Article

Comparative growth models of big-scale sand smelt (*Atherina boyeri* Risso, 1810) sampled from Hirfanlı Dam Lake, Kırşehir, Ankara, Turkey

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Abstract
In this current publication the growth characteristics of big-scale sand smelt data were compared for population dynamics within artificial neural networks and length-weight relationships models. This study aims to describe the optimal decision of the growth model of big-scale sand smelt by artificial neural networks and length-weight relationships models at Hirfanlı Dam Lake, Kırşehir, Turkey. There were a total of 1449 samples collected from Hirfanlı Dam Lake between May 2015 and May 2016. Both model results were compared with each other and the results were also evaluated with MAPE (mean absolute percentage error), MSE (mean squared error) and r^2 (coefficient correlation) data as a performance criterion. The results of the current study show that artificial neural networks is a superior estimation tool compared to length-weight relationships models of big-scale sand smelt in Hirfanlı Dam Lake.

Keywords growth model; length-weight relationships; artificial neural networks; big-scale sand smelt; Hirfanlı Dam Lake.

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1 Introduction

The relationship between the length and weight of a fish is used by fisheries researchers and managers (Le Cren, 1951). This is particularly useful for computing the biomass of a sample of fish from the length-frequency. The relationship between the length and weight of a sample of fish tends to have two important characteristics. First, the relationship is not linear. Second, the variability in weight increases as the length of the fish increases.

Artificial neural networks (ANNs) are information processing systems that consist of many interconnected processors, called neurons, resembling the elementary principles of the nervous system (Ramos-Nino et al., 1997; Zhang, 2010, 2011; Zhang and Zhang, 2008). ANNs have been employed in recent years as an alternative to conventional regression models, due to their ability to describe highly complex and non-linear problems in many fields of science. They normally have no restriction on the type of relationship between the growth parameters. ANNs directly explore the knowledge contained input-output patterns by adjusting the parameters of the non-linear. The neural network, with the error backpropagation procedure, is the basis of an interesting methodology that could be used in the same field as regression analysis, particularly with the non-linear relations (Rumelhart et al., 1986).

The Big-scale sand smelt, *Atherina boyeri* Risso, 1810 is a commercially important fish found throughout the Mediterranean and adjacent seas. It is euryhaline, mostly inhabiting coastal and shallow brackish waters including coastal lagoons, salt marshes and inland waters (Leonardos and Sinis, 2000; Pallaoro et al., 2002; Andreu-Soler et al., 2003; Bartulovic et al., 2004). This species inhabits the coasts of the northern Atlantic Ocean and basins of the Mediterranean Sea, Black Sea, and Caspian Sea (Kottelat and Freyhof, 2007). Several studies on the age and growth of Big-scale sand smelt have been reported in the literature, only a few have focused on populations inhabiting aquatic system (Mantilacci et al., 1990; Altun, 1999; Leonardos, 2001; Tarkan et al., 2007; Özeren, 2009; ApaydınYağcı et al., 2015, İlhan and Sarı, 2015; Gençoğlu and Ekmekçi, 2016; Erhan et al., 2016, Boundinar et al., 2016).

Much research has been performed on growth calculating using ANNs because they exhibit better results than traditional methods found in the literature (Suryanarayana et al., 2008; Türeli Bilen et al. 2011; Christiansen et al., 2015; Benzer, 2015, Benzer et al., 2015; Benzer and Benzer, 2016). These studies showed that neural network models are significantly better than length-weight relationships (LWR).

In this paper, the use of the neural networks approach was examined for regression problem with the aim of analyzing the level of relationships between length and weight variables in Hirfanlı Dam Lake by using the big-scale sand smelt.

2 Materials and Methods

2.1 Study area

The study was carried out in Hirfanlı Dam Lake (Fig. 1). Constructed in 1959, Hirfanlı Dam Lake is on river Kızılırmak, 70 km far from the south of Kırıkkale. It is located at 856 m altitude with a capacity of 7.63 x 109 m^3 and an area of 320 km^2. The depth, length and width of the lake are 58 m, 90 and 15 km, respectively. It is 24 km far from Ankara -Kırşehir Highway and 30 km from Ankara-Adana highway (DSİ, 1968).

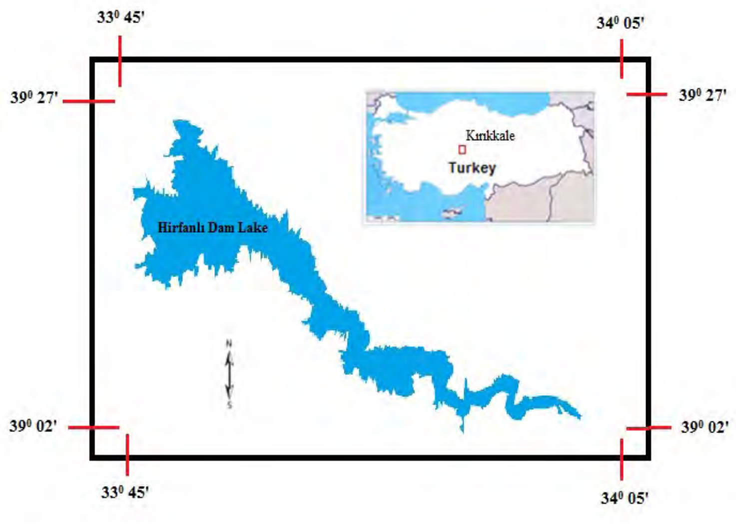

Fig. 1 Hirfanlı Dam Lake.

2.2 Data collection

The samples (*Atherina boyeri* Risso, 1810) were collected from Hirfanlı Dam Lake. During the study, 1449 fish specimens were caught between May 2015 and May 2016. The fish obtained from the lake were transported to the laboratory to record the total length (TL) to the nearest 0.1 cm and body weight (W) to the nearest 0.01 g. The sexes of each specimen were determined by microscopic examination of the gonads.

2.3 Growth models

2.3.1 Length - weight relation equation

LWR Equation is a traditional method used for the determination of the growth features of populations. Total Length (TL) was measured to the nearest 0.1 mm and analytical balances with a precision of 0.01 g were used to record weight (W). The length - weight (log-transformed) relationships were determined by linear regression analysis and scatter diagrams of length and weight were plotted (Le Cren, 1951).

$$\mathrm{W} = \mathrm{a\ L^b} \qquad (1)$$

where, W=weight of fish (g), L is observed total length (mm), ‘a’ is the regression intercept and ‘b’ is the regression slope. The logarithmic transformation of the formula above is;

$$\mathrm{Log\ W} = \log \mathrm{a} + \mathrm{b} \log \mathrm{L} \qquad (2)$$

The b value is often 3.0 and generally between 2.5 and 3.5. As the fish grows, changes in weight are relatively greater than changes in length, due to approximately cubic relationships between fish length and weight. The b values in fish is species specific and varies with sex, age, seasons, physiological conditions, growth increment and nutritional status of fish (Ricker, 1975).

2.3.2 Model by artificial neural networks approach

ANNs are an information processing paradigm that is inspired by biological nervous systems, such as the brain process information (Sivanondom et al., 2006). It is composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems (Huang et al., 2006). The basic element of an ANNs is Artificial Neurons. These neurons multiple their inputs (xi) with variable weights and values obtained from this process transform with an activation function (f(n)) to output value (yi). These formulas (Krenker et al., 2011) can be seen in equation (3) and (4).

$$\sum_{\mathrm{i=1}}^{\mathrm{p}} \mathrm{W_i x_i} + \mathrm{b} \qquad (3)$$

$$\mathrm{y} = \mathrm{f(n)} = \mathrm{f}(\sum_{\mathrm{i=1}}^{\mathrm{p}} \mathrm{W_i x_i} + \mathrm{b}) \qquad (4)$$

The supervised learning method trained with the network structure (Back-propagation Networks) will be used to solve problems in this study. The transfer function (5), (VN is normalized data, VN is data to be normalized, Vmin is the minimum value of the data, Vmax is the maximum value of the data) mostly used a sigmoid or a logistic function, gives values in the range of [0,1] and can be described as (normalization):

$$V_N = 0.8\ x\ \left(\frac{V_R - V_{min}}{V_{max} - V_{min}}\right) + 0.1 \qquad (5)$$

This study used the sigmoid activation function. ANNs can work with a small data set; and it seems better than other methods because it has such significant features as generalization, learning from data, working with unlimited number of variables and no need for any information about the problem in advance.

Mean Squared Error (MSE), Sum of Squared Error (SSE) and Mean Absolute Percentage Error (MAPE) were used as the two performance criteria. MSE was used as convergence criteria during the training of the network. Comparisons can be made with more than one method by MAPE, because it is easy to interpret with its relative measurements. The smaller the values of MAPE, the closer are the forecasted values to the actual values. MSE, SSE and MAPE were described by equations 6, 7 and 8, respectively.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_{ip} - Y_{io})^2 \quad (6)$$

$$SSE = \sum_{i=1}^{n}(Y_{ip} - Y_{io})^2 \quad (7)$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{e_i}{Y_i}\right| * 100 \quad (8)$$

where Y_{io} is the actual observation value, Y_{ip} is the prediction value, e_i is the difference between the actual value and prediction value, and n is the number of total observations.

The data were divided into three equal parts: training, validation and test sets. The Matlab functions were used for “training”, “testing”, and “validation”. They were used randomly; 70% in training, 15% in testing, and 15% in the validation of the fish.

2.4 Statistics

The correlation coefficient r was used to measure the strength and direction of the linear relationship between the two variables on the distribution line. Correlation is an effect size and so the strength of the correlation using the guide that Evans (1996) suggests for the absolute value of r (very weak: 0.00-0.19; weak: 0.20-0.39; medium: 0.40-0.59; strong: 0.60-0.79; very strong: 0.80-1.0) was described. Variables were reported as Mean ± Sx. The means were compared using the t-test (Hald, 1952; Panofsky and Brier, 1968). The statistical analyses were performed using SPSS software (SPSS Inc., USA) whereas the model was studied by the use of Matlab Release 2015a program.

3 Results and Discussion

3.1 Length - weight relations (LWR)

The length and weight (min-max) of the fish were 29 – 95 mm and 0.14 – 6.42 g, respectively. There were 36.06 % females, 63.94 % males. LWR models werefound for females, males and all individuals. The relationships were $W = 0.01747655\ L^{2.63}$ ($r^2 = 0.977$) for females, $W = 0.01306145\ L^{2.80}$ ($r^2 = 0.971$) for males and $W = 0.01399306\ L^{2.80}$ ($r^2 = 0.973$) for all individuals (Table 1 and Fig. 2).

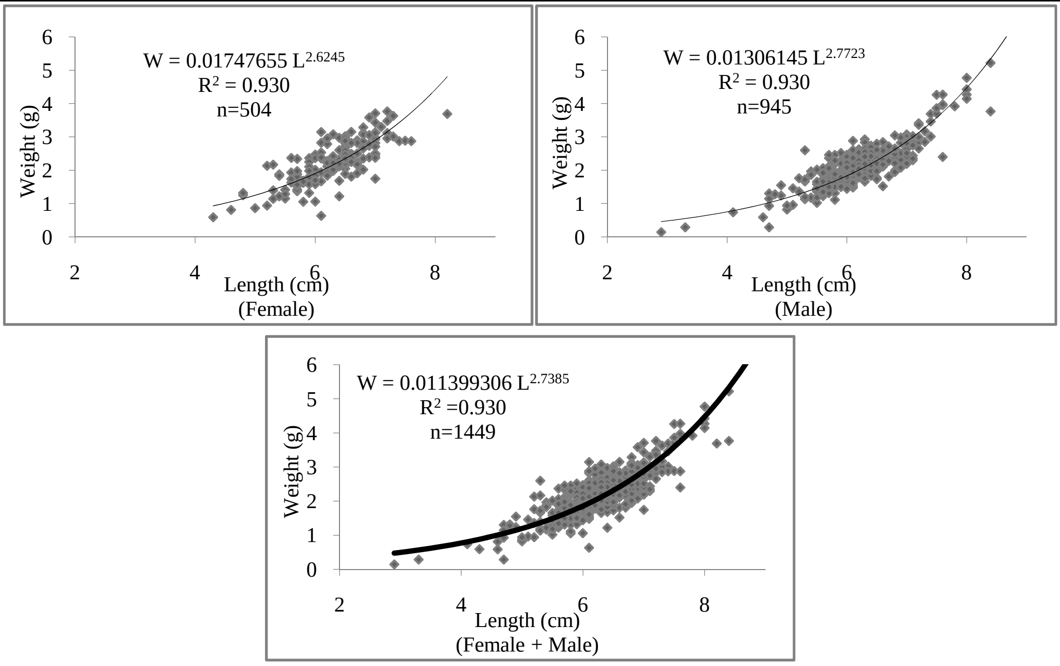

Fig. 2 Length - weight relationships of *Atherina boyeri* in Hirfanlı Dam Lake.

Table 1 Length - weight relationships of *Atherina boyeri* in Hirfanlı Dam Lake.

Length – Weight Relationships of *Atherinaboyeri*		r^2 (Coefficient correlation)
Female	$W = 0.01747655\ L^{2.6245}$	0.977
	Log W = -1,7575 + 2.6245 Log L	
Male	$W = 0.01306145\ L^{2.7723}$	0.971
	Log W = -1,884 + 2.7723 Log L	
Female + Male	$W = 0.01399306\ L^{2.7385}$	0.973
	Log W = -1,8541 + 2.7385 Log L	

3.2 Artificial Neural Networks (ANNs)

A total of 1449 length, weight data were used. 1015 of the obtained data were used in the learning process and 434 were used in the test and verification process. Prediction performances of artificial neural networks trained and tested with data length and weight variables in Hirfanlı Dam Lake by using the big-scale sand smelt were shown in Fig. 3.

3.3 Length - weight relations (LWR) and Artificial Neural Networks (ANNs) models

The results obtained by ANNs and LWR equation were compared to those obtained by the growth rate of the fish caught from Hirfanlı Dam Lake. LWR and ANNs MAPE results were examined. Thus, it can be seen that ANNs gives better results than LWR (Table 2 and Fig. 2). ANNs can be an alternative in theevaluation of growth estimation.

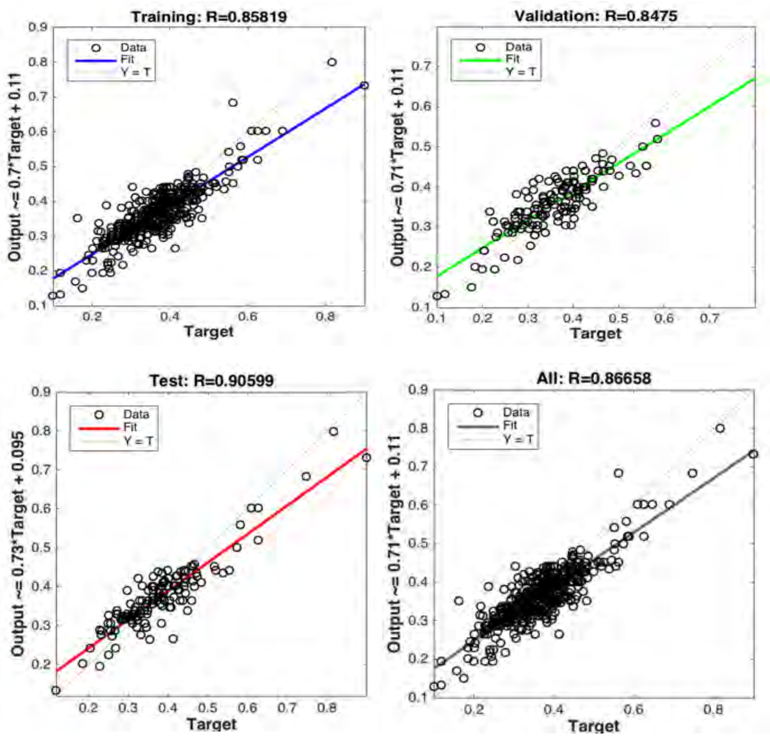

Fig. 3 Relationships with ANNs for training, validation, test and all.

Table 2 Results with LWR and ANNs.

	Length			Weight		
	Female	Male	Female+Male	Female	Male	Female+Male
Naturel Environment	6.2939	6.2211	6.2473	2.2661	2.1674	2.2029
ANNs Calculate:Matlab	6.2611	6.2278	6.2392	2.3275	2.1538	2.2448
MAPE (%)	0.5211	0.1077	0.1297	2.7095	0.6275	1.9020
Regression Relations	6.3829	6.3206	6.3429	2.184	2.0741	2.1132
MAPE (%)	1.4141	1.5994	1.5303	3.6230	4.3047	4.0719

ANNs performance criteria (MSE, SSE and r^2 - Coefficient correlation) has been found to give better results (Table 3).The MAPE criterion refers to estimation errors as a percentage, and can therefore negate the disadvantages that may arise when comparing models developed for studies with different unit values. These features of MAPE are considered to be superior to those of other evaluation statistics. Models with MAPE values less than 10% are classified as "high accuracy" and models with 10% to 20% are classified as accurate estimators (Witt and Witt, 1992). Similarly, Lewis (1982) categorized models with a MAPE value of less than 10% as "very good" in estimating, 10% to 20% as "good", 20% to 50% as "acceptable" and over 50% are classified as "wrong and faulty" models.

As seen in Table 3, ANNs gives better results than length - weight relations. In the literature, it is reported that ANNs MAPE ratios are low according to traditional methods (Tureli et al., 2011; Benzer and Benzer, 2016; Benzer et al., 2015; Benzer et al., 2016).

Table 3 Performans results with LWR and ANNs.

	MSE		SSE		MAPE (%)		r^2 (Coefficient correlation)
	Length	Weight	Length	Weight	Length	Weight	
LWR	0.478	0.519	694.06	752.52	1.5303	4.0719	0.97
ANNs	0.372	0.425	153.87	176.84	0.1297	1.9020	0.87

4 Conclusion

Consequently, length - weight regressions have been used frequently to estimate weight from length and length from weight. The results of the study were examined by adding the ANNs approach to the traditional estimation method (LWR). This research also provides growth information by length – weight relationships and artificial neural networks approach that would be useful for sustainable management of fisheries in Hirfanlı Dam Lake. Finally, it is recommended that the big-scale sand smelt population should be carefully monitored in the future to ensure sustainable economic yield by other mathematical approaches (artificial neural networks, box–Jenkins method, etc.) in Hirfanlı Dam Lake and other inland water resources.

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