THE USAGE OF ARTIFICIAL NEURAL NETWORKS IN MICROBIAL WATER QUALITY MODELING: A CASE STUDY FROM THE LAKE İZNİK

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Abstract. The aim of this study was to develop faecal pollution model structures with artificial neural networks (ANNs) for cost-effective lake water quality management studies. In this study 5 artificial neural networks model structures were applied to predict the Faecal coliform concentrations for 4 different coast areas "Göllüce, İnciraltı, Darka, Orhangazi" and all data of the coasts in Lake İznik-Turkey. The Levenberg–Marquardt and backpropagation algorithm was proposed for feed-forward neural networks training. According to performance functions root mean squared error (RMSE), neural network model structures provided acceptable results. Correlation values (R) were found between 0.590 and 0.999. Increasing the number of hidden layer in the model structures was not raised the model efficiency in each trial. Type and number of input parameters were more effective for some model efficiency. Increasing the number of hidden layer and inputs in the model structures did not raise the model efficiency in each trial. Because depending on the numbers and chemical compositions of the substrates in the lake water microorganism's metabolism and their growth rates could be influenced differently and the larger error values of the modeling results determined in Göllüce and Orhangazi Coasts which influenced by pollution sources. Water quality modeling studies and increasing of monitoring would provide more productive results for protection and management of coastal.
Keywords: *faecal pollution, mathematical modeling, deep lake, water management, Turkey*

Introduction

One of the main elements that compose the rich biodiversity in the world and Turkey is wetlands. While wetlands of different qualifications increase the ecosystem diversity on one hand, the species using these wetlands raise the species' and genetic diversity on the other hand (Karadeniz et al., 2009). However, wetlands, especially lakes, are considered to be potential agriculture-residential-industrial areas in the development plans for years because of their high values. Wetlands are polluted by domestic, industrial and agricultural pollutants, and thus their biological diversities are destroyed (Oktem et al., 2012).

Contaminations of the environment with pathogen, hazardous and toxic chemicals are the major problems facing the industrialized nations and urbanized regions today. Microbial pollution in coastal and wetland areas is quite important for human and other species (Cordier et al., 2014). Particularly, pathogens, which include bacteria, viruses and protozoans, can come from a variety of point and nonpoint sources. For over a century, bacterial indicator organisms have been used in the USA to assess the presence of faecal contamination, and consequently pathogens, in drinking and bathing waters (NRC, 2004). Commonly used indicators are total coliform, faecal coliform, faecal streptococci, Escherichia coli and Enterococcus (Mas and Ahlfeld, 2009).

Artificial Neural Networks studies starting in 1940s are performed in hydrology, meteorology, ecology and water quality fields (Morid et al., 2007; Ranković et al.,

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2010; Kim and Valdes, 2003; Partal and Kişi, 2007; Reimer and Sodoudi, 2004; Mishra and Desai, 2006; Belayneh and Adamowski, 2012). Several lake water quality studies were related to especially phytoplankton production, algal blooms, dissolved oxygen and other spatial and temporal variability of limnological properties and eutrophication (Soyupak et al., 2003; Karul et al., 2000). Microbial contaminants are non-conservative, irregularly distributed and may even increase in concentration due to growth in the environment. The interrelationship and interactions between microbial communities in water creates additional modeling challenges that have been overcome by applications of ANNs to multi-parameter databases. Important and meaningful results were obtained with modeling of pathogens with ANN (Neelakantan et al., 2002; Brion and Lingireddy, 2003; Mas and Ahlfeld et al., 2007; Ogwueleka and Ogwueleka, 2010; WHO, 2010; Wu et al., 2014).

The purposes of this study were to design and develop ANN model structures for prediction of fecal coliform in order to evaluate microbial contamination and to predict the pollution impact on bathing, agricultural, aquaculture, recreation and tourism areas of Lake İznik as this has national and international importance, and also to observe the differences among the modeling results in the lake coasts occurring due to sewage inputs or nonpoint sources according to relevant environmental conditions. This study would be supportive of data management and could be the basis for basin and coastal management and the early warning system studies for public health. Also, this study was important with regards to international environmental scientific developments because the feed forward neural network (FNN) models could supply cost-effective environmental management tools for the investigation of any monitoring stations and pathogenic pollution.

Materials and methods

Study area and data

Lake İznik, the largest lake in the Marmara region and the fifth largest in Turkey, is located between the districts of İznik and Orhangazi in the Province of Bursa. It is located between 40°23′ and 40°30′N latitudes and 29°20′ and 29°42′E longitudes. The lake, which is located 85 m above sea level, has a length of 32 km and a maximum width of 12 km. It is about 15-16 km from the Bay of Gemlik. It has a surface area of 310 km^2 and a water volume of 12.2 billion m^3. The maximum depth of the lake (80 m) has been measured near Karacakaya (Ozturk et al., 2005; Yağcı and Ustaoğlu, 2012). It has 1 outlet, Karsak stream, and 5 inlets, Orhangazi, Kuru, Karasu, Ekinlik and Söloz streams. Karsak stream connects the lake to the Sea of Marmara but it has a number of natural and artificial barriers that marine fishes are unable to cross (Özuluğ, et., al., 2005).

Lake İznik, one of the 76 wetlands of international importance in Turkey, is a natural protected (NP) wetland according to the criteria of The Convention on Wetlands of International Importance (The Ramsar Convention) (RAMSAR, 2007). The ecosystem of Lake İznik was declared to be a natural protected area in 1990 and conforms to the international criteria with its characteristics (BGPEFD, 2008) and The Lake İznik and İznik basin had been an area of settlement throughout the history. The archeological findings in the tumulus in İznik depression suggest that human settlement started 7150 years ago. İznik town later became an important cultural center during the Roman, Byzantine and Ottoman empires (Ülgen et al., 2012).

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Moreover, Lake İznik is a significant bird watching area in Turkey; there are eight host and five stationary bird species, 13 in total, in this area (Akpınar et al., 2010). Lake İznik is a significant water resource not only with its water capacity but also in terms of agriculture, industry, water productions and recreational activities for the region (Başar et al., 2004). Therefore pollution monitoring and preservation of the Lake are important nationally and internationally.

Point and nonpoint (diffuse) pollution sources existed in the watershed, which discharge pollutants into the lake. The pollution loading sources of Lake İznik are agricultural, animal, sewage, forest, aerial (Akkoyunlu et al., 2011) and industrial (Oktem et al., 2012). Partially treated and untreated sewage and nonpoint pollution of fertilizers and pesticides from surrounding agricultural areas reached the lake (Akçaalan et al., 2014; Albay and Aykulu, 2002). Lake water is also used for irrigation and the lake is a popular place for recreation during summer months. Around the lake, especially in Orhangazi region in the west banks of the lake, the planless misuse of 1st class farming lands (open to settlement), which are appropriate for irrigation farming, puts the future of the Lake İznik in danger (Meşeli, 2010).

It is a well-known fact that the pollution in Lake İznik increases proportionately to the population growth. The common use of the septic tanks in Orhangazi and İznik around the lake causes the pollution of the lake to increase. Also there are 45 villages were around the lake and pollution loads of their domestic waste water affects the lake. But a certain amount of the used water (70-90% in general) is thought to return to the sewages (Oktem et al., 2012). Moreover, Lake İznik is polluted by the waste water of the Orhangazi Industrial Area, the tankages of İznik and Osmangazi, Marmara Birlik Olive Processing Plants in İznik, and by Ispak industrial plants in Orhangazi. Moreover, the lake was under threat because of the small olive oil plants around it and chemistry, automotive, metal and food industry sectors were present in the lake basin (WWF, 2011). Industries using the water of the lake in processing goods discharge their waste water to the lake without sufficient purification. Phosphorus in the industrial pollution was determined to be 3 times higher than that in the domestic waste water; and nitrogen in the industrial pollution was determined to be 1.5 times higher than that in the domestic waste water. In addition Istanbul-Bursa highway passes through Orhangazi on the west coasts of the Lake İznik and this heavy traffic caused air pollution (Oktem et al., 2012).

Several studies investigated the extent of anthropogenic pollution, such as nutrients, lead, and polycyclic aromatic hydrocarbons (PAH) in the sediment of the recent past and identified differences in the spatial distribution and sedimentation history (Franz et al., 2006; Ünlü et al., 2010; Viehberg et al., 2012). The spatial distribution of Pb indicating anthropogenic pollution sources coincides with elevated concentration in the delta area of the Sölöz stream which feeding of the Lake İznik. Interestingly, Ünlü et al. (2010) identified high concentrations of polycyclic aromatic hydrocarbons in the same area, thus supporting human-induced contamination (Viehberg et al., 2012).

Samples were taken from 4 different stations from 2010 to 2015. Sampling stations and regions were given in *Table 1* and features of the sampling stations were as follows:

Göllüce Village is located in the district limits of İznik sub-province. It is on the main road interconnecting with Gemlik and İznik sub-provinces. There are aggregated reeds at the entrance to the lakeside public beach. İnciraltı public beach is nearby the İznik sub-province. The Darka area is a public beach in front the Darka Holiday Village. Orhangazi Area is near the outlet of the Lake and Orhangazi sub-province. All

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sampling stations and regions are in the swimming areas. Location of Lake İznik and sampling stations were shown in *Figure 1*.

Table 1. *Sampling stations and region*

Station no.	Sampling regions	Number of data	Coordinates
1	Göllüce area	27	40°22'56.49"N, 29°35'36.73"E
2	İnciraltı area	27	40°25'46.64"N, 29°42'45.24"E
3	Darka area	27	40°24'37.25"N, 29°42'12.04"E
4	Orhangazi area	27	40°28'50.37"N, 29°20'48.76"E
	Total data	108	

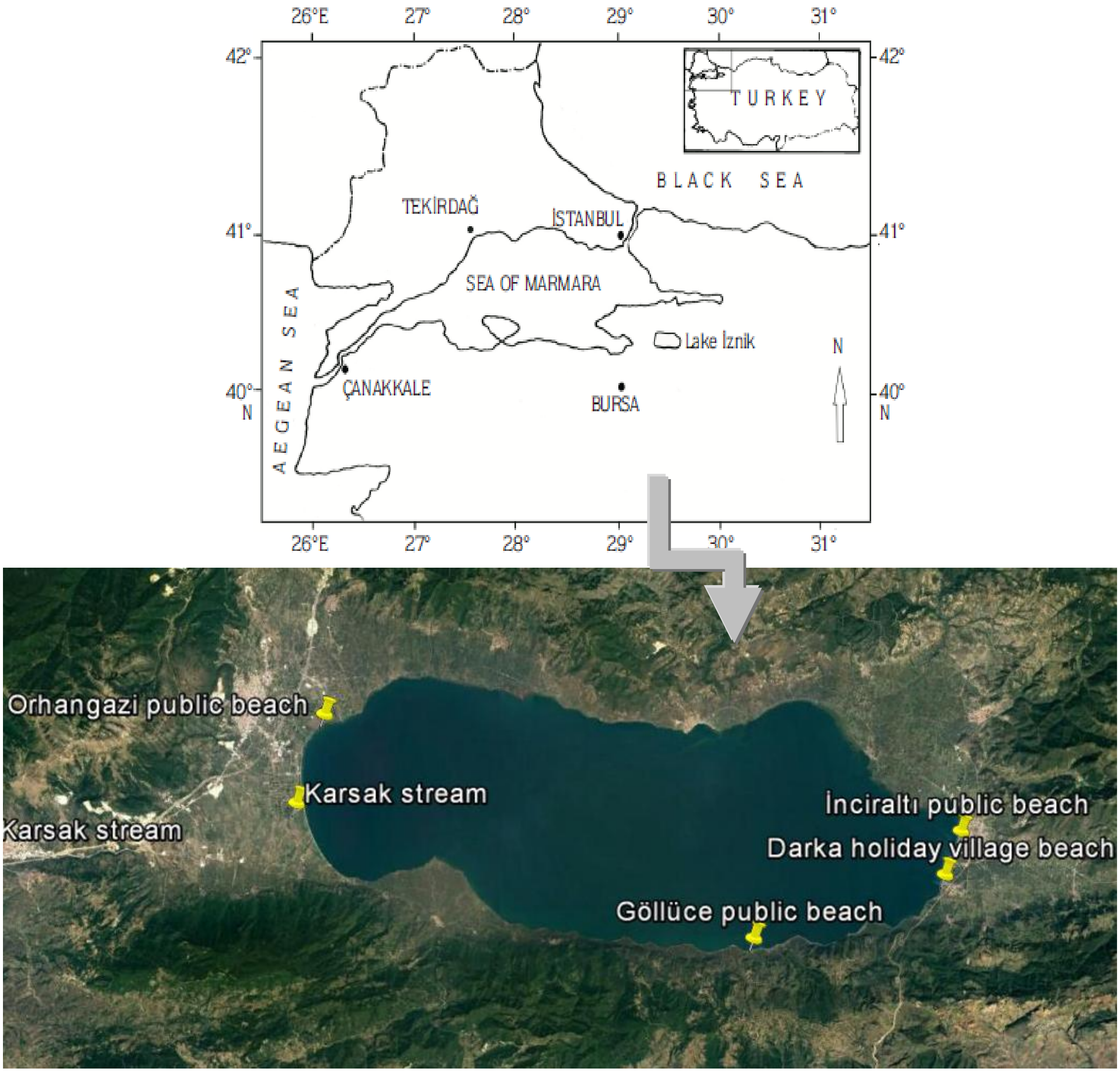

Figure 1. *Location of Lake İznik and sampling stations (Ozuluğ et al., 2005 and Google Earth, 2016)*

In this study, the microbiological pollution levels of the beaches in Lake İznik were examined with using the data obtained from the Bursa Provincial Directorate of Public

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Health. Total coliform, fecal coliform and fecal streptococci parameters were evaluated and modeled. The samples collected for measurements were taken from 30 cm below of the surface and put into the polyethylene (PE) single use bottles of 500 mL volume, kept in the thermo isolated boxes, having cooling bars at +4 °C, and brought to the lab in 24 h at the most. Bacterial count were performed by membrane filtration (MF) method and determined as CFU/100 mL (APHA, 1992; YSKY, 2006).

ANN model and training algorithm

Artificial neural networks are formed of a set of simple elements, the alleged artificial neurons. These elements are inspired by biological nervous systems. Models of neural networks are separated into two categories: feed forward neural networks and recurrent neural networks. Feed forward neural networks propagate data linearly from input to output and they are the most popular and most widely used models in many practical applications. (Hornik, 1991) Showed the feed forward neural network (FNN) with as few as a single hidden layer and arbitrary bounded and smooth activation functions can approximate a continuous nonlinear function (Şen, 2004). The multilayer FNN represented in *Figure 2* (Rankovic et al., 2010; Efe and Kaynak, 2002; Okkan and Mollamahmutoğlu, 2010).

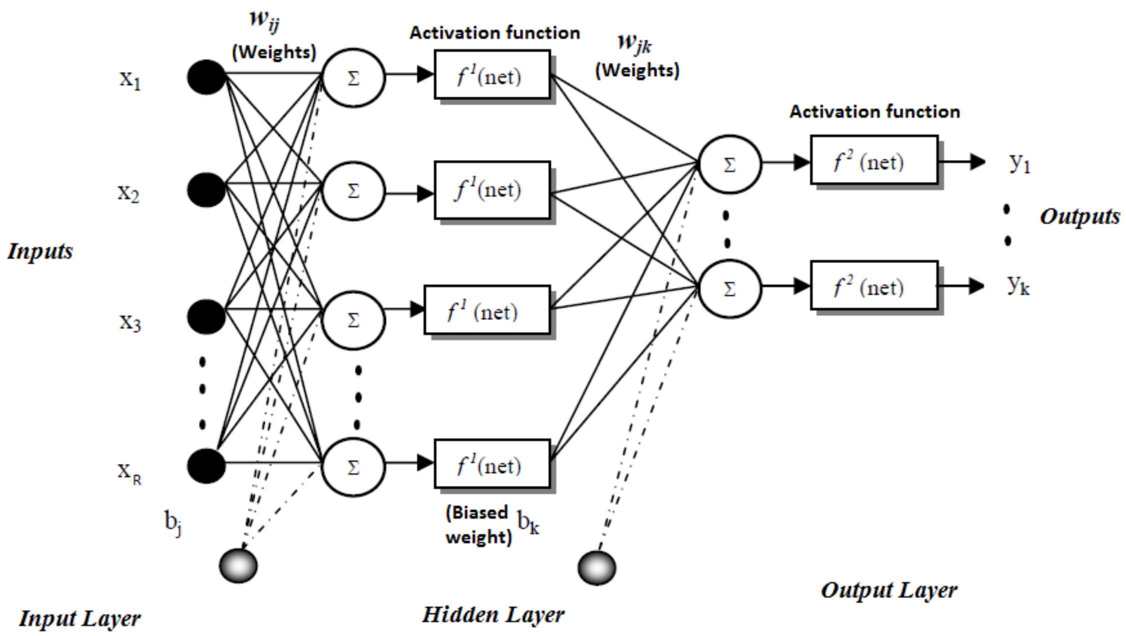

Figure 2. *Multi layer feed forward neural network*

As shown in *Figure 2*, the elements constituting ANN are input layer, hidden layers (number of hidden layers are one or might be more), output layer linkages between the layers and linkage weights.

The data of the problem is in the input and output layers. Productivity and importance of information in the input layer are provided with the weights. Net (basis) function expresses that productivity of input data to neuron. For an analytical study, the connection networks are mathematically represented by a basis function u (w, x). The

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net value is a linear combination of the inputs and the output of a neuron can be expressed as *Equation 1:*

$$out = f(n) \tag{Eq.1}$$

where (*Eq. 2*)

$$n = \sum_{j=1}^{R} w_j x_J + b \tag{Eq.2}$$

x_1, x_2, …, x_R are the input signals; w_1, w_2, ..., w_R are the weights of neuron; b is bias value; and f(·) is the activation function.

Activation function is a function determining the neuron output with processing the net inputs obtained from net function. The linear and sigmoid are common used activation functions in the construction of artificial neural networks.

An example of the sigmoid is the logistic function, defined by *Equation 1:*

$$f(n) = \frac{1}{1+e^{-n}} \tag{Eq.3}$$

Also, as sigmoid function can be used hyperbolic tangent function and it gives the outputs range between [0-1] (*Eq. 2;* Haykin, 1999):

$$f(n) = \frac{1-e^{-n}}{1+e^{-n}} \tag{Eq.4}$$

The inputs x_1, x_2, ..., x_R are multiplied by weights $w_{i},j_{(1)}$ and summed at each hidden neuron i. Then the summed signal (*Eq. 5*):

$$n_{i(1)} = \sum_{j=1}^{R} w_{i,j(1)} x_J + b_{i(1)} \tag{Eq.5}$$

The node activates a nonlinear function $f_{(n)}$. The output y at a linear output node can be calculated as *Equation 6:*

$$y = \sum_{i=1}^{z} w_{1,i(2)} \frac{1-e^{-\left(\sum_{i=1}^{R} x_j w_{i,j(1)} + b_{i(1)}\right)}}{1-e^{-\left(\sum_{i=1}^{R} x_j w_{i,j(1)} + b_{i(1)}\right)}} + b_{1(2)} \tag{Eq.6}$$

where R is the number of inputs, z is the number of hidden neurons, wi.j(1) is the first layer weight between the input j and the i^{th} hidden neuron, w1,i(2) is the second layer weight between the i^{th} hidden neuron and output neuron, bi(1) is a biased weight for the ith hidden neuron and b1(2) is a biased weight for the output neuron (Rankovic et al., 2010).

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The learning algorithms using in ANN are heuristics, partial Newton methods, matched gradient methods and Levenberg Marquardt methods. In this study feed forward neural network structure was used and Levenberg Marquardt training algorithm supervised training algorithms was preferred for training. Pupose Levenberg Marquardt algorithm is the least squares calculation method based on maximum neighborly idea (Hagan and Menhaj, 1994). The sum of squared errors of any one of the element in the training set (N number of elements) could be calculated as follows (*Eqs. 7* and *8*)*:*

$$E(w) = \frac{1}{2}\sum_{i=1}^{N}(y_{mi} - y_i)^2 = \frac{1}{2}(y_m - y)^T(y_m - y) \quad \text{(Eq.7)}$$

$$w = [w_{1,1(1)}, w_{1,2(1)}, \dots, w_{z,R(1)}, b_{1(1)}, b_{2(1)}, \dots, b_{z(1)}, w_{1,1(2)}, w_{1,2(2)}, \dots, w_{1,z(2)}, b_{1(2)}]^T \quad \text{(Eq.8)}$$

Two number of different hidden layer neuron for each input neurons was tested in this study. This was because; in the recent study were two different approaches used in determining the number of hidden layer neurons. The first approach for a network model which in the N number of neuron in the input layer: (N + 1) / 2 and the second approach: (2 * N + 1) were introduced (Hagan and Menhaj, 1994; Oğuztürk, 2010).

Performance and sensitivity analysis of ANN

The performance of the forecasts from the data-driven models was evaluated. The Pearson correlation coefficient is one of the most commonly used performance in selecting proper inputs for the ANN (Rankovic et al., 2010). Correlation coefficient is described as the degree of correlation between the empirical and modeled values (*Eq. 9*):

$$r = \frac{\sum_{i=1}^{N_0}(y_i - \bar{y})(y_{mi} - \bar{y}_m)}{\sqrt{\sum_{i=1}^{N_0}(y_i - \bar{y})^2 \sum_{i=1}^{N_0}(y_{mi} - \bar{y}_m)^2}} \quad \text{(Eq.9)}$$

where y_i and y_{mi} enounce the network output and measured value from the i^{th} element; $\bar{y}$ and $\bar{y}_m$ conceive their average respectively, and N_o describes the number of measurements.

Another performance measure is mean absolute error (MAE). The MAE is used to measure how close forecasted values are to the observed values. It is the average of the absolute errors. The smaller values of MAE and MSE (mean square error) provide the better performance (Belayneh and Adamowski, 2012). MAE and MSE are estimated as follows (*Eqs. 10* and *11*):

$$MAE = \frac{1}{N_0}\sum_{i=1}^{N_0}|y_{mi} - y_i|^2 \quad \text{(Eq.10)}$$

$$MSE = \frac{1}{N_0}\sum_{i=1}^{N_0}(y_{mi} - y_i)^2 \quad \text{(Eq.11)}$$

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ANN application

In this study, the total coliform, fecal coliform and fecal streptococci parameters, which were measured between the years of 2010 and 2015, were modeled. The total number of measurements used in modeling for each parameter was 108 and 27 number of data was evaluated for each of lake coasts and parameters.

The amount of data needed to train a neural network is very much problem-dependent. The quality of training data (i.e., how well the available training data represents the problem space) is as important as the quantity (i.e., the number of records, or examples of input-output pairs). The key is to use training data that generally span the problem data space. For relatively small datasets (fewer than 20 input variables, 100 to several thousand records) a minimum of 10 to 40 records (examples) per input variable is recommended for training (NNMP, 2016). The total data number used in ANN modeling studies, related to water quality, ranged from 60 and 442 (Brion and Lingireddy, 2003; Mas and Ahlfeld, 2007; Radojevic et al., 2013). For these reasons the total number of data used in this study is suitable for water quality studies.

In this study, all the ANN model structures were created with the MATLAB ANN toolbox (Matlab, R2015). The tangent sigmoid transfer function was the activation function for the hidden layer, while the activation function for the output layer was a linear function. All the ANN models in this study were trained using the Levenberg Marquardt (LM) back propagation algorithm. The LM back propagation algorithm was chosen because of its efficiency.

All the ANN models the cross validation technique was used to partition the data sets; 80% of the data was used to train the models, while the remaining 20% of the data was used to test and validate the models, with 10% used for testing and 10% used for validation (Principe et al., 1999; Keskin et al., 2011; Keskin et al., 2009; Belayneh and Adamowski, 2012). In microbiological modeling studies, between 60 and 80% of the total data were used in training process, between 10 and 20% were used in test and validation stage (Brion and Lingireddy, 2003; Mas and Ahlfeld, 2007; Radojevic et al., 2013).

The training set was used to compute the error gradient and to update the network weights and biases. The error from the validation set was used to monitor the training process. If the network overfits the data the error in the validation set will begin to rise. The testing data set is an independent data set and is used to verify the performance of the model.

The data based on monthly average values was used in this study and 4 model structure (a, b, c, d) were tested for each 5 model (Model 1-Total data of the Lake, Model 2-Göllüce area, Model 3-İnciraltı area, Model 4-Darka area and Model 5-Orhangazi area). The results in the model structures related to ANN modeling experiments with a different number of hidden layers were defined in a comparative way.

In the (a) and (b) model structures total coliform and fecal streptococci and in the (c) and (d) model structures total coliform were chosen as input parameters. In all of the model structures, fecal coliform was selected as output parameter.

Total coliform parameter does not always indicate fecal contamination or the presence of the pathogens in water. Some bacteria, which are non-fecal source, answer to the definition of coliform bacteria. Most of the fecal streptococci bacteria are fecal source and in practice, they are the most important indicator of contamination with human feces. However, certain types and their subtypes are also present in plant

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material. Fecal streptococci rarely grow in contaminated water and are more resistant than coliform bacteria. Fecal coliforms are a subgroup of the total coliform bacteria and are of fecal origin. While total coliforms may be given some permission since they are phytogenetic and soil born, fecal coliforms are allowed to a very limited number of permission (Casadevall and Pirofski, 2014; Alberts et al., 2002). For this reason, Fecal coliform was chosen as an output parameter and modeled with the aim of estimating the sewages containing human and animal waste and providing support to the prevention works afterwards.

Results and discussion

Water quality and basic statistic of the data set

According to the "Blue Flag Criteria" (TÜRÇEV, 2013), microbial contaminant levels for the last 4 years are required in order to determine the level of pollution of beaches. Therefore, the measurements performed at the Lake coasts during the swimming season, in other words in summer months, between the years of 2010 and 2015, were evaluated within the context of this study. The results of the measurements were evaluated according to "Table of Criteria for Water Quality Required for Swimming and Recreation in Swimming Water Quality Act" (*Table 2*).

Table 2. *Table of criteria for water quality required for swimming and recreation (YSKY, 2006)*

Parameters	Reference values	Mandatory values
Total coliform /100 ml	1000 (2006-2014 years) 500 (2015 year)	10000
Faecal coliform /100 ml	200 (2006-2014 years) 100 (2015 year)	2000
Faecal streptococci /100 ml	100	1000

According to this table; if the measured values are under the reference values, the water is in good quality, between the reference values and mandatory value is in medium quality and above the mandatory value, is in poor quality.

When the variation of microbial pollution in the coastal areas was examined the parameters were changed with good and medium quality. However, according to the values of 2015, faecal coliform and faecal streptococci parameters were found to be in good class and the pollution decreased in the all coasts. It was determined that total coliform and faecal streptococci concentrations were no statistical difference among the months but slight increase in these parameter's concentrations were observed in the each month until late spring to early fall. These parameters could be soil and plant origin. Therefore intensive agricultural activity and rain in these months may increase the concentrations (Akkoyunlu et al., 2011; WWF, 2011). According to the statistical calculations (ANOVA tables) for all of the Lake there was no difference among the months and monitoring stations of the coasts. But the differences among the years for faecal coliform and faecal streptococci parameters were found significant ($p \leq 0.05$) statistical. According to the ANOVA analysis results for the each station the monthly alterations of faecal streptococci in Darka and Orhangazi public beaches were found as significant ($p \leq 0.05$) statistically (Demirci and Can, 2015). Basic statistic of the data set for this water quality and modeling studies was given in *Table 3*.

Table 3. *Basic statistic of the data set*

Coasts	Parameters (CFU / 100 ml)	Mean	Std	Max	Min
Göllüce Public Beach	Total coliform	511.148	636.474	3210	5
	Faecal coliform	135.093	132.533	521.5	2
	Faecal streptococci	73.537	63.613	220	2
İnciraltı Public Beach	Total coliform	310.296	315.901	1500	28
	Faecal coliform	110.222	113.191	440	7.5
	Faecal streptococci	65.370	89.917	420	2
Darka Holiday Village	Total coliform	310.611	301.155	1200	15
	Faecal coliform	66.889	75.676	400	2.5
	Faecal streptococci	51.889	62.364	250	3
Orhangazi Public Beach	Total coliform	518.185	690.173	3300	5
	Faecal coliform	110.259	110.555	425	2
	Faecal streptococci	78.130	92.063	400	2
Lake	Total coliform	412.560	520.574	3300	5
	Faecal coliform	105.616	111.137	521.5	2
	Faecal streptococcus	67.231	77.799	420	2

Moreover, the correlation of the three parameters with each other was considered statistically significant ($p < 0.05$). In previous scientific studies, when the correlation between indicator bacteria has been examined, it has been determined that the numbers of indicator bacteria decreased or increased in parallel with each other (Demirci and Can, 2015; Gürün and Kımıran-Erdem, 2013).

The effect of neural network structure on performance function (RMSE) and model estimation power (R)

The effect of neural network structure by changing of inputs and number of hidden neurons (layer) on model performance was investigated. Root Mean Square Error (RMSE) has been adopted as a measure of performance (as performance function) for comparing the effectiveness of tested structures (Belayneh and Adamowski, 2012; Soyupak et al., 2006). The performance function (RMSE) values and correlation coefficients (R) obtained for training, validation, testing and whole data sets. The model structures and their performance functions (RMSE) values and correlation coefficients (R) of the data sets were presented in *Table 4*. In all model structures, Faecal coliform was chosen as output parameter.

In “Model 1” all data of Lake İznik a and b structures, total coliform and faecal streptococci parameters were chosen as inputs. These models were run quite efficiently. But RMSE values of model 1-b were smaller than model 1-a, R correlation numbers of model 1-b were bigger than model 1-a except verification values. Enhancing of hidden

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neuron numbers in Model 1-b was raised to whole data set of R correlation number. In model 1 –c and d total coliform parameter was selected as input. These models were run efficiently. In model 1-d, hidden neuron numbers were raised. For this reason RMSE values of training and testing stages decreased and these R values and R number of whole data increased. İznik sub-province had advanced biological treatment plant with membrane technology and its sewerage system had completed. But the first stage of the treatment plant was put into use just (BUSKİ, 2016). Even so the treatment plant was not run at full capacity the pollution in the lake decreased (Demirci and Can, 2015). Also the monthly variations of the parameter's concentration was not been considered as statistically significant (Demirci and Can, 2015). This situation could be attributed that the pollution load was not belong to a specific period and point pollution sources disturb the ecological balance of the environment because of their uninterrupted waste inputs and therefore change the competitive environment among microorganisms continuously (Gürün and Kımıran Erdem, 2013). As a consequence, it was estimated that there was some inaccuracy in the model results and R values were not too high. Bursa Metropolitan Municipality planned to start up the second stage of the biological treatment plants in İznik sub-province. So it was estimated that microbiological and chemical pollution in the Lake would decrease (BBB, 2016).

In Göllüce Coasts "model 2" a and b structures, total coliform and faecal streptococci parameters were inputs as model 1. These models were run efficiently. RMSE values of model 2-a and b training and testing stages were bigger than model 1-a and b but verification RMSE values were smaller than model 1. Also verification R values were bigger than model 1, others not. It was found that the performance of model 2 (Göllüce area) less than model 1 (All Data of the Lake). Livelihood of the village of Göllüce was fruit and vegetable farming, especially olive cultivation. Therefore pesticides and fertilizers polluted this coast as diffuse sources. Moreover entering of domestic wastewater was in this coast because of incomplete sewerage system (LGP, 2016).

Microbial growth on and utilization of environmental contaminants as substrates have been studied by many researchers. Most times, substrate utilization results in removal of chemical contaminant, increase in microbial biomass and subsequent biodegradation of the contaminant (Okpokwasili and Nkweke, 2005). Wastewaters from industrial, municipal and agricultural sources are characterized by presence of mixtures of chemicals. Pollutant mixtures may contain only organic chemicals or may also include inorganic substances such as heavy metals. Co-contamination of natural environments with mixtures of pollutants is an important problem. The removal of one component may be inhibited by other components in the mixture and different conditions may be required to degrade different compounds within the mixture. Strong interactions among components of a pollutant mixture have been reported (Egli, 1995; Klečka and Maier, 1988; Meyer et al., 1984; Saéz and Rittmann, 1993). The utilization pattern can change with different mixture compositions, depending on the chemical nature and concentration of the substrate, oxygen concentration and microbial growth rates. In addition to biodegradation stimulation due to increased growth at low substrate concentrations, stimulation of one compound by another in a mixture can be by induction of catabolic enzymes required for degradation of the second pollutant (Arvin et al., 1989). This mechanism produces simultaneous degradation of pollutants in mixtures and has been reported for pentachlorophenol and chlorinated aromatics, toluene and *p*-xylene (Okpokwasili and Nkweke, 2005).

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Table 4. *The model structures and their performance functions (RMSE) values and correlation coefficients (R) of the data sets*

Coast area	Model No.	Inputs	Outputs	ANN	RMSE			R			
					Training	**Validation**	**Testing**	**Training**	**Validation**	**Testing**	**Whole data set**
All data of the lake (Model 1)	Model 1a	Total coliform Faecal streptococci	Faecal coliform	2-2-1	74.859	40.435	64.555	0.755	0.866	0.944	0.77
	Model 1b	Total coliform Faecal streptococci	Faecal coliform	2-5-1	61.829	71.010	29.998	0.843	0.801	0.948	0.84
	Model 1c	Total coliform	Faecal coliform	1-1-1	80.205	74.946	53.999	0.701	0.758	0.791	0.71
	Model 1d	Total coliform		1-3-1	76.559	98.575	19.931	0.766	0.635	0.833	0.76
Göllüce Public Beach (Model 2)	Model 2a	Total coliform Faecal streptococci	Faecal coliform	2-2-1	101.040	9.751	112.817	0.678	0.995	0.939	0.72
	Model 2b	Total coliform Faecal streptococci	Faecal coliform	2-5-1	86.518	14.042	89.323	0.753	0.998	0.943	0.80
	Model 2c	Total coliform	Faecal coliform	1-1-1	74.568	206.662	88.096	0.679	0.990	0.971	0.69
	Model 2d	Total coliform		1-3-1	85.081	70.479	50.687	0.793	0.880	0.927	0.79
İnciraltı Public Beach (Model 3)	Model 3a	Total coliform Faecal streptococci	Faecal coliform	2-2-1	65.290	32.746	37.764	0.842	0.999	0.899	0.85
	Model 3b	Total coliform Faecal streptococci	Faecal coliform	2-5-1	55.068	33.122	104.545	0.817	0.985	0.998	0.86
	Model 3c	Total coliform	Faecal coliform	1-1-1	76.811	26.362	22.684	0.715	0.873	0.993	0.79
	Model 3d	Total coliform		1-3-1	61.428	24.584	132.438	0.785	0.883	1.000	0.78
Darka Holiday Village (Model 4)	Model 4a	Total coliform Faecal streptococci	Faecal coliform	2-2-1	27.567	16.169	174.660	0.659	0.883	0.998	0.59
	Model 4b	Total coliform Faecal streptococci	Faecal coliform	2-5-1	29.681	11.991	11.371	0.947	0.999	0.982	0.95
	Model 4c	Total coliform	Faecal coliform	1-1-1	62.617	50.989	13.630	0.645	0.694	0.930	0.63
	Model 4d	Total coliform		1-3-1	25.872	9.532	12.136	0.949	0.907	0.956	0.95
Orhangazi Public Beach (Model 5)	Model 5a	Total coliform Faecal streptococci	Faecal coliform	2-2-1	60.452	48.69257	115.34	0.769	0.968	0.978	0.79
	Model 5b	Total coliform Faecal streptococci	Faecal coliform	2-5-1	18.9066	31.68544	42.662	0.986	0.975	0.999	0.98
	Model 5c	Total coliform	Faecal coliform	1-1-1	66.6663	63.32148	73.752	0.756	0.990	0.976	0.80
	Model 5d	Total coliform		1-3-1	75.671	24.87342	85.111	0.742	0.937	0.991	0.75

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Model 1 (All of the Lake data) had more data than model 2. Therefore performance of model 2 might be fallen. Also, it was found that pollution concentrations of Göllüce coast higher than Lake Average. Because it was considered that pollution loads and varieties concentrated in Göllüce coast. For this reason metabolisms and growth rate of microorganisms were affected and model performance dropped.

In model 2-c and d total coliform parameter was selected as input. These models were run efficiently. In model 2-d, hidden neuron numbers were raised. For this reason RMSE values of validation and testing stages decreased and R values of validation and whole data were increased. The structure of b in model 2 like model 1 was the most efficient structure among the others. Increasing of the numbers of input parameters and neurons in hidden layer raised the model 2 performance.

In İnciraltı coasts "Model 3" a and b structures, total coliform and faecal streptococci parameters were inputs as model 1 and model 2. These model structures were run more efficiently and R values were bigger than model 1 and model 2. When model 3 (c and d) compared with model 1 and model 2 it was seen that model 3 c and d structures run better than model 1 c and d especially model 3 c. There was no difference between model 3 c and d. İnciraltı coast was cleaner than Göllüce coast as shown in *Table 3*. Also, there was cleaner than the lake average in terms of total coliform. Therefore microbial modeling was efficiently due to decrease interactions between pollutants. The raising of neuron numbers of hidden layers in the structures had same number of inputs applied in model 3 (İnciraltı coast) was not enhance model efficiency. The raising of neuron numbers of hidden layers in the structures had same number of inputs in the more contaminated coasts (model 1 and model 2) increased the model efficiency. The raising of input's numbers in the all structures in model 3 enhanced the model efficiency.

In Darka Holiday Village "Model 4" inputs and outputs parameters were like other models. In a and b structures RMSE values were less than other models excluding testing value of a structure. For this testing RMSE value R number of whole data set "a" less than other model structures even the smallest R value. Structure b was one of the most efficient running models. When c and d were compared structure d better than c and other d structures of models. Darka Holiday Village was the cleanest coast in the Lake according to *Table 3*. The pollution in Darka coast was caused mainly domestic waste water originating from holiday village not from agriculture (BBB, 2016; Municipality of İznik, 2016). Unlike the clean area of İnciraltı, increasing of neurons in hidden layers raised the performances of the structures in the Model 4 had same and different numbers of inputs.

According to comparison of Orhangazi coast "Model 5" with other models RMSE values of structure b smaller than other model's structures and it could be said that the most effective one. R values of all Model 5 structures were found 0.75 and over. When and b were compared rising of hidden layer number was increased the performance. According to comparison of c and d rising of hidden layer number was not increased the performance. In the Orhangazi area which was one of the most contaminated coasts enhancing of inputs and hidden layer numbers provided better model performance. Orhangazi was one of the places where agriculture and industry were the most intense in Bursa (BBB, 2016). In sites co-contaminated with metals and organic compounds, metal toxicity inhibits the activity of organic degrading microorganisms, impacting both their physiology and ecology, thus reducing the rate of biodegradation of the organic compounds (Said and Lewis, 1991; Roane et al., 2001; Maslin and Maier, 2000). Also,

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faecal contamination and growth of pathogens were associated with environmental parameters such as rainfall, temperature, wind, sunlight or different hydrometeorological and hydrodynamic variables (WHO, 2010).

Model structures experimented in this study had shown that the results of the statistical model might not always be in linear trend and gave results with a small inaccuracy. In addition, all these experiments had shown that to increase the number of neurons in hidden layer had not increased at every turn the model efficiency. Species and number of the input parameters might be more effective in the coasts where cleaner than the others with lower concentrations. However, when the whole models were examined the increasing of numbers of inputs with neurons in the hidden layers raised the model performances at every trial. Thus the structure of “b” was found as the most efficient structure in the all models.

As a result, it was found that all model structures of the 4 coasts and all data of the lake were successfully. R and RMSE values calculated were in the acceptable range (Soyupak et al., 2003; Brion and Lingireddy, 2003; Yonar and Kılıç, 2014; Mas and Ahlfeld, 2007; Ogwueleka and Ogwueleka, 2010; Radojevic et al., 2013). In water pollution and quality studies when number of data and tests were increased RMSE and MSE values were calculated smaller (Soyupak et al., 2003; Yonar and Kılıç, 2014). *Figure 3* displays the observed time series and forecasted values with the model structures. In addition, the corresponding scatter plots are also presented.

Conclusions

This study is important to support the modeling studies of microbiological parameters and to more effective monitoring can be done by measuring fewer parameters with the predictions made. Because there are limited number of studies in deep lakes this study is original in terms of artificial neural network modeling of coliform bacteria in deep lakes. The ANN structures were successfully used to forecast the faecal coliform concentrations in Göllüce, İnciraltı, Darka, Orhangazi Coasts-Lake İznik. Multilayer feed forward networks were used. This study indicated that a neural network could be used to predict microbial pollution in deep lakes.

In the regions, where point sources of pollution were continuous, the modeling study gave a result with a certain margin of error since they disturb the ecological balance of the environment and therefore change the competitive environment among microorganisms continuously. Besides, the error values (RMSE) of the modeling results of the coasts had more pollution load and pollutant diversity (Göllüce and Orhangazi areas) were found to be higher than the others coasts of Darka and İnciraltı, which are relatively cleaner, since the metabolism of microorganisms was effected by the number and chemical structure of substrates (pollutants), existing in the environment, and depending on this, their rates of growth were affected. *This study showed that the use of artificial neural networks to forecast of microbial pollution of lake coasts where wide variety of contaminants (industrial and domestic) was found might not provide accurate results.*

For this reason summer and winter data could be assessed separately and together, and repeat of the models by increasing the number of data would enhance the model performance. The effect of neural network structure by changing of inputs and neuron’s number of hidden layer on model performance was investigated. *This study showed also that increasing the number of inputs together with the neurons in hidden layer raised the performance of each model structure.*

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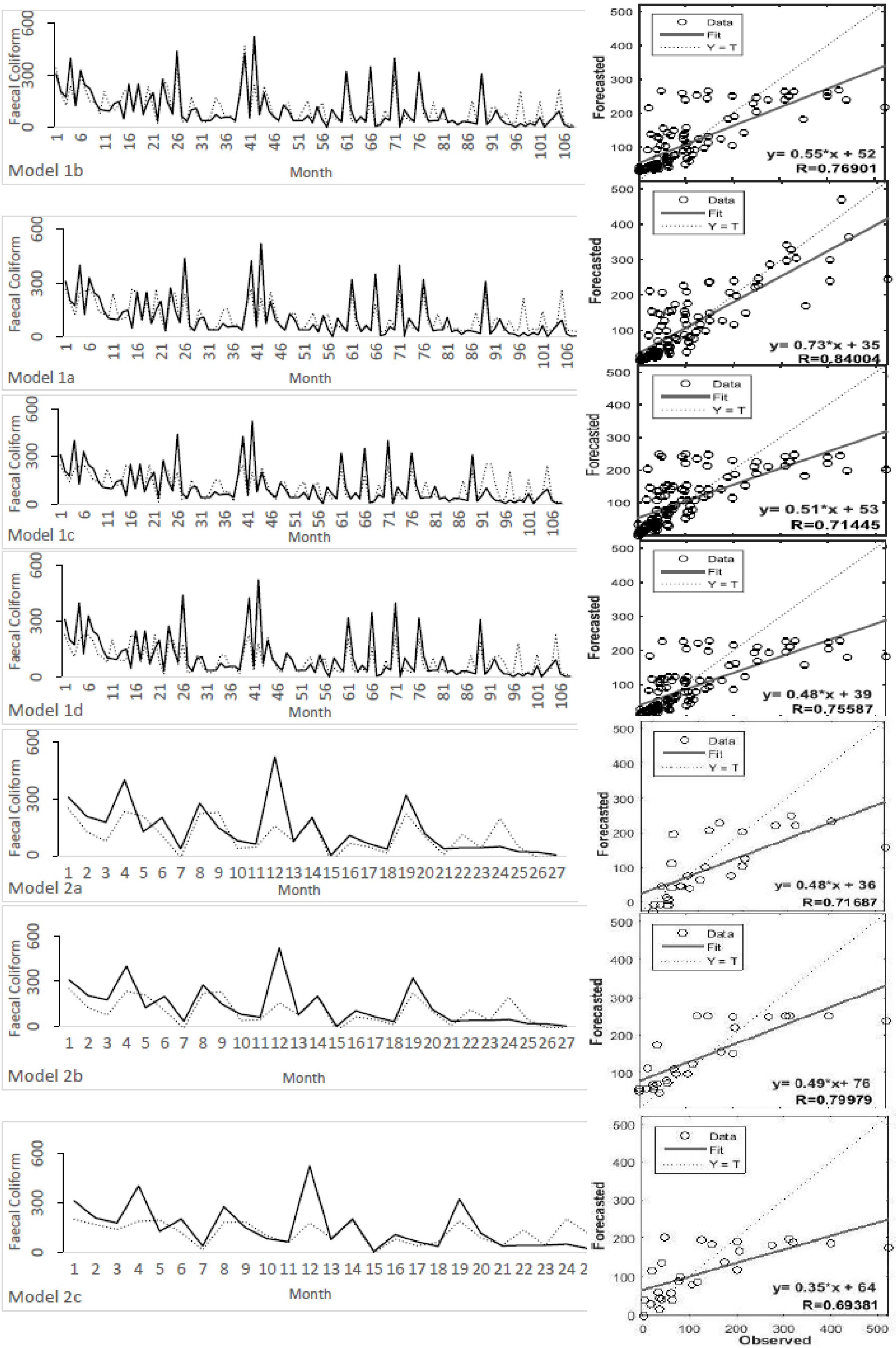

Figure 3. *The observed time series and forecasted values with the model structures*

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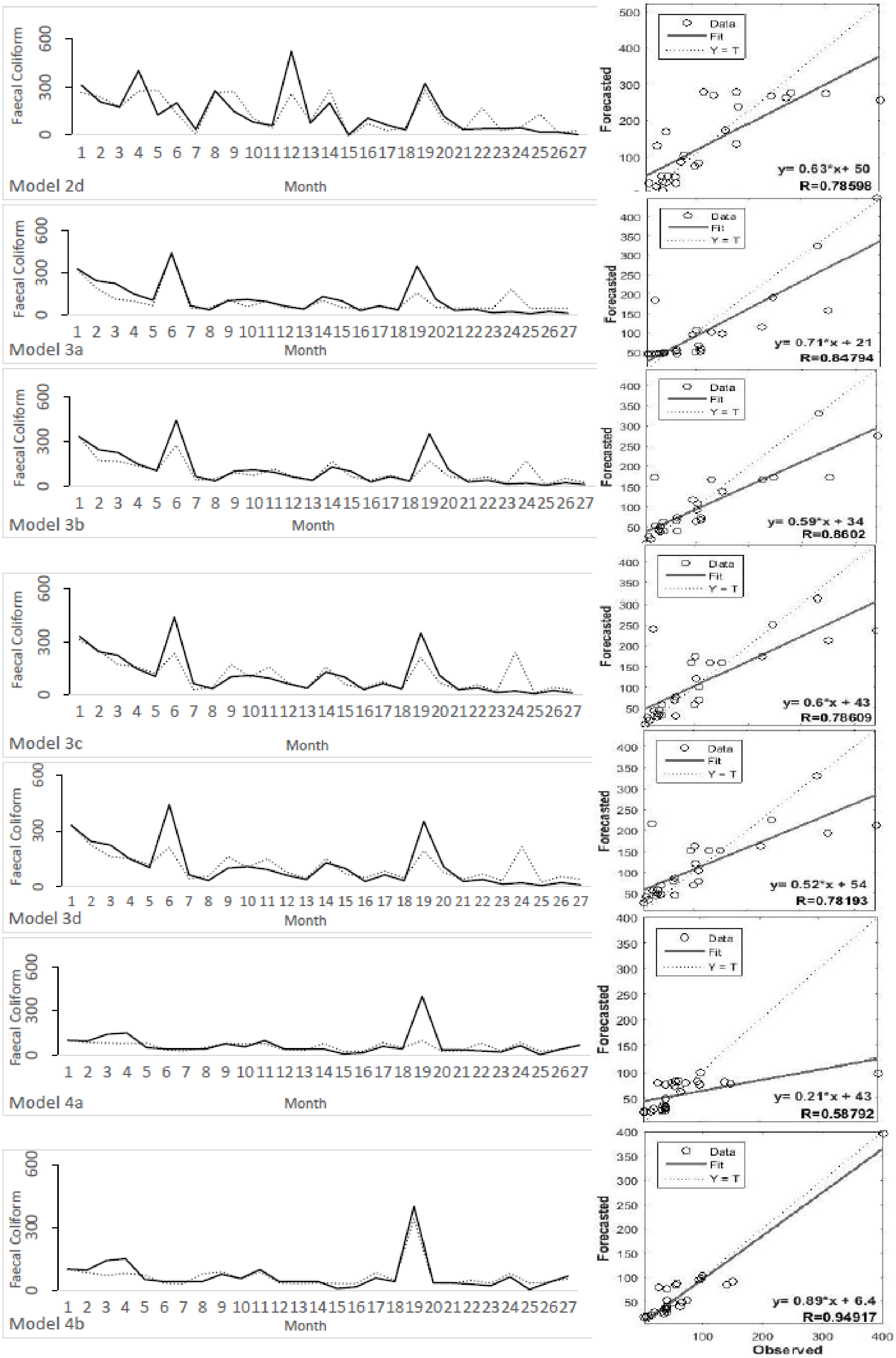

Figure 3. *(Continued) The observed time series and forecasted values with the model structures*

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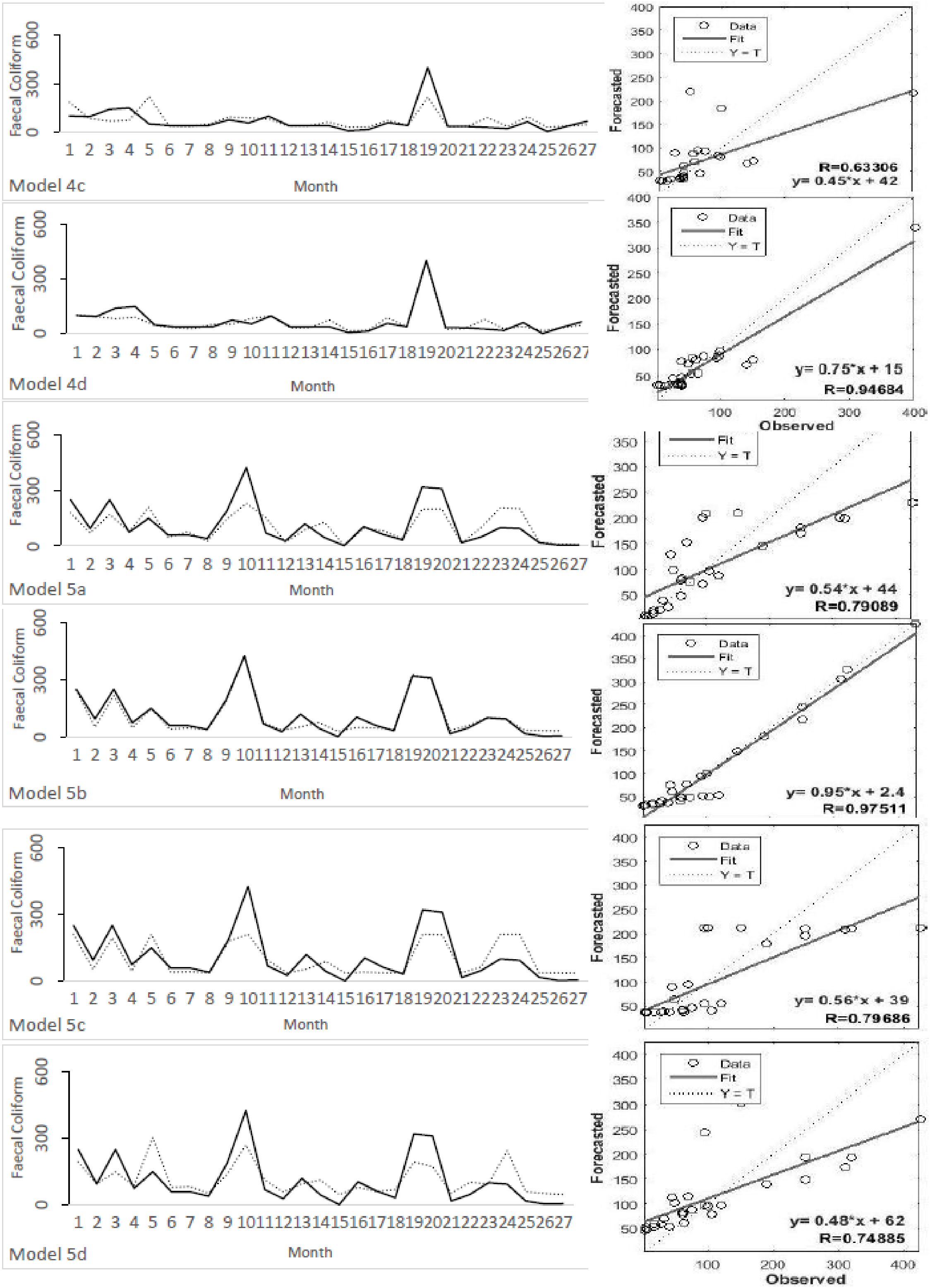

Figure 3. *(Continued) The observed time series and forecasted values with the model structures*

The development and application of microbial source tracking methods in order to identify sources of faecal pollution could also provide useful additional data. For future studies and providing information to the more effective integrated coastal and basin

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management, it is necessary to simulate pathogen organisms through different statistical and process based dynamic water quality models, using environmental and hydrodynamic parameters in water and in the atmosphere, and compare the model results. Also, different artificial neural network model structures should be applied for different microbiological parameters, and model performances should be examined in the future. In addition to that it will be useful to establish early warning systems, which are very important for public health, on the examined coasts by using the results of the modeling studies. Investigations to improve the knowledge-base of the area would also be of greatest importance to validate coastal and lake models and identify, for example, the role of diffuse sources from animal and agricultural soil origins which could carry human pathogenic bacteria or viruses.

The fact that monitoring and modeling works to protect of Lake İznik has national and international ecological values of in respect to water birds, endemic flora and fauna, tourism, recreation, fishing and agricultural are vitally important for the conservation of natural equilibrium in the world. Consequently continuation and development of modeling studies will be important in the future to provide information to the protection and supervision mechanisms.

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