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Comparison between traditional models and artificial neural networks as estimators of the growth of the Tigris scraper *Capoeta umbla* (Teleostei: Cyprinidae) in the Munzur River, Turkey

Comparación entre modelos tradicionales y redes neuronales artificiales como estimadores del crecimiento del raspador del Tigris *Capoeta umbla* (Teleostei: Cyprinidae) en el río Munzur, Turquía

Ebru Ifakat Ozcan*, ***Osman Serdar***

Munzur University, Faculty of Fisheries. Tunceli, Türkiye.
**Corresponding author: ebruozer@munzur.edu.tr*

ABSTRACT

In this study, a comparison of traditional growth methods (length-weight relationships and von Bertalanffy growth function) with artificial neural networks in growth models was carried out in the growth of 783 specimens of *Capoeta umbla* from the Munzur River, Turkey from September 2019 to May 2021. The length-weight relationships of *C. umbla* $W = 0.0085L^{3.013}$ R^2=0.943 was determined for all individuals. The ages of the specimens were from 0 to 11 years old. The von Bertalanffy growth function was $L_t = 46.15\ [1\text{-}e^{-0.139\ (t + 2.57)}]$ and $W_t = 856.32\ [1\text{-}e^{-0.139\ (t + 2.57)}]^{3.013}$ for all individuals. Φ' value was 2.471 all individuals. The training stopped and the best validation performance was fixed at 8.1473×10^{-5} at epoch 42. The validation checks were reached as 6, at epoch 48 and the gradient = 5.6566×10^{-5}, at epoch 48. The target output R value was 0.98584 for training, 0.98969 for validation, 0.98757 for testing and 0.9868 for all. The calculated MAPE values were 0.140 and 0.578 for artificial neural networks, 1.168 and 2.726 for length–weight relationships, 5.721 and 4.013 for von Bertalanffy growth function, respectively. The calculated SSE values for length and weight were 0.0128 and 30.864 for artificial neural networks, 1.3985 and 350.786 for length–weight relationships. The results of the present show that artificial neural networks can be superior estimators than length–weight relationships and von Bertalanffy growth function. Therefore, artificial neural networks models are an effective tool to describe body weight and length in fish.

Key words: Growth properties; mean absolute percentage error (MAPE); length–weight ratio; von Bertalanffy growth function; Index of Average Percentage Error

RESUMEN

En este estudio, se realizó una comparación de los métodos de crecimiento tradicionales (relaciones longitud–peso y función de crecimiento de von Bertalanffy) con las redes neuronales artificiales en el crecimiento de 783 ejemplares de *Capoeta umbla* del río Munzur, Turquía de septiembre de 2019 a mayo de 2021. Se determinó la relación longitud-peso $W = 0.0085L^{3.013}$ R^2=0,943 para todos los individuos. Las edades de los ejemplares fueron de 0 a 11 años. La función de crecimiento de von Bertalanffy fue $L_t = 46{,}15\ [1\text{-}e^{-0{,}139\ (t + 2{,}57)}]$ y $W_t = 856{,}32\ [1\text{-}e^{-0{,}39\ (t + 2{,}57)}]^{3{,}013}$ para todos los individuos. El valor de Φ' fue 2,471 para todos los individuos. El entrenamiento se detuvo y el mejor rendimiento de validación se fijó en $8{,}1473 \times 10^{-5}$ en la época 42. Las comprobaciones de validación fueron alcanzado como 6, en la época 48 y el gradiente = $5{,}6566 \times 10^{-5}$ en la época 48. El valor R de salida objetivo fue de 0.98584 para el entrenamiento, de 0,98969 para la validación, de 0,98757 para las pruebas y de 0,9868 para todos. Los valores MAPE calculados fueron de 0,140 y 0,578 para redes neuronales artificiales, 1,168 y 2,726 para relaciones longitud–peso, y 5,721 y 4,013 para función de crecimiento de von Bertalanffy, respectivamente. Los valores SSE calculados para longitud y peso fueron 0,0128 y 30,864 para redes neuronales artificiales, y 1,3985 y 350,786 para relaciones longitud–peso. Los resultados del estudio actual muestran que las redes neuronales artificiales pueden ser estimadores superiores a relaciones longitud–peso y función de crecimiento de von Bertalanffy. Por tanto, los modelos de redes neuronales artificiales son una herramienta eficaz para describir el peso y la longitud corporal de los peces.

Palabras clave: Propiedades de crecimiento; error porcentual absoluto medio; relaciones longitud–peso; función de crecimiento de von Bertalanffy; índice de error porcentual promedio

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INTRODUCTION

Nowadays, with the increase in the world population, the need for animal protein has increased [1]. In order to meet this animal protein need, the biological characteristics of the species must be known in order to effectively manage fish stocks. Growth in fish can vary even among same species, different regions. These differences may result from the physical, chemical and biological characteristics of the environment, especially genetic characteristics and nutrition [2].

The body of *Capoeta umbla* (Heckel, 1843) is slightly cylindrical in shape. Its upper side displays a dark coloration, while its sides appear brown-yellow. The lower side of the body is off-white and provided with small scales [3]. The standard length is minimum 3.9 and maximum 4.7 times the maximum body length. There is a pair of barbels on the corners of the mouth. The mouth structure is slightly curved or straight, regardless of gender. The head is pointed, the nose is blunt, the mouth is large. Head length is minimum 2.5 and maximum 3.5 times mouth width. 2/3 of the last unbranched ray of the dorsal fin is toothed and slightly strong in some individuals [3]. Previously, several studies have been conducted on the biology of *C. umbla* in different aquatic bodies [4, 5, 6, 7, 8, 9, 10, 11, 12].

Artificial neural networks (ANNs) are computer systems designed to emulate the learning function that is a fundamental feature of the human brain. They carry out the learning process using examples. These networks consist of interconnected process elements (artificial nerve cells). A weight value for each link. This is the information that the artificial neural network has hidden in the weights. It is distributed throughout the network. It produces the outputted by passing it through the activation function and sends it to other cells (process elements) over the connections of the network [13]. By experimenting with data, artificial neural networks can learn and generalise; it has a non linear structure and is better shows better results than linear methods [14]. The method determines non-linear relationships without the need to assume them [15]. It also allows using an unlimited number of variables. Increasing interest in artificial neural networks in fisheries, especially in recent years, is due to the fact that these issues require accurate estimates. Many studies on artificial neural networks have shown that they provide preferable results than traditional methods [16, 17, 18, 19, 20, 21, 22, 23, 24]. ANNs due to their ability to mimic nonlinear systems, It is more effective than other traditional methods [25].

This study was based on the comparison of traditional equations (LWRs, VBGF) and artificial neural networks (ANNs) on the growth of *C. umbla* in the Munzur River. It will determined whether artificial neural networks can used as a alternative and reliable method in growth models.

MATERIALS AND METHODS

Turkey's Munzur River originates from the foothills of Visit Hill on the Munzur Mountains in the north of Ovacık and merges with Pülümür Stream in the central district and flows into Keban Dam Lake. Uzunçayır Dam Lake was established on the Munzur River to produce energy [26, 27].

For the study, 783 specimens of *C. umbla* were collected from local fishermen seasonally from different regions of the Munzur River (FIG. 1) [28] from September 2019 to May 2021. The body weights of the fish were determined on a scale with 1 g precision (Dahongying, ACS-809T model, Korea), and their lengths were determined with an ichthyometer with 1 mm graduations. Sexual determination of fish was performed according to Lagler *et al.* [29]. In smaller fish sex determination was determined with the help of a compound microscope (Nikon, ECLIPSE C*i* model, Japan). The chi-square test ($\chi 2$) was used to determine whether the sex ratio (female/male) in the sample was statistically different from the expected 1:1 ratio [30]. For age determination, between 10 and 15 scales taken from the fish were placed in paper envelopes. The dirty scales have been washed in a bath of warm water. Age readings were made with a compound microscope with glycerin dripped slides (OLYMPUS, BX53 model Japan).

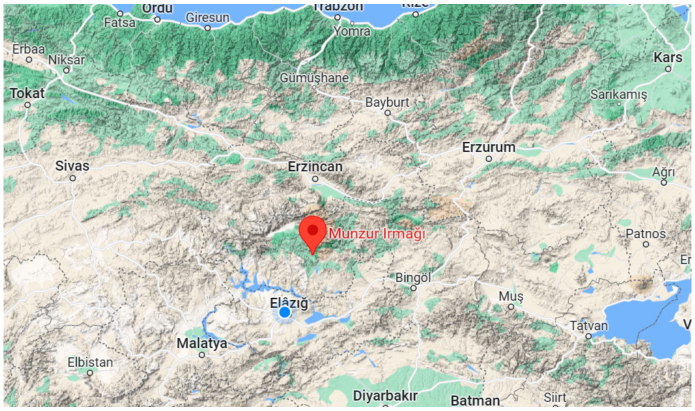

FIGURE 1. Relative location of the study area

The length-weight relationships were determined equation: $W = a*L^b$ [31] (W = total weight, a and b = regression constants, L = total length).

To check if there was difference between the ages, the Index of Average Percentage Error (IAPE) was used. The formula was as follows [32] $IAPE = 1/N \sum (1/R) \sum (xij-xi/xj)$ (N = Number of fish whose age is determined, R = Number of readings, xij = Mean age calculated from the *jth* fish, xij = *ith* age determination of the *jth* fish).

The von Bertalanffy formulae for growth in length and weight have been used for the mathematical calculation of growth in length and weight. von Bertalanffy growth function: $L_t = L_\infty[1-e^{-k(t-to)}]$; $W_t = W_\infty [1-e^{-k(t-to)}]^b$ [31] (L_t = The total length (cm) at age t, L_∞ = the asymptotic length (theoretical maximum length), W_∞ = the asymptotic weight (theoretical maximum weight), k = The Brody growth coefficient (proportional to rate at which L_∞ is reached), t = The age (years), t_0 = The age at zero length).

The growth achieved in the parameters studied in this research has been compared with previous studies using the Phi Prime. Growth performance (index) value (Ø') (Phi-prime): $Ø = log(k)+2log(L_\infty)$ [33].

The condition factor, the feeding capacity of the fish's environment, is calculated as follows: $CF = (W/L^b).100$ [34].

Microsoft Office Excel 2013 and SPSS 24.0 packages were also used for statistical analysis of the data obtained.

Artificial neural networks (ANNs)

Artificial neural networks have been inspired by the human brain, and the mathematical process of learning modeling has emerged as a result of the effort. ANNs consists of three layers: input, hidden and output layers. In addition, the model consisting of 8 neurons (3 in the input layer, 4 in the hidden layer and 1 in the output layer) is designed as fully connected feed-forward backprop propagation algorithm. The input layer transfers the data from the sensors and the set to the network. The information from the input layer is multiplied by weight coefficients in the hidden layer and passed through activation functions and then passed to the output layer. The output layer contains the output values previously given to the ANNs using error calculation functions. Error between values produced by ANNs. The weighting coefficients are redone when the error values are not good [35]. In artificial neural networks, the goal is to find the optimal weight and bias values that yield the best performance for the given model. These weight and bias values influence the network's ability to accurately map inputs to outputs during the learning process, ultimately determining the effectiveness of the model in solving the desired task. At each epoch, weights and biases are updated. these calculated values are defined as learning. Representation of an artificial neural networks is given in FIG. 2. System training uses the feed-forward backpropagation algorithm.

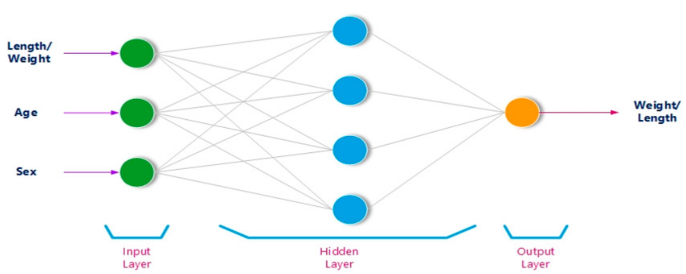

FIGURE 2. Representation of an artificial neural networks.

Weighting and biasing, mathematical equation of neuron model [36] are given in the equations below.

$$w = w - \varepsilon \frac{\partial C}{\partial w}$$

$$b = b - \varepsilon \frac{\partial C}{\partial b}$$

$$y(k) = F\left(\sum_{i=0}^{m} wi(k) \cdot xi(k) + b\right)$$

yi(k)=output value in discrete time *k*, *F*=transfer function, *xi(k)*=input value in discrete time *k* where *i* goes from 0 to m, *wi(k)*=weight value in discrete time *k* where *i* goes from 0 to m, *b*=bias.

Two performance measures used in the study were sum squared error (SSE) and mean absolute percentage error (MAPE). SSE was used as a convergence criterion during network training. MAPE is often used to evaluate the accuracy of predicting models. MAPE is usually expressed in percentage (%).The MAPE (%) equation has been used for comparison between ANNs and other methods. MAPE is an error measure, a low result is a measure that shows high performance that is inversely proportional to power [22, 37]. SSE and MAPE are given in the equations below.

$$SSE = \sum_{i=1}^{n} e_i^2 \qquad MAPE = \frac{1}{n}\sum_{i=1}^{n} \left|\frac{ei}{Yi}\right| \times 100$$

(*n*= number of total observations, *ei*= difference between actuals and estimates, *Yi*= actual observation value).

MATLAB Ver R2016a Neural Network Toolbox used in ANN predictions consists of three parts: learning (70%), testing (15%) and validating (15%) [17].

RESULTS AND DISCUSSION

The total length of *C. umbla* caught during the research were 6.8 cm to 38.5 cm in females and 7.9 cm to 40.2 cm in males. The length frequency values of the samples of *C. umbla* living are given in FIG. 3 from Munzur River. The length group is dominant 15.0-19.9 cm in female and 20.0-24.9 cm in male (FIG. 3). TABLE I shows the total length values of *C. umbla* in the studies carried out by different researchers. Differences between these values may be influenced by the region, time, method and many ecological factors [38]. Of the 783 samples caught, 444 were female and 339 were male. The female/male ratio is calculated as 1/0.764, chi-square (χ^2) test showed that significantly different from the theroretical 1:1 ratio (P<0.05).

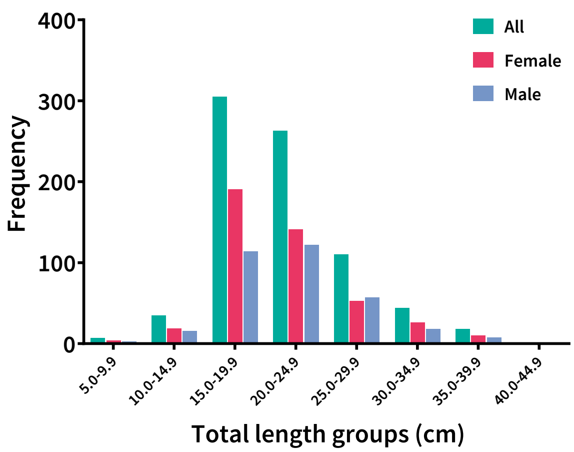

FIGURE 3. Distribution of total length groups-frequency of *Capoeta umbla* in Munzur River

TABLE I
Population characteristics of *Capoeta umbla* in different regions

Habitat	Sex	n	Age	Total length (cm)	*a*	*b*	R^2	L_∞	*k*	to	Φ′
Hazar Lake [4]	♀	180	2–13	18.70–47.20	0.0000083	3.006	0.96	68.61	0.07	-2.04	2.517
	♂	164	2–13	19.50–46.00	0.0000050	3.097	0.96	71.49	0.06	-2.63	2.486
	♀+♂	346	1–13	15.00–47.20	0.0000029	3.186	0.94	68.62	0.07	-2.20	2.517
Karasu River [5]	♀	506	1–12	10.40–34.20	0.0117	2.991	0.99	45.70	0.14	-0.83	2.465
	♂	665	1–10	10.90–32.30	0.0139	2.936	0.99	42.30	0.14	-0.98	2.398
Tercan Dam Lake [6]	♀	165	1–6	11.62–31.84	0.000500	2.321	0.98	41.64	0.19	-0.69	2.517
	♂	158	1–6	12.35–31.06	0.000192	2.485	0.98	40.60	0.22	-0.29	2.559
	♀+♂	323	1–6	12.00–31.65	0.000677	2.674	0.98	41.11	0.20	-0.54	2.528
Tuzla Stream [6]	♀	161	1–6	12.11–32.67	0.000290	2.400	0.98	54.17	0.12	-1.54	2.546
	♂	146	1–6	12.67–31.00	0.000141	2.532	0.99	46.08	0.15	-1.34	2.503
	♀+♂	307	1–6	12.42–32.34	0.000208	2.458	0.98	52.15	0.14	-1.35	2.580
Hazar Lake [7]	♀	237	1–10	14.31–44.65	0.056	2.466	0.95	49.22	0.20	-1.88	2.685
	♂	127	1–10	13.71–44.80	0.104	2.262	0.93	56.17	0.13	-1.62	2.612
	♀+♂	364	1–10	13.95–44.68	0.070	2.390	0.95	53.77	0.16	-1.84	2.665
Uzunçayır Dam Lake [8]	♀	158	1–11	15.33–43.05	0.0112	2.927	0.96	47.01	0.16	-1.58	2.550
	♂	288	1–12	13.20–42.70	0.0111	2.930	0.95	44.91	0.14	-1.82	2.450
	♀+♂	446	1–12	14.17–42.70	0.0110	2.932	0.96	46.85	0.14	-1.95	2.490
Özlüce Dam Lake [10]	♀	153	1–12	18.35–45.55	0.0066	3.092	0.95	50.59	0.14	-1.99	2.550
	♂	223	1–11	17.30–39.70	0.0072	3.064	0.89	47.12	0.12	-2.78	2.430
	♀+♂	376	1–12	17.49–45.55	0.0071	3.070	0.94	49.83	0.13	-2.13	2.510
Karasu River [11]	♀	115	0–7	–	0.0086	3.070	0.98	46.05	0.133	-1.202	2.450
	♂	117	0–9	–	0.0099	3.020	0.98	53.49	0.098	-1.670	2.447
Pülümür River [12]	♀	644	0–11	7.1–38.8	0.0096	2.973	0.97	49.25	0.128	-1.68	2.492
	♂	743	0–11	7.3–38.3	0.0103	2.954	0.98	44.42	0.155	-1.37	2.485
	♀+♂	1387	0–11	7.1–38.8	0.0100	2.963	0.98	45.29	0.146	-1.42	2.476
Munzur River (This study)	♀	444	0–11	6.8–38.5	0.0084	3.015	0.948	45.45	0.116	-2.45	2.38
	♂	339	0–11	7.9–40.2	0.0088	3.007	0.935	54.61	0.086	-2.08	2.41
	♀+♂	783	0–11	6.8–40.2	0.0085	3.013	0.943	46.15	0.139	-2.57	2.47

(n: sample size, a: intercept, b: slope, R^2: coefficient of determination, L_∞: asymptotic length, t_0: theoretical age, k: body growth coefficient, Ø: growth performance index)

Length-weight relationship of *C. umbla* were determined $W = 0.0084L^{3.015}$ (R^2=0.948, SE of *b*=0.0029 and 95 % confidence intervals of *b*=2.680–3.359) in females, $W = 0.0088L^{3.007}$ (R^2=0.935, SE of *b*=0.0033 and 95 % confidence intervals of *b*=2.625–3.236) in males and $W = 0.0085L^{3.013}$ (R^2=0.943, SE of *b*=0.0022 and 95% confidence intervals of *b*=2.652–3.359) in all individuals (FIG. 4). The growth of *C. umbla* is isometric in the Munzur River. The length-weight relationships of this species studied by different researchers are given in TABLE I. These values can different even between same species in different locations. Differences can be observed due to seasonal changes in nutrient levels and reproduction [39]. All environmental factors as well as reproductive period, sex, sampling method and time, number of samples, season and region may give different results in ‘*b*’ values [38]. Condition factor of *C. umbla* varies between 0.894±0.007 in females, 0.911±0.008 in males and 0.901±0.006 in all individuals from Munzur River.

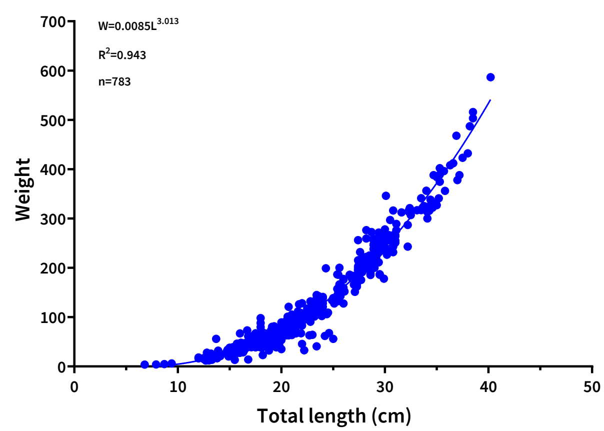

FIGURE 4. Length-weight relationship for all individuals of *Capoeta umbla* in Munzur River

The age range of *C. umbla* is 0 to 11 years, with the dominant age group being 2 years (FIG. 5). The longest specimen was an 11-years old male, that measured 40.2 cm. Age readings are reliable when the Index of Average Percentage Error (IAPE) from two independent age readers is between 5% and 15% [40]. In this study, IAPE was found 9.2% as a result of age readings of *C. umbla* in the Munzur River.

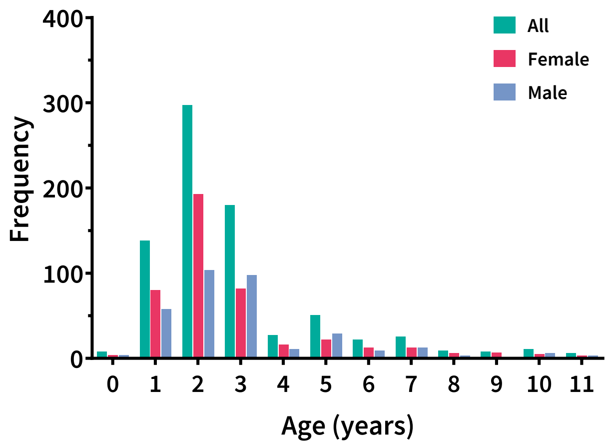

FIGURE 5. Age-frequency of *Capoeta umbla* in the Munzur River

The parameters of the von Bertalanffy growth model of *C. umbla* were: $L_t = 45.45\ [1\text{-}e^{-0.116(t+2.45)}]$; $W_t = 768.22\ [1\text{-}e^{-0.116(t+2.45)}]^{3.015}$ in females; $L_t = 54.61\ [1\text{-}e^{-0.086(t+2.08)}]$; $W_t = 941.13[1\text{-}e^{-0.086(t+2.08)}]^{3.007}$ in males; and $L_t = 46.15\ [1\text{-}e^{-0.139(t+2.57)}]$ (FIG. 6); The weight equation for all specimens was: $W_t = 856.32\ [1\text{-}e^{-0.139(t+2.57)}]^{3.013}$. The value of Φ' was 2.380, 2.409 and 2.471 for female, male and all individuals, respectively. The age and von Bertalanffy growth parameters of *C. umbla* by different researchers are shown in TABLE I. The differences between the groups may be due to the fishing environment, time, method, structure of the nets, number of fish used and the characteristics of the environment.

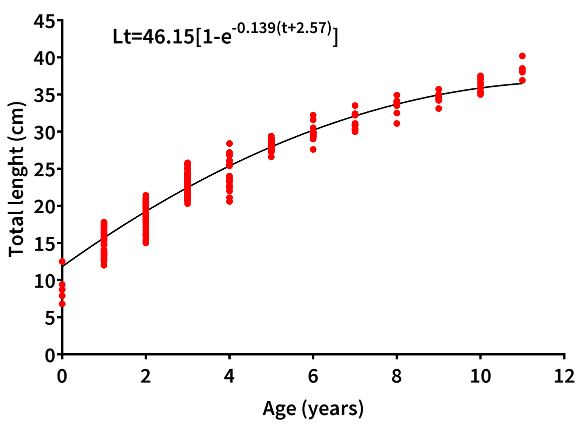

FIGURE 6. Age-length relationship for all individuals of *Capoeta umbla* in the Munzur River

The neural network training in MATLAB. Plots (performance, training state and regression) in artificial neural networks model are given FIG. 7.

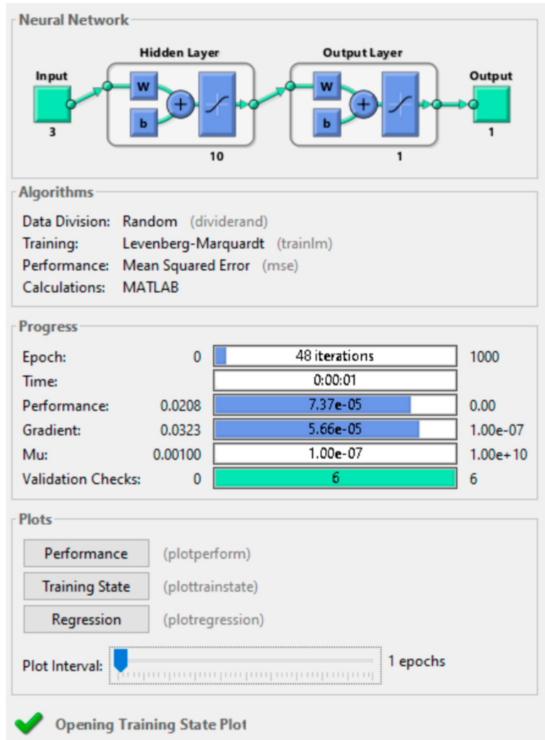

FIGURE 7. Neural Network Training in MATLAB

FIG. 8 shows change as a result of ANN training with the Matlab program. The network training reached the optimal result in 48 iterations and increasing the number of epoch does not help the program. The training stopped and the best validation performance was also fixed at 8.1473 × 10^{-5} at epoch 42 (FIG. 8). In their study for *C. umbla* from Karasu River, Ozcan and Serdar [11] reported that the network training reached the optimum in 11 epochs and the best validation performance was 0.00033534 at epoch 5. Ozcan [24] reported that the training best validation performance in epoch 4 was 0.00083535 and the validation error reached 10 epochs for *A. sellal* in Munzur River.

In FIG. 9, the validation checks of the artificial neural network model for training are given as 6, at epoch 48 and gradient=5.6566 × 10^{-5}, at epoch 48. Ozcan and Serdar [11] reported that the validation checks as 6, at epoch 11 and gradient=0.00053887, at epoch 11 for *C. umbla* from Karasu River. Ozcan [24] reported that validation controls for training neural networks as 6 in epoch 10 and gradient = 0.00010533 in epoch 10 for *A.sellal* in Munzur River.

Calculated MAPE values 0.140 and 0.578 for ANNs, 1.168 and 2.726 for LWRs, 5.721 and 4.013 for VBGF, respectively. ANNs MAPE (%) values were calculated better than the LWRs and VBGF MAPE values. MAPE criterium is widely used for acuracy evaluation of model fit. TABLE II shows actual data and ANNs, LWRs, VBGF with MAPE (%) results of *C. umbla*. The results of the network lie

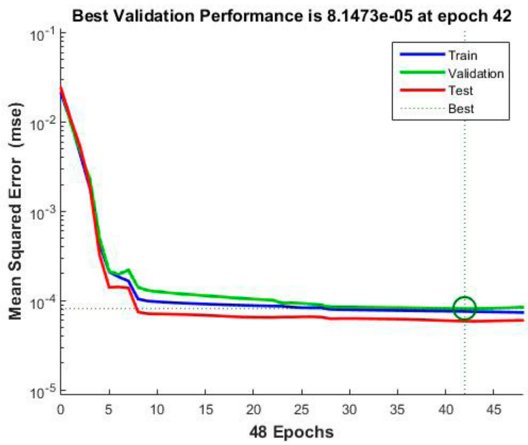

FIGURE 8. Iterative representation of the mean squared error

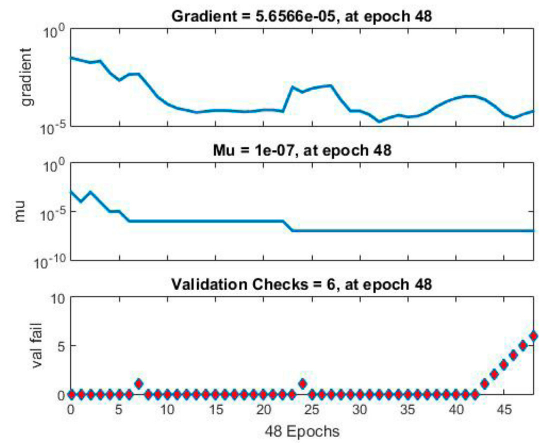

FIGURE 9. Artificial neural networks training state

TABLE II
Actual data and ANNs, LWRs, VBGF with MAPE (%) results

Sex	Age	Actual Data		ANNs (MATLAB)		ANNs MAPE (%)		LWRs CALCULATED		LWRs MAPE (%)		VBGF CALCULATED		VBGF MAPE (%)	
		L	W	L	W	L	W	L	W	L	W	L	W	L	W
♀	0	8.58	5.10	8.64	5.16	0.699	1.176	8.32	5.06	3.030	0.784	9.24	5.47	7.692	7.255
♂		9.25	7.05	9.17	6.85	0.864	2.837	8.95	6.88	3.243	2.411	8.94	6.57	3.351	6.809
♀	1	15.69	36.40	15.69	36.39	0.000	0.027	15.83	34.94	0.892	4.011	14.99	33.99	4.461	3.777
♂		15.69	37.60	15.69	37.59	0.000	0.027	15.98	34.84	1.848	7.340	14.71	36.18	6.246	2.308
♀	2	19.31	63.68	19.30	63.67	0.052	0.016	19.20	64.27	0.570	0.926	18.33	62.21	5.075	1.051
♂		19.29	64.73	19.29	64.71	0.000	0.031	19.33	64.10	0.207	0.973	17.16	64.05	11.04	2.847
♀	3	22.78	108.20	22.78	107.35	0.000	0.831	22.88	106.01	0.439	2.024	21.30	105.12	6.497	1.601
♂		22.57	104.30	22.56	103.48	0.044	0.863	22.56	103.21	0.044	1.045	21.32	102.63	5.538	1.239
♀	4	25.17	145.28	25.15	154.52	0.079	6.405	25.23	144.56	0.438	0.496	23.94	143.48	4.887	7.032
♂		24.28	137.23	24.26	135.59	0.082	1.239	24.71	129.81	1.771	5.407	22.24	127.58	8.402	4.452
♀	5	28.28	219.69	28.25	219.69	0.106	0.000	29.09	211.14	2.864	3.892	26.30	209.91	7.001	11.36
♂		28.09	213.29	28.08	213.24	0.036	0.000	28.01	197.00	0.285	7.637	24.90	189.06	11.36	2.882
♀	6	29.74	236.63	29.73	236.61	0.034	0.000	29.79	234.57	0.168	0.871	28.40	229.81	4.506	4.055
♂		29.81	237.23	29.81	237.24	0.000	0.000	29.80	235.46	0.034	0.746	27.35	227.61	8.252	4.168
♀	7	30.86	267.53	30.87	267.46	0.032	0.037	31.05	261.63	0.616	2.205	30.26	256.38	1.944	5.412
♂		31.32	285.44	31.31	285.47	0.032	0.000	31.74	274.18	1.341	3.945	29.60	269.99	5.492	3.862
♀	8	33.12	318.45	33.01	318.46	0.332	0.000	32.94	324.04	0.543	1.755	31.93	306.15	3.593	5.604
♂		34.27	318.67	34.30	318.67	0.088	0.000	32.96	308.29	3.822	3.257	31.66	300.81	7.616	2.857
♀	9	34.70	344.40	34.72	344.41	0.058	0.000	33.80	342.12	2.594	0.662	33.41	334.56	3.718	1.439
♂		33.10	316.80	33.06	316.91	0.121	0.032	32.90	322.60	0.604	1.831	33.55	312.24	1.360	3.343
♀	10	36.44	386.40	36.46	386.46	0.055	0.000	36.13	381.93	0.851	1.157	34.73	373.48	4.693	3.600
♂		35.72	387.27	35.70	387.20	0.056	0.000	35.56	406.03	0.448	4.844	35.29	401.21	1.204	4.110
♀	11	38.23	474.40	38.20	474.07	0.078	0.084	37.90	498.14	0.863	5.004	35.90	493.90	6.095	3.101
♂		38.53	523.43	38.35	521.90	0.507	0.287	38.33	511.86	0.519	2.210	36.88	512.20	4.282	2.145
		Average MAPE (%)				0.140	0.578			1.168	2.726			5.721	4.013

on a 45° line, indicating that the distribution of the data is good and close to the target [41]. Since MAPE shows the forecast errors as a percentage, it has more meaning than other statistical methods [42]. Ozcan and Serdar [11] found that MAPE values 0.979 and 1.593 for ANNs, 1.637 and 3.567 for LWRs, 3.904 and 4.912 for VBGF of *C. umbla* from Karasu River. Ozcan [24] found that MAPE values 0.349 and 1.655 for ANNs, 1.267 and 3.342 for LWRs, 4.000 and 4.122 for VBGF of *A. sellal* in Munzur River. Models with a MAPE of less than 10% are classed as “very good”, between 10% and 20% as “good”, between 20% and 50% as “acceptable” and more than 50% as “imprecise and incorrect” [43, 44].

The regression plots in FIG. 10 show the outputs of the network; the training-validation-test groups are evaluated separately according to their target values. If it is desired to increase the performance of the network, the network can be retrained. The best fit between targets and outputs is shown by the linear regression line. ANNs were randomized as follows: 548 in training (70%), 117.5 in testing (15%) and 117.5 in validation (15%) for *C. umbla*. The targeted output R value was 0.98584 (training), 0.98969 (validation), 0.98757 (testing) and 0.9868 (all). As can be seen from here, the learning process has been carried out with great success. Ozcan and Serdar [11] found that the targeted output R value was 0.99629 for training, 0.99765 for validation, 0.98934 for testing and 0.99399 for all of *C. umbla* from Karasu River. Ozcan [24] found that the targeted output R value was 0.87275 for training, 0.96297 for validation, 0.94942 for testing and 0.90697 for all of *A. sellal* in Munzur River. When the R value is between 0.95 an 1, further education is more successful [45]. The calculated SSE values for length and weight was calculated as 0.0128 and 30.864 for ANNs. The SSE value was found 1.3985 and 350.786 for length and weight for LWRs. MAPE and SSE were used for comparison of ANNs and traditional methods of fit and have been found to give better results. It is estimated that a comparison of MAPE and SSE values can give sound results [17, 46].

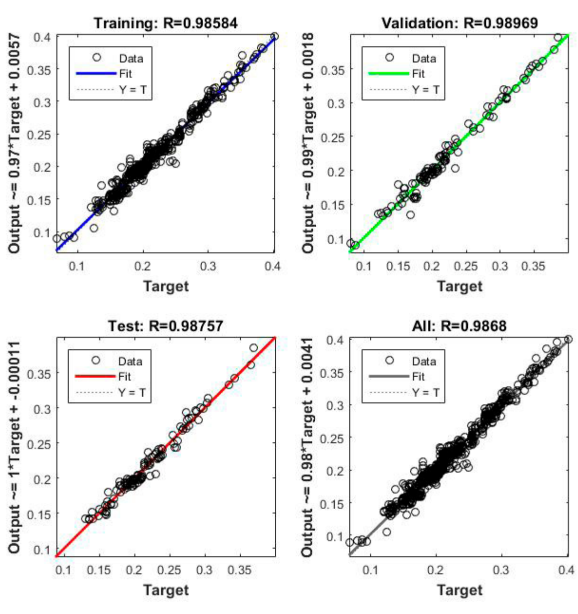

FIGURE 10. Artificial neural network training, validation, testing and all data results

CONCLUSION

This study determined that artificial neural networks are a reliable alternative method for making accurate predictions and evaluating fish growth characteristics in fisheries management. The measured and predicted data were very similar to the results obtained by the Artificial Neural Network (ANN) in this study. When all theobtained results were evaluated together with the Mean Absolute Percentage Error (MAPE) and the Sum Squared Error (SSE), the ANN gave better results than other traditional methods. For this reason, in this study it can be concludedthat the use of ANN models is more effective and reliable than the Length-Weight Ratio (LWR) and the von Bertalanffy Growth Function (VBGF).

Conflict of Interests

The authors declare that there is no conflict of interest.

Author Contributions

E.I.O. wrote the main manuscript, performed ANNs analysis; contributed data and analysis, validation, review and edited the manuscript; O.S. for fishing and providing the sample, review and edited the manuscript. All authors reviewed the manuscript.

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