Athens Journal of Sciences- Volume 11, Issue 2, June 2024 – Pages 75-88

The Growth of Crayfish, which Serves as an Indicator of Clean and Healthy Water Ecosystems in the Mediterranean Region

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The narrow-fingered freshwater crayfish, also known as Pontastacus leptodactylus in scientific terms and referred to as such in Turkish, is a prevalent species in the inland waters of the Mediterranean region. This crayfish serves as an indicator of clean and healthy water ecosystems due to its high sensitivity to pollution and environmental changes. Its presence signals the maintenance of water quality and a balanced ecosystem. In a study on 283 freshwater crayfish in Hirfanlı Dam Lake during July and August 2023, it was observed that 53.36% were male and 46.64% were female. Length ranged from 80.44 mm to 121.11 mm, and weight varied between 11.61 g and 43.93 g. Average length and weight for males were 95.9874 ± 6.4603 mm and 24.1861 ± 5.3696 g, for females were 95.0981 ± 5.5519 mm and 21.5193 ± 3.4488 g, and for combined sexes were 95.5724 ± 6.0594 mm and 22.9422 ± 4.7579 g. The length-weight relationship (LWR) was established for females ($W=0.00166359 \times TL^{2.0767}$), males ($W=0.00019587 \times TL^{2.5651}$), and all individuals ($W=0.00037111 \times TL^{2.4162}$). Exponential values "b" for LWR were 2.0767 ($r^2=0.993$), 2.5651 ($r^2=0.986$), and 2.4162 ($r^2=0.987$), respectively. The study compared traditional LWR approaches with artificial intelligence methods for growth analysis, suggesting the latter as a viable alternative in assessing freshwater crayfish growth in aquatic systems.

Keywords: *length-weight relationships, crayfish, Mediterranean region, inland water, artificial intelligent*

Introduction

Freshwater crayfish, commonly known as crayfish (*Astacus leptodactylus* Eschscholtz, 1823), stands out as a species of considerable ecological and economic significance on a global scale. Within our nation (Turkey), it represents a species sourced from inland waters, featured among export commodities (Kozák et al. 2015, Yazıcıoğlu et al. 2018). Crayfish are invertebrates distributed worldwide, excluding Antarctica and the African continent, with nearly 540 species (Madrigal-Bujaidar et al. 2017). Particularly known for their potential in food consumption, the narrow-clawed crayfish (*Astacus leptodactylus* Eschscholtz 1823), is one of the well-recognized and valuable European freshwater species, residing in a wide range of freshwater habitats and estuaries (Köksal 1988).

The freshwater crayfish are acknowledged as effective bioindicators for assessing the health of aquatic ecosystems. These organisms play a significant role

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https://doi.org/10.30958/ajs.11-2-1 doi=10.30958/ajs.11-2-1

in aquatic food webs, attaining substantial biomass as macroinvertebrates. Moreover, they prove to be valuable bioindicators in determining water quality and responding to physiological and contaminant stressors (Garabaghi et al. 2022).

Koutrakis et al. (2007) state, based on genetic and morphological data of crayfish species such as *Austropotamobius torrentium*, *Astacus astacus*, and *Astacus leptodactylus*, that the region is rich in biodiversity and provides a suitable habitat for these species in Greece. *Astacus leptodactylus* is the only significant freshwater crayfish species in Turkey, and it is naturally and widely observed in lakes, ponds, and streams throughout the country (Gören and Karayücel 2022). In their study presenting the global systematic list of freshwater crayfish, Crandall and De Grave (2017) specified *Pontastacus leptodactylus* Eschscholtz, 1823, as a synonym of *Astacus leptodactylus* Esch., 1823.

Fisheries research and management frequently employ biometric relationships as a method to convert field-collected data into appropriate indices (Anderson and Gutreuter 1983, Roul et al. 2020). However, when it comes to analyzing fisheries data, the most widely utilized tool is the length-weight relationships (LWRs) (Türker et al. 2018). LWRs are instrumental in calculating body condition indices and predicting weight based on a known length (Froese et al. 2011, Dash et al. 2023).

Studies encompassing morphometric analyses and evaluations on *Astacus leptodactylus/Pontastacus leptodactylus* have been identified as (Benzer and Benzer 2018, Berber et al. 2020, Gören and Karayücel 2022, Garabaghi et al. 2022, Benzer and Benzer 2022, Gültepe et al. 2023, Boyalık et al. 2023, Dartay 2023, Alvanou et al. 2024, Roljić et al. 2024).

The key variables in modeling the growth of an aquatic organism are typically the length and weight. Fundamentally, a length-weight relationship model is derived through linear regression, which is employed to calculate the correlation between the growth in length and the growth in weight (Munro and Pauly 1983). These models play a crucial role in understanding the organism's development and assessing populations in aquatic ecosystems. During underwater visual censuses, transforming length data into weight data is common, allowing for biomass estimation and monitoring organism populations in ecosystems (Samoilys 1997). However, the relationship between length and weight is often non-linear (Froese 2006), and transformations using linear regression methods may lead to low predictive values. In such cases, traditional statistical analysis methods, especially single or multiple linear regression models, may be limited in terms of quantification and prediction (Suryanarayana et al. 2008, Türeli Bilen et al. 2011, Benzer et al. 2017, Benzer and Benzer 2019, Benzer and Benzer 2022).

Currently, the application of Artificial Neural Networks (ANNs) in predictive modeling presents a promising alternative to traditional statistical approaches, particularly in cases where non-linear patterns exist. Artificial neural networks are computer algorithms that simulate the activity of neurons and information processing in the human brain (Zou et al. 2009). Unlike more commonly used regression models, neural networks do not require a specific functional relationship or distribution assumptions about the data, eliminating the need for data transformation. This characteristic makes neural network modeling a powerful tool for exploring complex, non-linear biological problems, such as those encountered in fisheries research (Suryanarayana et al. 2008).

Artificial neural networks bring flexibility and a comprehensive approach, enabling more effective resolution of non-linear relationships and complexities than conventional statistical models (Ezziane 2006, Benzer and Benzer 2023a). Consequently, artificial neural networks provide an efficient means of understanding and predicting intricate biological processes, such as the growth and development of organisms in aquatic ecosystems. Therefore, artificial neural networks emerge as a more reliable and effective tool in situations where non-linear patterns prevail than traditional methods.

There have been numerous studies on predictive modeling using neural networks for the growth of aquatic organisms, specifically focusing on fish (Benzer and Benzer 2016, Benzer and Benzer 2017, Özcan and Serdar 2018, Özcan and Serdar 2019, Özcan 2019, Benzer and Benzer 2020, Benzer and Benzer 2023b, Akkan et al. 2024) and crayfish (Türeli Bilen et al. 2011, Benzer et al. 2015, Benzer and Benzer 2018, Benzer and Benzer 2022).

The main purpose of this study is to assess the length-weight measurements of crayfish supplied from the ecosystem using both traditional methods and the Artificial Neural Networks approach, a sub-branch of artificial intelligence.

Methodology

As part of a project conducted by Gazi University, a classification study will be carried out to determine the genders of crayfish in different regions. However, the focal point of this study is the traditional and artificial intelligence-assisted assessment of size and weight, specifically on crayfish samples collected from Hirfanlı Dam Lake. Hirfanlı Dam, located between Şereflikoçhisar in Kırşehir province, was constructed between 1953 and 1959 for the purposes of energy production and flood control. Additionally, the villages surrounding Hirfanlı Reservoir within the borders of Ankara, Kırşehir, and Aksaray provinces cover an area of 26,300 hectares, making fishing a significant source of income (DSI 1968).

Local fishermen engaged in commercial fishing with fyke nets captured crayfish during the 2023 fishing seasons. A total of 283 crayfish, consisting of 132 females and 151 males, were scrutinized in the study. The captured crayfish were identified, transported to the laboratory, and subjected to the necessary metric measurements to determine their gender. Measurements, including carapace length (CL), abdomen width (Aw), abdomen length (AL), carapace width (Cw), chela length (ChL), chela width (Chw), total length (TL), and total weight (TW), were taken using a caliper with a sensitivity of 0.5 mm, and their weight was measured with a scale having a sensitivity of 0.01 g.

For most crayfish species, the connection between length (L) and weight (W) can be effectively captured by the "length-weight relationship" equation (Ricker, 1973):

$$W = a\,L^{b}$$

In this equation, W represents the weight of the crayfish in grams, L signifies the length in centimeters, and the variables '*a*' and '*b*' denote constants that define the relationship between length and weight.

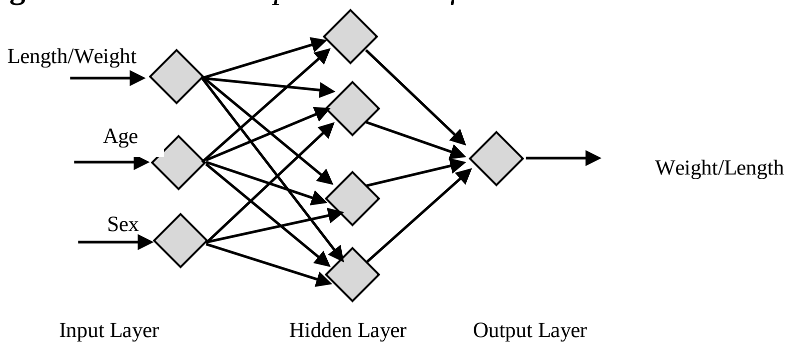
Taking cues from the complex data analysis and learning abilities exhibited by the human brain, ANNs have been proposed to streamline the intricate process of analyzing complex data and, in the end, arriving at well-informed decisions by simulating the neural system found in the human brain. In this study, the Back-Propagation Networks, a supervised learning method with a specific network structure, will address problem-solving, and the data evaluation will be conducted using the WEKA application.

Generally, ANNs consist of three primary layers, commencing with the input layer and concluding with the output layer, which is intricately linked to one or more hidden layers where data undergoes intricate processing. The activation function or transfer function in ANNs commonly takes the form of a sigmoid, although there is room for variation (Hopfield 1988). For this study, a well-regarded ANNs model known as the multilayer perceptron has been devised, featuring a hidden layer with five nodes and operating with a learning rate of 0.03 and momentum of 0.2 (Figure 1).

Metrics play a pivotal role in monitoring and measuring the model's performance during both training and testing phases. The Mean Absolute Percentage Error (MAPE) serves as an error measure, with a lower result indicative of higher performance, inversely proportional to performance (Wang and Xu 2004). Mathematically, the performance metric within ANNs can be expressed as:

$$MAPE = \frac{100}{n}\sum_{j}\frac{|e_j|}{|A_j|}$$

Figure 1. *Schematic Representation of the ANNs*



Results and Discussion

The investigation identified that out of the total 283 crayfish captured, 132 individuals (46.64%) were identified as females, while 151 (53.36%) were males, resulting in a female-to-male ratio of 0.87/1.00. The metric lengths of crayfish, including TL, CL, AL, Aw, ChL, Chw, and Cw, displayed variations spanning from 80.44 to 121.11, 38.14 - 62.26, 40.22 - 65.09, 16.57 – 39.49, 45.63 – 99.91, 6.88 - 19.89, 18.08 - 75.50 mm, respectively. Additionally, crayfish's weight fluctuated between 11.61 and 43.93 g, with an average weight of 22.92 g (Table 1).

Table 1. *Metric Parameters for Crayfish*

Parameter	Sex	Average ± S_x	Min-Max	t test
TL	♀ ♂ ♀♂	95.098 ± 0.483 94.540 ± 0.525 95.570 ± 0.360	80.44 – 112.38 82.00 – 121.11 80.44 – 121.11	p<0.05
TW	♀ ♂ ♀♂	21.466 ± 0.293 22.780 ± 0.436 22.910 ± 0.281	14.92 - 32.94 11.61 - 43.93 11.61 - 43.93	p<0.05
CL	♀ ♂ ♀♂	46.139 ± 0.273 47.600 ± 0.289 47.260 ± 0.209	38.14 - 57.17 40.74 - 62.26 38.14 - 62.26	p<0.05
AL	♀ ♂ ♀♂	48.958 ± 0.269 46.850 ± 0.307 48.300 ± 0.209	40.22 – 59.27 41.26 – 65.09 40.22 – 65.09	p<0.05
Aw	♀ ♂ ♀♂	21.283 ± 0.156 19.840 ± 0.208 20.750 ± 0.136	17.30 - 27.27 16.57 - 39.49 16.57 - 39.49	p<0.05
ChL	♀ ♂ ♀♂	56.544 ± 0.429 65.910 ± 0.721 63.230 ± 0.575	45.63 – 69.21 49.17 – 99.91 45.63 - 99,91	p<0.05
Chw	♀ ♂ ♀♂	10.612 ± 0,140 11.540 ± 0,200 11.410 ± 0,135	6.88 - 15.68 7.50 - 19.89 6.88 - 19.89	p<0.05
Cw	♀ ♂ ♀♂	24.653 ± 0.401 24.760 ± 0.518 25.160 ± 0,334	20.20 - 71.96 18.08 - 75.50 18.08 - 75.50	p<0.05

S_x = Standard error

The TL, AL, and Aw measurements were higher in females than males, whereas TW, CL, ChL, Chw, and Cw were lower in females than males (Table 1). However, the differences between females and males in TL, TW, CL, AL, Aw, ChL, Chw, and Cw were statistically insignificant ($p < 0.05$).

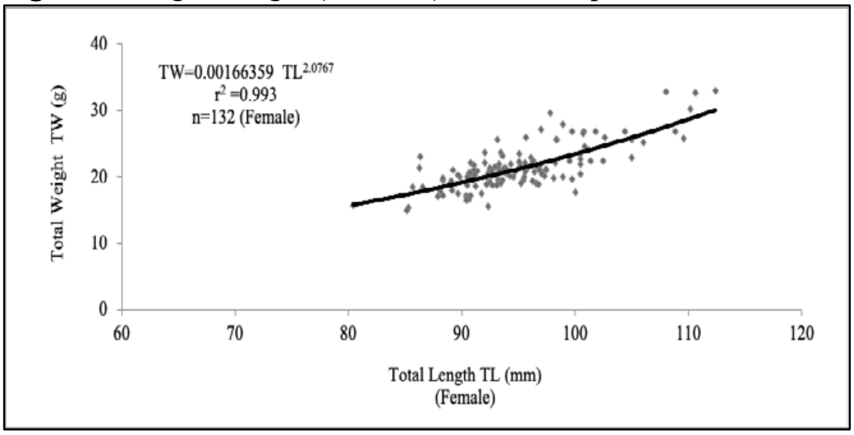
Table 2. *LWR Parameters, Equations and Correlation Coefficients*

Species	Sex	Relationship	R^2
TL – TW	♀ ♂ ♀♂	$TW = 0.00166359 \times TL^{2.0767}$ $TW = 0.00019587 \times TL^{2.5651}$ $TW = 0.00037111 \times TL^{2.4162}$	0.993 0.986 0.987

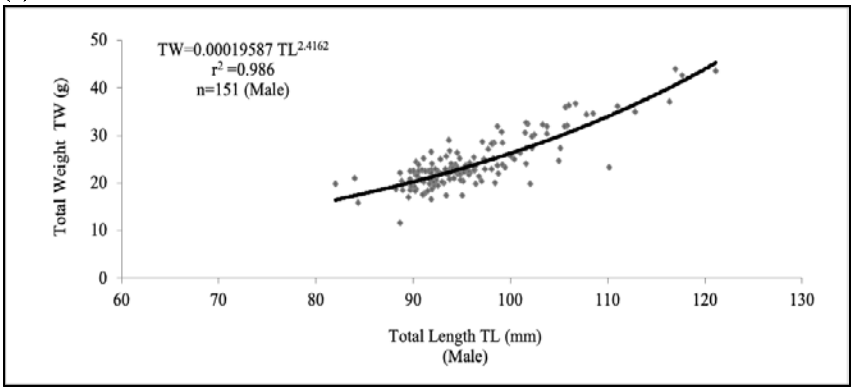
The analysis of the crayfish revealed distinct TL – TW relationships across genders: for females (Figure 2a), $TW = 0.00166359 \times TL^{2.0767}$ ($R^2 = 0.993$), for males (Figure 2b), $TW = 0.00019587 \times TL^{2.5651}$ ($R^2 = 0.986$), and for all genders (Figure 2c), $TW = 0.00037111 \times TL^{2.4162}$ ($R^2 = 0.987$). Figure 2 provides separate graphical representations of these relationships for female, male, and all individuals, while the distribution of male, female, and all individuals can be observed in a single figure (Figure 2d). Additionally, the TL-TW data underwent artificial neural network evaluation using MATLAB, and are depicted in Figure 3.

In this investigation involving crayfish specimens, TL-TW values were analyzed across three distinct categories: Crayfish data, regression data, and ANNs data. The resultant mean absolute percentage errors (MAPE) are detailed in Table 3. Furthermore, it's noteworthy that mean absolute error serves as a prominent loss function, particularly in trend estimation within statistical analyses, representing a crucial metric for assessing the prediction accuracy of an estimation method.

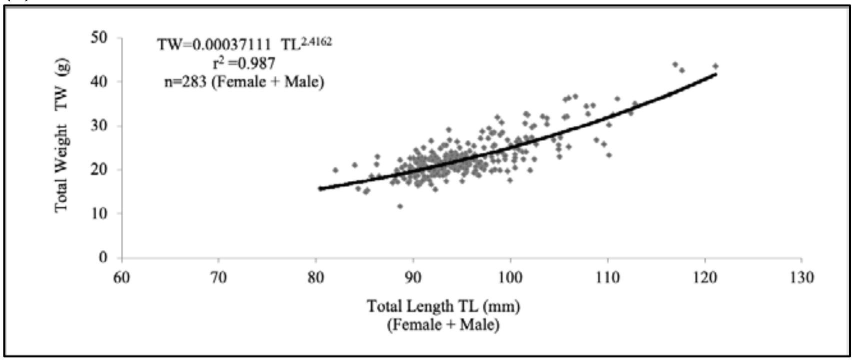
Figure 2. *Length-Weight (TL – TW) Relationships*



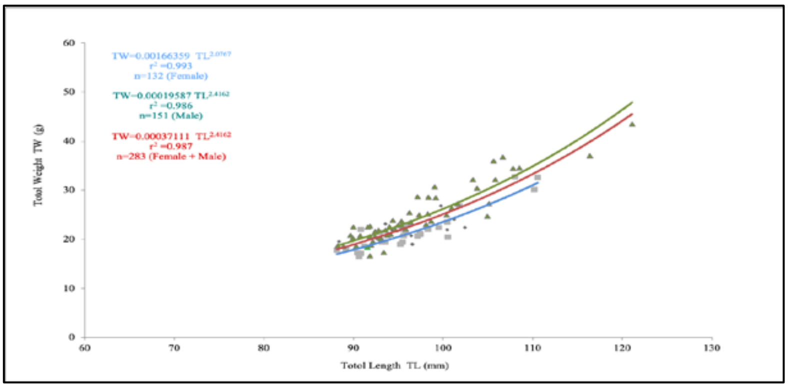
(a)



(b)



(c)



(d)

Figure 3. *Length-Weight (TL – TW) Relationships (ANNs)*

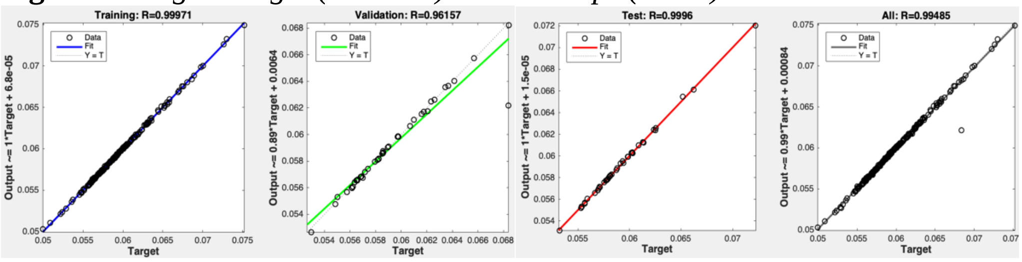


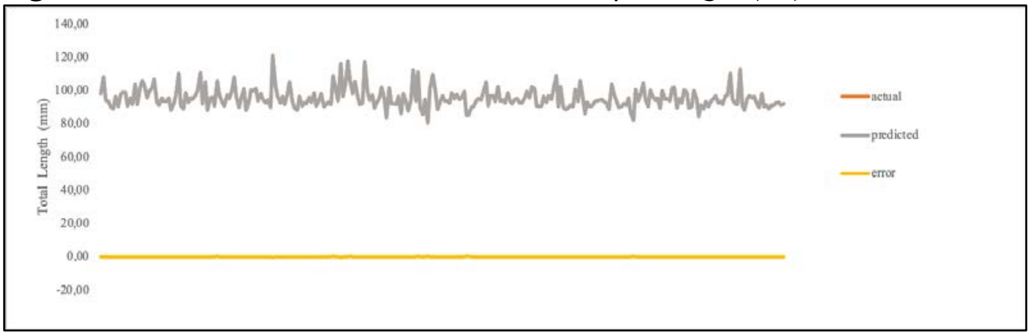
Table 3. *ANNs and LWR Values with MAPE*

	LWRs				ANNs			
	LWRs		MAPE		ANNs		MAPE	
	L	W	L	W	L	W	L	W
♀	21.3331	95.4969	0.62	0.42	20.82	95.10	3.09	0.004
♂	23.7932	96.6017	1.65	0.64	21.66	95.99	11.68	0.003
♀♂	22.6152	96.1423	1.34	0.59	21.27	95.58	7.76	0.003

When considering the ANNs' MAPE values across females, males, and all individuals compared to the LWRs' MAPE values, it is evident that the former are lower, indicating the accuracy and effectiveness of the ANNs' predictions. This suggests that the artificial neural networks perform quite well in estimating the length-weight relationships. However, while not as pronounced as in length predictions, the performance in weight predictions is also notably good (Table 3).

Several factors may contribute to these outcomes. Firstly, the ANN model's complexity and the training data's quality may enhance accuracy. Additionally, a balanced dataset and appropriate model tuning play significant roles. Lastly, the comparison between LWRs' and ANNs' predictions reveals the superior precision and accuracy of the ANNs' model. This underscores the superiority of artificial neural networks over traditional methods in LWRs predictions. These findings emphasize the importance of utilizing and refining artificial neural networks in future research, highlighting their potential to provide a broader accuracy range in LWRs predictions.

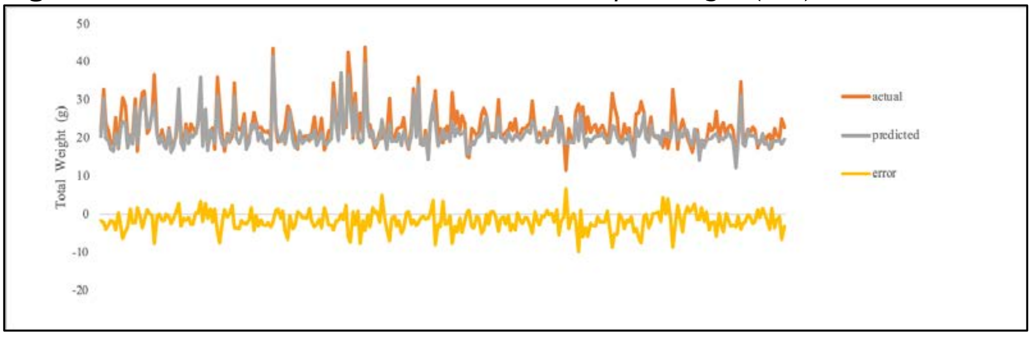
Figure 4. *Actual and Predicted Data with Errors for Length (TL)*



When we examine the comparison between actual and predicted values based on gender, it's evident that prediction errors vary. For instance, in the female group, errors range from -0.12 to 0.287, while in the male group, errors range from -0.638 to 0.272. This indicates variability in the accuracy of predictions across different samples (Figure 4).

Furthermore, while some predictions show small errors, others exhibit larger deviations. Overall, it's observed that errors are balanced between positive and negative values, indicating that predictions both overestimate and underestimate the true values. Further analysis could be conducted to explore the factors contributing to these differences, including the features used in prediction models, the complexity of algorithms, and the quality of training data. Adjustments in these aspects could improve the accuracy of future predictions.

Figure 5. *Actual and Predicted Data with Errors for Weight (TW)*



When examining the weight prediction data, it can be observed that the predicted weights differ from the actual values. In some cases, the predictions are either significantly higher or lower than the actual weights, while in other cases, they are closer. For instance, some predictions exhibit large discrepancies ranging from -7.722 to 5, while others show smaller variances between -0.10 and 4.447.

Further analysis of this data could help understand why some predictions are more accurate than others and identify factors influencing prediction accuracy. This deeper analysis could lead to the development of strategies to improve predictions.

Table 4. *ANNs Crayfish Results in Literature*

Location	Gender	MAPE (%) ANNs		MAPE (%) LWR		Reference
		L	W	L	W	
Mogan Lake (Ankara, Turkey)	♀	1.234	11.552	0.482	0.866	Benzer et al. 2015
	♂	9.763	7.114	1.237	1.713	
	♀♂	0.108	1.703	1.750	1.727	
Hirfanlı Dam Lake (Kırşehir, Turkey)	♀	12.36	4.97	1.53	4.29	Benzer et al. 2017
	♂	5.85	1.85	2.13	5.82	
	♀♂	8.39	7.41	2.33	6.63	
Eğirdir Lake (Isparta, Turkey)	♀	1.277	3.909	0.771	2.074	Benzer et al. 2017
	♂	0.140	1.206	1.365	3.725	
	♀♂	0.436	2.409	1.435	4.087	
Uluabat Lake (Bursa, Turkey)	♀	2.18	5.28	1.94	5.20	Benzer and Benzer 2018
	♂	2.21	5.75	2.22	6.28	
	♀♂	2.65	0.64	3.01	5.89	
Yeniçağa Lake (Bolu, Turkey)	♀	1.491	3.685	1.695	3.828	Benzer and Benzer 2020
	♂	1.768	4.710	2.391	5.098	
	♀♂	0.064	1.153	2.069	4.603	
İznik Lake (Bursa, Turkey)	♀	0.44	3.64	2.63	6.44	Benzer and Benzer 2022
	♂	0.26	2.79	3.75	9.22	
	♀♂	0.09	4.35	3.63	8.96	
Hirfanlı Dam Lake (Kırşehir, Turkey)	♀	3.09	0.004	0.62	0.42	This study
	♂	11.68	0.003	1.65	0.64	
	♀♂	7.76	0.003	1.34	0.59	

When the results of this study are compared with the literature (Table 4), it is observed that the performance of ANNs in predicting freshwater crayfish populations is influenced by the differences in MAPE values reported in various studies conducted in different lakes and ponds in Turkey. There are notable differences in MAPE values among female (♀), male (♂), and combined (♀♂) crayfish populations. The MAPE values reported in this study are lower than those reported in the literature for the same locations and genders. This indicates that the ANNs used in this study may be more effective in predicting freshwater crayfish populations with lower error rates than previous approaches. Consistently, the ANNs in this study exhibit relatively low MAPE values compared to the literature across different locations and genders. This suggests a degree of reliability in the prediction capabilities of ANNs despite variations in environmental factors or crayfish populations. While the ANNs in this study generally perform well compared to previous approaches, there are still instances where MAPE values are relatively high, indicating potential for improvement. Future research could focus on further enhancing ANNs models or incorporating additional features to increase prediction accuracy.

Conclusions

In conclusion, this study suggests that ANNs can be considered as a significant alternative for predicting freshwater crayfish populations. The findings indicate that ANNs are effective in predicting freshwater crayfish populations, influenced by variations in MAPE values reported in various studies conducted in different lakes and ponds. This study emphasizes that ANNs emerge as a potential strong alternative for predicting freshwater crayfish populations with lower error rates than previous methods.

Overall, the ability of ANNs to predict freshwater crayfish populations could serve as a valuable tool in managing and conserving such ecosystems. The findings of this study encourage further research to enhance ANN models or improve prediction accuracy in future studies. These improvements could contribute significantly to monitoring and managing freshwater crayfish populations more effectively.

Additionally, in the future, a classification study will be conducted regarding freshwater crayfish, aiming to determine the genders of these particular freshwater crayfish using artificial intelligence algorithms. This study aims to contribute to our understanding of the ecological dynamics of these species and to develop comprehensive management strategies for freshwater ecosystems.

Acknowledgments

This study was financially supported by the Gazi University Project Resources Center Fund (BAP Project Number: SPD/2023-8461).

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