, subject of the study, was studied in the second stage. In the ANN structure used in the model, the number of the hidden neuron is 16, Sum-Squared Error is 0,005 and the number of the iteration for training was determined as 40,000 (Figure 6).

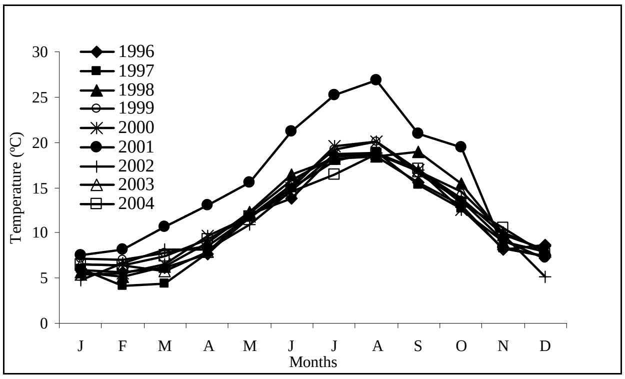

Figure 2. Water Temperatures of Degirmendere River.

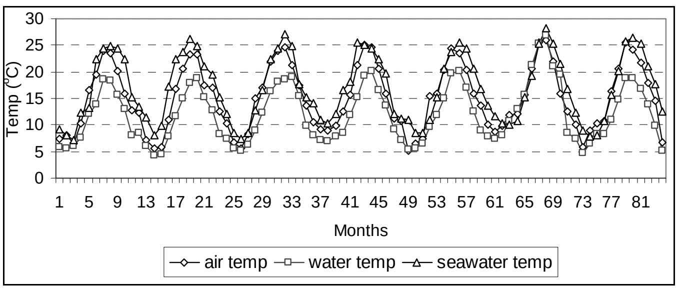

Figure 3. Comparison of air, stream water and sea water temperatures.

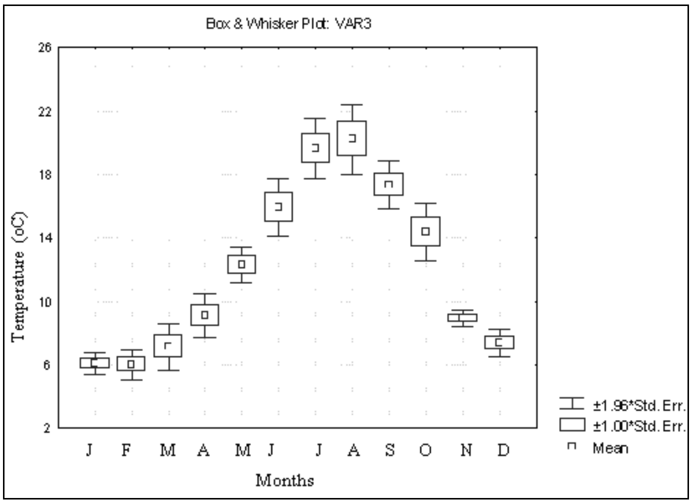

Figure 4. Box&Whisker Analyses of the stream water temperatures which used in the model.

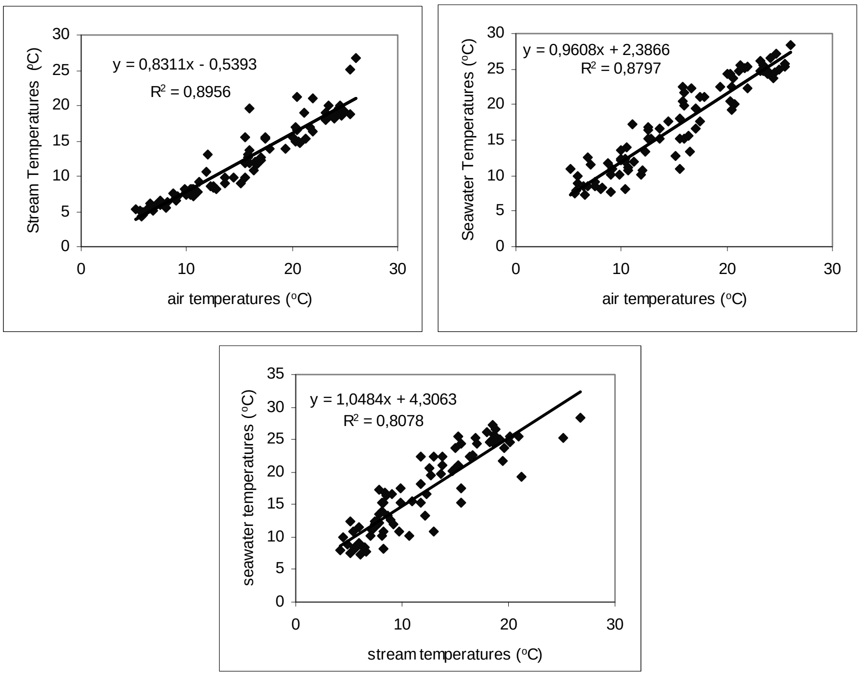

Figure 5. Correlations of the input parameters.

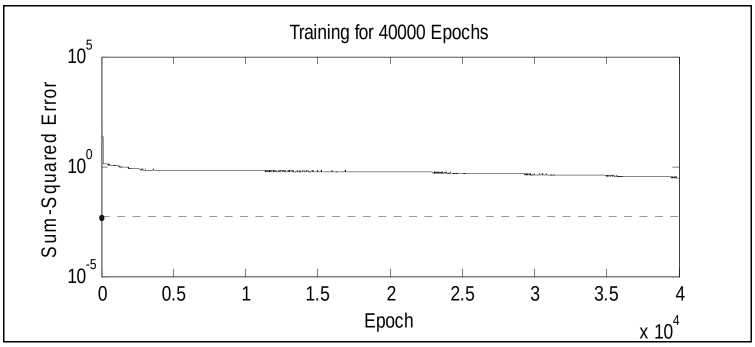

Figure 6. Sum-Squared Error of ANN model.

The outputs of the test results of ANN algorithm were shown in Figure 7. As seen in the Figure; ANN results give coherent results in the timely prediction of the stream water temperatures. The r value between model predictions and measured results was calculated as 0.92 (Figure 8).

Discussion

As it is known, artificial neural networks can find a field of application in very different subjects (Boznar *et al*., 1993; Chelani *et al*., 2002, Gardner, 2000; Ozcan *et al*., 2006; Quilly, 2004). In this study, it is aimed that the stream water temperatures belonging to Degirmendere, a stream in the northern east of Turkey, are modeled with the use of ANN modeling technique.

Training of the multi-layered model of the Artificial Nerve Network models is done by the change of some parameters through iterative method and by discovery of the most appropriate values and the composition of weight space. These parameters are generally the number of the hidden layers and the number of the neurons used in these layers, activation function used in the neurons and learning co-efficient. The structure of the ANN used in this study was formed as 3 inputs, 16 hidden layers and 1 input (3, 16, 1). When the Figure 7 is examined it is seen that the ANN structure follows the changes in the water temperatures coherently. As a result of the regression analysis carried out between model outputs and measurement results obtained in the study, the value of $r = 0.92$ was calculated (Figure 8). It is thought that this r value expresses a good modeling. It is also thought that the use of the 4-year data as the input parameter in the study has increased the learning ability of the model.

Water temperature is one of the most important factors determining the overall health of fish and other aquatic organisms. If water temperatures warm beyond a critical threshold, particularly during sensitive life stages of fish, survival can markedly decrease (Mullane *et al*., 1995). When the other literature studies which had done before have been examined, in the light of the model outputs and statistical evaluations and regarding the complex and nonlinear structure of the study environment, it was seen that the ANN modeling technique can be utilized in the timely prediction of the temperatures of the stream waters. In this context, it is thought that ANN modeling technique and model outputs which was put forward in this study will be beneficial especially in the streams in which the fishery culture is done and in the predictions of the stream water temperatures.

The temperature of stream water is complex and is includes air temperature, rainfall and time of runoff. The relations between pH, dissolved oxygen and other measurable stream variables are often strong, though

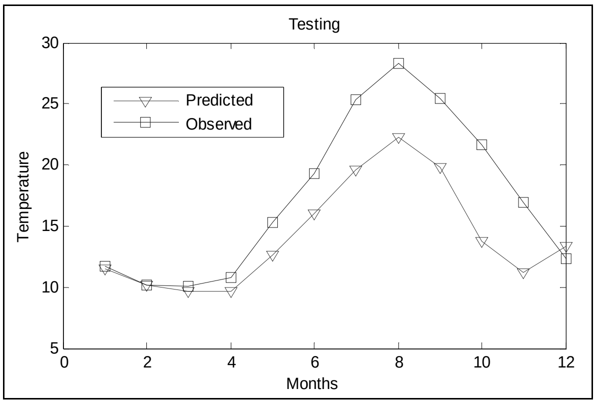

Figure 7. Comparison of ANN outputs and observed values.

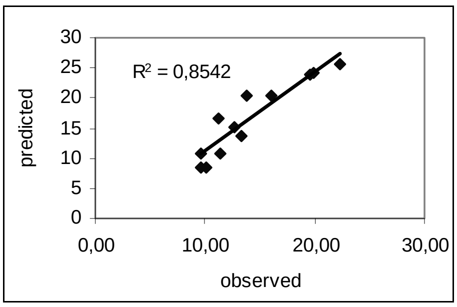

Figure 8. Regression lines for ANN predicted of stream temperature and observed stream temperature for test data set.

typically nonlinear and specific to an individual watershed (Quilty *et al*., 2004). ANNs are ideal for modeling temperature based on these relations. Artificial neural networks are well suited to modeling the nonlinear relations between water quality (physical, chemical etc.) and meteorological (air temperature, rainfall etc) variables. The results of the neural network training were considered to be very accurate and the validation test also indicated very satisfactory prediction accuracy (Saila *et al*., 2004). In our ANN approach, the effects of all input/output parameters can be evaluated and various outputs can be obtained for different environments and predicted stream water temperatures of Firtina Creek. These predictions are important not only for the people who work on fish aquaculture but also for making decisions about established or soon to be established Fishery Policies (Sivri *et al*., 2007).

Acknowledgements

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