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Forecasting of Water Levels by Artificial Neural Networks Technique in Lake Michigan-Huron

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Abstract

Water is an indispensable resource for all living things on Earth. Therefore, it is important to pay attention to current water consumption and to comply with safety precautions. Many water sources in the world experience ups and downs in the water level. Lake Michigan-Huron is an 8 km long body of water formed by the merging of Lake Michigan and Huron. The Huron and Michigan hydrological description is a single lake because the water from the Strait of Mackinac, which connects these lakes, balances what it expects. The flow is generally eastward, but the water moves in both directions depending on the local structure. Lake Michigan-Huron combined is the largest freshwater lake in the world. The aim of this study is to estimate the changes in water levels of Lake Michigan-Huron in the USA. In this study, the estimation of water levels on a monthly basis was investigated by using three different artificial neural network (ANN) models in order to predict the Michigan-Huron Lake water levels one month in advance. The ANN models used are Multilayer ANN (MANN), Radial Based ANN (RBANN) and Generalized Regression ANN (GRANN). The data sample consists of a 104-year (1918-2021) record of mean lake water level. 75% of all data were used for the training phase and 25% for the testing phase. Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and coefficient of determination (R^2) were used as evaluation criteria. When the results are examined, all models give very good predictions during the training and testing phases. However, according to the test results, the model algorithms that give the most successful results are RBANN, MANN and GRANN, respectively.

1. Introduction

Humans have been interested in water since its inception, trying to study water movements, recognize features, identify detection hazards, and make the most of the water outside. The branch of science that manages the distribution and properties of water on Earth is called hydrology. The science of hydrology, which provides its relationship with the internal environment and efforts to control its environment, began to gain more importance. As a result of the hydrological operation, the basic structures that maintain their water consumption and attitudes can be identified (Koca, 2014).

Due to the changes in water bodies, long research has been started. Water is an indispensable resource for human life. Therefore, research on the quality and quantity of existing water resources has intensified, and the storage facility of closed water basins such as lakes has gained importance (Teltik et al., 2008).

The water level of many lakes in the world is observed to rise and fall due to various reasons. In the studies, it is thought that the reasons for the change in the lake level are meteorological and hydrological features (evaporation, precipitation, flow, etc.), tectonic movements, changes in the ozone layer and climate change (Teltik et al. 2008). In addition, the use of water resources to provide more water than normal in order to meet the water needs of agricultural activities and cities also causes the capacity of water reserves such as lakes to decrease (Albek et al., 2017). Some studies on the use of ANN in the literature, In the study of Desmukh and Tanty (2015), a comprehensive review was made on the artificial neural network (ANN) used in the field of hydrology-related problems. They stated that it can be

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well exemplified by artificial intelligence with precipitation-flow modeling, stream flow modeling, water quality modeling and its applications in groundwater (Desmukh and Tanty 2015). In 2018, Arslan et al., A study was carried out to examine the seasonal variation of Adana Seyhan Dam Lake area. In their study, they achieved highly accurate results in the classification of water structures with the artificial neural network method (Arslan et al. 2018). A study was conducted by Aksoy et al. in 2020 on the estimation of the water level in Yalova Gökçe Dam using ANN. According to the data they obtained as a result of the analyzes, the dam water level for 2019 was 73.77, while the actual water level of the dam was measured as 72.13 meters. As a result, it is thought that the use of ANN algorithms will be beneficial in estimating the water level of Gökçe Dam (Aksoy et al. 2020). In 2012, Okkan and Dalkılıç conducted a study on the modeling of monthly flows of the Kemer Dam using radial-based neural networks. When they evaluated the results of their study in terms of minimum and maximum currents, the results of the RBANN model were successful for most months. In addition, it is thought that the problems encountered in other artificial neural network models can be overcome with RBANN (Okkan and Dalkılıç, 2012).

The purpose of this study was to analyze the water level of Lake Michigan-Huron in the United States and to determine changes in the lake's water level. For this purpose, monthly lake water levels in Lake Michigan-Huron between 1918-2021 were estimated with radial-based artificial neural networks and the predictions in various data sets (the training set is 3 parts, and the test set is 1 part, and the test set is constantly changing.) were compared with the observed data.

2. Material And Method

2.1. Material

In the study, monthly water levels year from January 1918 to December 2021 were used. Data obtained from "https://www.lre.usace.army.mil/Missions/Great-Lakes-Information/Great-Lakes-Information.aspx#ICG_ETH_22302". Statistical information of the data used is given in Table 1.

The data are monitored as monthly average (m) and there are no discontinuities in the data. In addition, station information in Excel format is available for all researchers free of charge.

Table 1. Statistical information for water levels (m)

Michigan-Huron	
Average	176.44
Standard error	0.0116
Median	176.45
Standard Deviation	0.410
Sample Variance	0.168
Kurtosis	-0.787
Skewness	0.101
Smallest	175.57
Largest	177.5
Number of Data	1248

75% of all data were used in the training phase and 25% in the testing phase. At this stage, four different combinations of training (75%) and testing (25%) were tried (Figure 1).

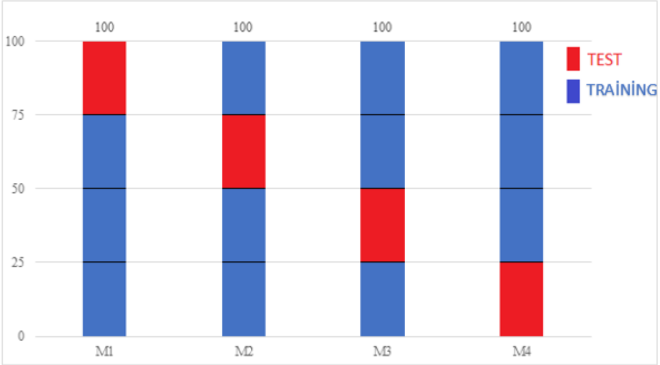

Figure 1. Percentage of training and testing data

Correlation analysis was performed using the MATLAB program to better understand the input combinations in the models and is visualized in Figure 2.

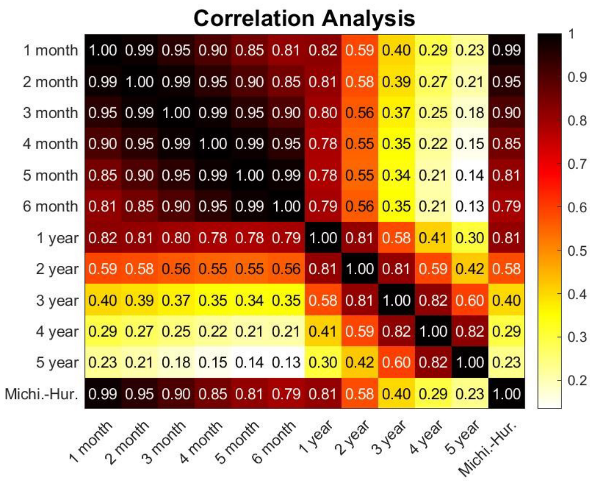

Figure 2. Correlation matrix

Figure 2 shows the correlation values of the input data. Looking at the table, it is seen that the correlation coefficient decreased and the relationship between the variables decreased after the 2nd year.

2.2. Study Area

Lake Michigan is the third largest of the five great lakes in the northern United States and is connected to Lake Huron by the Strait of Mackinac (Demir, 2022). It is located 176 meters above sea level and its deepest point is 281 meters. Lake Huron is also located in North America and is the 4th largest lake in the world.

Lake Huron is connected to Lake Michigan by the Straits of Mackinac and to Lake Superior by a series of straits. Huron and Michigan are hydrologically a single lake because the flow of water through the straits keeps water levels in overall balance. Although the flow is generally eastward, water moves in both directions depending on local conditions. Combined, Lake Michigan-Huron is the world's largest freshwater lake by area (Michigan-Huron, 2023). The study area is given in Figure 3.

Figure 3. Lake Michigan-Huron (Demir and Yaseen, 2022)

The most important factor in choosing this study area is that when Michigan-Huron Lake is considered as a whole, it is the largest freshwater lake in the world in terms of surface area and the data are continuous.

2.3. Method

ANN are a method based on the biological nervous system in humans. ANN consist of elements called neurons, which are connected in parallel and have a non-linear structure. It is used in object recognition, system modeling, signal processing and solving complex engineering problems. Artificial neural networks realize the learning process with examples. In other words, it can be defined as the machine-transferred version of the human learning mechanism (D'Addona, 2014).

In this study, 3 different ANN models were used, namely Radial Based Artificial Neural Networks, Generalized Regression Artificial Neural Networks and Multilayer Artificial Neural Networks.

2.4. Radial Based Neural Network

RBANN model can be considered as a combination of a data modeling technique for a high-dimensional space and a schema such as an ANN network. In the RBANN model, three layers are defined as input layer, hidden layer and output layer, but unlike the classical ANN structure, a nonlinear clustering analysis and radial based activation functions are used in the transition from the input layer to the hidden layer in the radial-based neural network model
(Okkan and Dalkılıç, 2012).

The mathematical representation of radial basis neural networks is as follows.

$$\emptyset_j = exp\lfloor -\|x - c_j\| / \sigma_j^2 \rfloor \qquad (1)$$

Here is x the input vector, c_j j. It is the center of the Gaussian function and σ_j is the standard deviation. Equation $\|x - c_j\|$ indicates the Euclidean distance between vectors x and c_j. j. the activation level of the intermediate node is equal to $\emptyset_j$ .Interlayer outputs;

$$y_{ki} = \pi\emptyset_i(x, c, \sigma) \qquad (2)$$

k. the output of the node is given by Equation 2.

$$o_k = \sum_{j=1}^{J} w_{kj} y_{kj} \qquad (3)$$

Here w_{kj} k. With the exit node j. is the weight between the middleware node (Kılıç et al., 2012). The basic structure of RBANN is given in Figure 4.

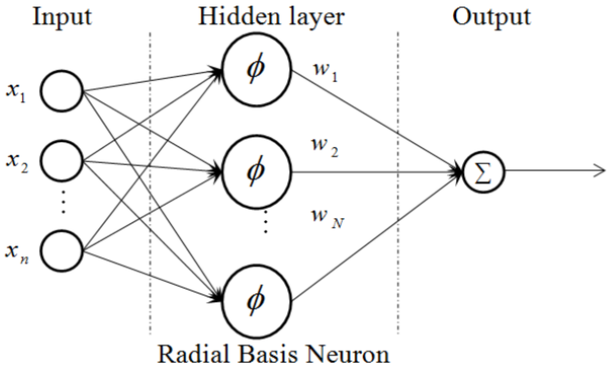

Figure 4. Radial-based neural network structure (Chen et al. 2019)

In Figure 4, the RBANN structure basically consists of three parts and the output data is obtained by multiplying the input data with the weights after reaching the hidden layer.

2.5. Generalized Regression Artificial Neural Network

GRANN does not require an iterative training procedure like the back propagation method. In this model, an approximate estimation function is generated directly from the training data. In addition, in the GRANN model, when the size of the training data is large, the estimated error approaches zero with a slight restriction in the function. By definition, regression predicts the most likely value of a dependent variable "y" based on the independent variable "x" given "x" and the training set. GRANN is a method that estimates the joint Probability Density Function of "x" and "y" given a training set. Since the probability density function is obtained from the data without pre-acceptance, the system is generally ideal. The basic structure of GRANN is given in Figure 5.

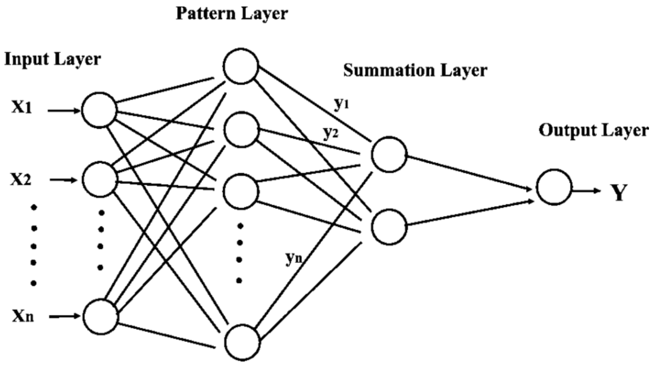

Figure 5. Generalized regression artificial neural network structure (Usluoglu et al. 2008)

2.6. Multilayer Neural Network

MANN is one of the most widely used artificial neural network models. In multilayer artificial neural networks, neurons are organized in layers. The first layer is the input layer, and it provides the information about the problem to be solved to the ANN. Another layer is the output layer, where the processed information is transmitted to the outside. There is a hidden layer between the input and output layers. Multilayer neural networks can have more than one hidden layer. In the MANN model, it is feed-forward because forward information flow occurs. It propagates backwards until the error is minimal. The basic structure of MANN is given in Figure 6.

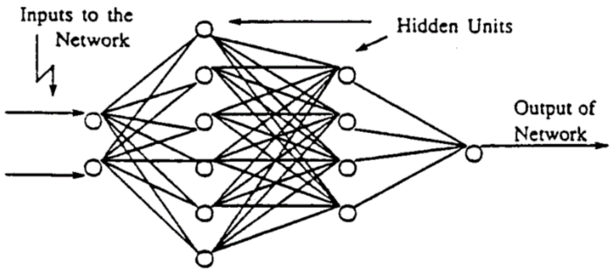

Figure 6. Multilayer neural network structure (Ciliz and Isik, 1996)

3. Results

In the modeling phase, the data were first shifted by lag time, and then the estimation results were obtained by separating them into training and test sets. The estimated data with the observed data were evaluated by considering the comparison criteria. Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and coefficient of determination (R^2) were used as comparison criteria. The formulas of the comparison criteria are given in Equation 4-6.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Y_p - Y_o)^2} \quad (4)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|Y_p - Y_o| \quad (5)$$

$$R^2 = \left(\frac{N*(\sum Y_o*Y_p)-(\sum Y_o)*(\sum Y_p)}{\sqrt{(N*\sum Y_o^2)-(\sum Y_o)^2*(N*\sum Y_p^2)-(\sum Y_p)^2}}\right)^2 \quad (6)$$

N is the number of data used in the equations, Yp represents the estimated value in the model, Yo represents the observed value. Since Equation (4-5) has error results for our comparison criteria, the unit of error results in the model is m.

High error results show that the model is far from real data, that is, it gives unsuccessful results. If the error values are close to zero, it indicates that the results of the model are close to the real data.

The coefficient of determination R^2 can take a value between 0 and 1. It is interpreted that the closer the value is to 1, the higher the model's fitness and accuracy.

In the study, data sets with 12 inputs were created (Figure 2). These; 1 month lag (T-1), T-2, T-3, T-4, T-5 and T-6 with 1 year lag (Y-1), Y-2, Y-3, Y-4 and Y-5.

Month numbers representing the periodicity of the data were used recursively as the 12th input set. 75% of all data were used in the training phase and 25% in the testing phase. At this stage, four different combinations were tried, namely training (75%) and testing (25%). These are M1 (the part with the oldest data), M2, M3 and M4 (the part with the most recent data). Model results are given in Tables 2-3-4 according to the training and testing phases. The flow chart of the study is given in Figure 7.

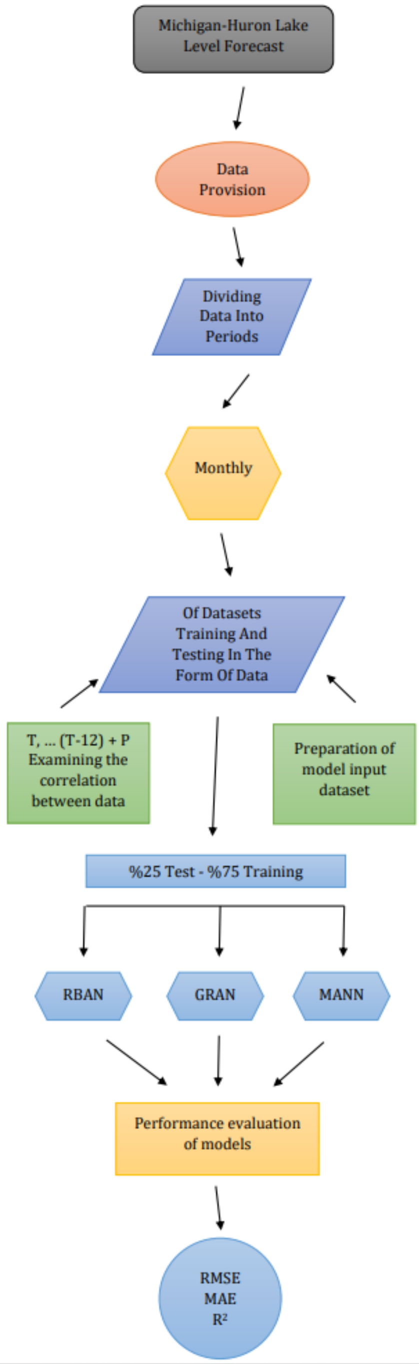

Figure 7. Flow chart of study

Table 2. RBANN training and test results

		Inputs	Training			Testing		
			RMSE	MAE	R^2	RMSE	MAE	R^2
RBANN	M1	1	0.069	0.055	0.970	0.066	0.054	0.964
		2	0.046	0.037	0.986	0.044	0.035	0.984
		3	0.044	0.034	0.987	0.042	0.033	0.986
		4	0.043	0.033	0.988	0.041	0.031	0.987
		5	0.042	0.033	0.989	0.039	0.030	0.987
		6	0.042	0.032	0.989	0.039	0.030	0.988
		7	0.041	0.032	0.989	0.038	0.030	0.988
		8	0.041	0.032	0.989	0.038	0.030	0.988
		9	0.042	0.032	0.989	0.039	0.031	0.987
		10	0.042	0.033	0.988	0.040	0.031	0.987
		11	0.043	0.033	0.988	0.040	0.031	0.987
		12	0.039	0.030	0.990	0.038	0.030	0.988
	M2	1	0.067	0.054	0.973	0.071	0.057	0.962
		2	0.045	0.036	0.988	0.048	0.037	0.983
		3	0.043	0.034	0.989	0.045	0.035	0.985
		4	0.042	0.033	0.989	0.044	0.034	0.986
		5	0.042	0.033	0.989	0.043	0.033	0.986
		6	0.041	0.031	0.990	0.042	0.032	0.987
		7	0.041	0.032	0.990	0.041	0.031	0.988
		8	0.040	0.032	0.990	0.041	0.031	0.988
		9	0.041	0.032	0.990	0.042	0.031	0.987
		10	0.042	0.033	0.989	0.043	0.032	0.987
		11	0.042	0.033	0.989	0.042	0.032	0.987
		12	0.039	0.031	0.991	0.040	0.031	0.988
	M3	1	0.069	0.055	0.964	0.066	0.054	0.945
		2	0.045	0.036	0.985	0.049	0.039	0.973
		3	0.043	0.034	0.986	0.046	0.036	0.975
		4	0.042	0.032	0.987	0.045	0.035	0.976
		5	0.041	0.032	0.987	0.044	0.034	0.977
		6	0.040	0.031	0.988	0.042	0.033	0.978
		7	0.040	0.031	0.988	0.043	0.033	0.978
		8	0.040	0.031	0.988	0.044	0.034	0.977
		9	0.040	0.031	0.988	0.044	0.035	0.977
		10	0.041	0.032	0.987	0.044	0.035	0.976
		11	0.042	0.032	0.987	0.047	0.037	0.975
		12	0.040	0.031	0.988	0.046	0.036	0.976
	M4	1	0.068	0.055	0.971	0.068	0.055	0.963
		2	0.048	0.038	0.985	0.046	0.037	0.983
		3	0.044	0.034	0.988	0.044	0.035	0.984
		4	0.042	0.033	0.989	0.042	0.033	0.986
		5	0.041	0.032	0.989	0.041	0.033	0.986
		6	0.040	0.031	0.990	0.042	0.033	0.986
		7	0.040	0.031	0.990	0.041	0.032	0.987
		8	0.040	0.031	0.990	0.042	0.033	0.986
		9	0.041	0.032	0.990	0.042	0.033	0.986
		10	0.041	0.032	0.989	0.042	0.033	0.986
		11	0.042	0.032	0.989	0.043	0.034	0.985
		12	0.039	0.030	0.990	0.040	0.032	0.987

In the Table 2, the most successful result in the test phase was obtained in 7 inputs. The scatter plot of the best method is given in Figure 8.

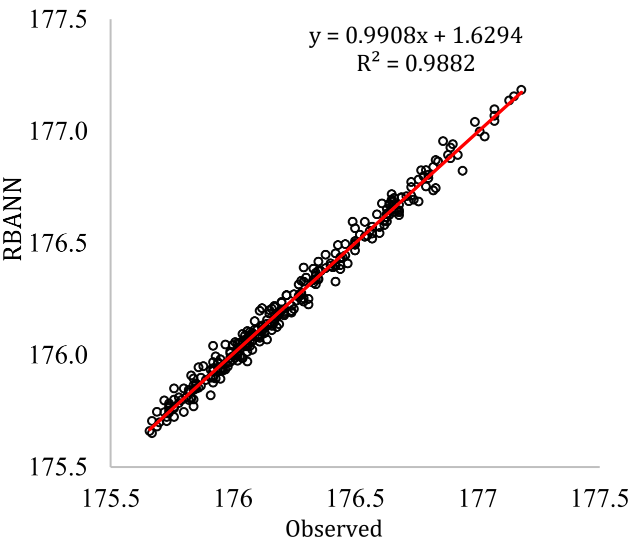

Figure 8. Scatter plot

When the values in the graph are examined, it is seen that the results obtained using the radial-based artificial neural network model are compatible with the water level data of the observed lake, and the graph equation approaches the y=x line, and the R^2 value is 0.9882. The variation of these estimates in the time series is shown in Figure 9.

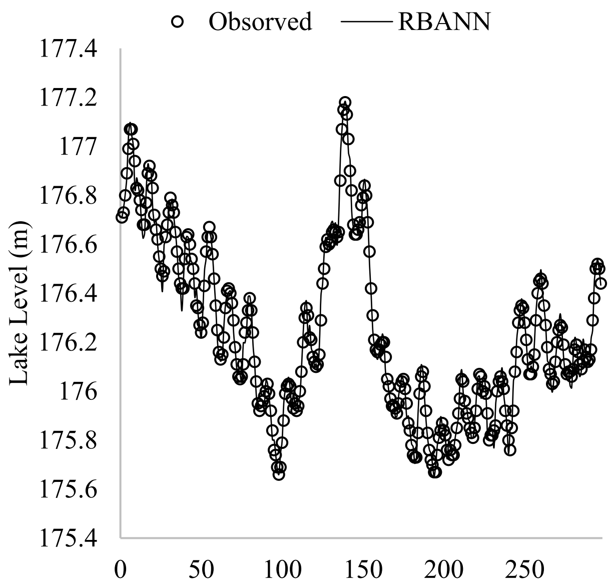

Figure 9. Timeline graph of test data

Figure 9 shows the estimates of test data for the M1 package. RBANN appears to capture the highs and lows of the test data well. It is clearly seen that the model is able to capture the highest and lowest data.

Table 3. GRANN training and test results

		Inputs	Training			Testing		
			RMSE	MAE	R^2	RMSE	MAE	R^2
GRANN	M1	1	0.066	0.053	0.972	0.069	0.055	0.962
		2	0.024	0.017	0.996	0.060	0.049	0.971
		3	0.010	0.004	0.999	0.065	0.051	0.966
		4	0.004	0.001	1.000	0.071	0.057	0.960
		5	0.002	0.000	1.000	0.078	0.062	0.952
		6	0.001	0.000	1.000	0.085	0.066	0.943
		7	0.001	0.000	1.000	0.100	0.081	0.920
		8	0.000	0.000	1.000	0.118	0.095	0.891
		9	0.000	0.000	1.000	0.139	0.112	0.853
		10	0.000	0.000	1.000	0.157	0.126	0.815
		11	0.001	0.000	1.000	0.175	0.139	0.778
		12	0.000	0.000	1.000	0.134	0.108	0.860
	M2	1	0.065	0.053	0.974	0.072	0.058	0.962
		2	0.025	0.018	0.996	0.062	0.049	0.971
		3	0.012	0.007	0.999	0.071	0.056	0.963
		4	0.005	0.002	1.000	0.073	0.058	0.962
		5	0.002	0.001	1.000	0.076	0.061	0.957
		6	0.001	0.000	1.000	0.082	0.064	0.951
		7	0.001	0.000	1.000	0.102	0.081	0.929
		8	0.002	0.001	1.000	0.134	0.110	0.867
		9	0.002	0.001	1.000	0.150	0.120	0.836
		10	0.003	0.001	1.000	0.168	0.138	0.800
		11	0.003	0.001	1.000	0.172	0.140	0.791
		12	0.000	0.000	1.000	0.149	0.121	0.843
	M3	1	0.066	0.053	0.967	0.073	0.059	0.934
		2	0.027	0.019	0.994	0.065	0.050	0.949
		3	0.017	0.010	0.998	0.077	0.060	0.928
		4	0.010	0.005	0.999	0.084	0.065	0.916
		5	0.006	0.002	1.000	0.092	0.070	0.902
		6	0.006	0.002	1.000	0.101	0.076	0.884
		7	0.001	0.000	1.000	0.117	0.088	0.835
		8	0.002	0.000	1.000	0.146	0.113	0.757
		9	0.001	0.000	1.000	0.142	0.113	0.788
		10	0.001	0.000	1.000	0.156	0.122	0.761
		11	0.002	0.000	1.000	0.181	0.144	0.727
		12	0.000	0.000	1.000	0.155	0.123	0.791
	M4	1	0.066	0.053	0.973	0.070	0.056	0.961
		2	0.026	0.018	0.996	0.059	0.047	0.972
		3	0.010	0.005	0.999	0.065	0.052	0.967
		4	0.004	0.001	1.000	0.068	0.054	0.964
		5	0.002	0.000	1.000	0.074	0.057	0.956
		6	0.001	0.000	1.000	0.083	0.064	0.945
		7	0.000	0.000	1.000	0.095	0.075	0.929
		8	0.001	0.000	1.000	0.122	0.094	0.884
		9	0.001	0.000	1.000	0.139	0.110	0.855
		10	0.001	0.000	1.000	0.154	0.122	0.824
		11	0.001	0.000	1.000	0.160	0.127	0.804
		12	0.000	0.000	1.000	0.139	0.113	0.849

In the Table 3, the most successful result in the test phase was obtained in 2 inputs. The scatter plot of the best method is given in Figure 10.

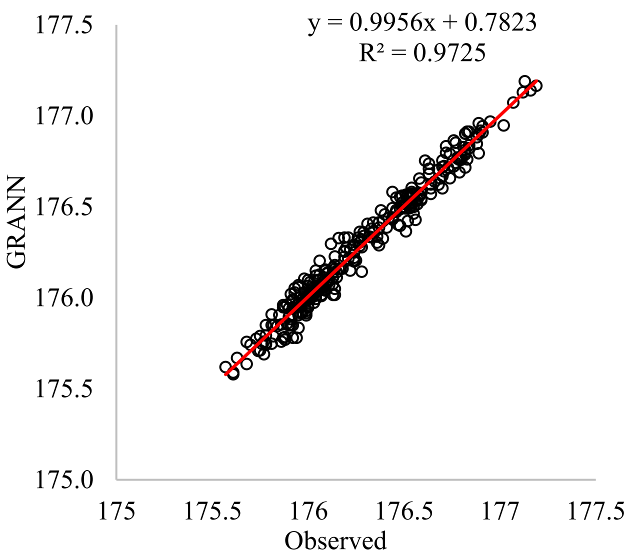

Figure 10. Scatter plot

When the values in the graph are examined, it is seen that the results obtained using the GRANN model are compatible with the water level data of the observed lake, and the graph equation approaches the y=x line, and the R^2 value is 0.9725. As the coefficient of determination approaches 1 in the scatterplot, the model and the estimations overlap. In other words, the model can give more accurate predictions. The variation of these estimates in the time series is shown in Figure 11.

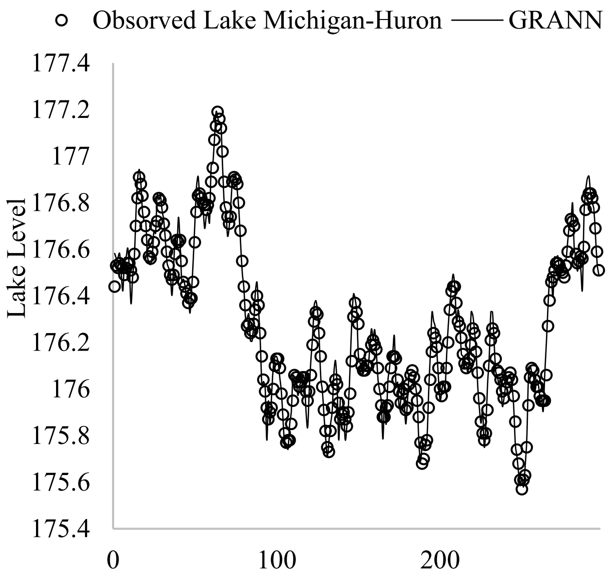

Figure 11. Timeline graph of test data

Figure 11 shows estimates of test data for the M4 package. GRANN seems to capture almost all the data. Although the lake water level fluctuations show instantaneous changes in the time series, it is seen that the model catches these changes.

Table 4. MANN training and test results

		Inputs	Training			Testing		
			RMSE	MAE	R^2	RMSE	MAE	R^2
MANN	M1	1	0.069	0.055	0.970	0.067	0.054	0.964
		2	0.047	0.037	0.986	0.045	0.035	0.984
		3	0.043	0.034	0.988	0.044	0.034	0.984
		4	0.045	0.035	0.987	0.042	0.033	0.985
		5	0.042	0.032	0.989	0.040	0.031	0.987
		6	0.039	0.030	0.990	0.039	0.030	0.987
		7	0.039	0.030	0.990	0.039	0.030	0.988
		8	0.039	0.030	0.990	0.038	0.030	0.988
		9	0.038	0.030	0.991	0.040	0.031	0.987
		10	0.040	0.031	0.990	0.039	0.031	0.987
		11	0.039	0.030	0.990	0.048	0.035	0.981
		12	0.042	0.033	0.989	0.040	0.030	0.987
	M2	1	0.067	0.054	0.973	0.072	0.058	0.962
		2	0.208	0.166	0.736	0.254	0.210	0.529
		3	0.045	0.035	0.988	0.046	0.035	0.985
		4	0.042	0.032	0.989	0.045	0.034	0.985
		5	0.041	0.032	0.990	0.044	0.034	0.986
		6	0.041	0.032	0.990	0.043	0.033	0.987
		7	0.039	0.030	0.991	0.041	0.031	0.988
		8	0.039	0.030	0.991	0.041	0.031	0.988
		9	0.040	0.031	0.990	0.043	0.033	0.986
		10	0.042	0.033	0.989	0.042	0.032	0.987
		11	0.038	0.030	0.991	0.044	0.034	0.986
		12	0.043	0.033	0.989	0.044	0.033	0.986
	M3	1	0.069	0.055	0.964	0.068	0.055	0.943
		2	0.045	0.036	0.984	0.049	0.039	0.973
		3	0.044	0.034	0.985	0.050	0.038	0.973
		4	0.042	0.032	0.987	0.046	0.036	0.975
		5	0.041	0.031	0.987	0.045	0.035	0.976
		6	0.041	0.032	0.987	0.049	0.038	0.973
		7	0.038	0.029	0.989	0.045	0.034	0.977
		8	0.039	0.030	0.989	0.044	0.034	0.978
		9	0.040	0.031	0.988	0.045	0.035	0.976
		10	0.038	0.029	0.989	0.051	0.038	0.971
		11	0.038	0.029	0.989	0.055	0.042	0.968
		12	0.034	0.026	0.991	0.039	0.031	0.982
	M4	1	0.068	0.055	0.971	0.069	0.055	0.962
		2	0.047	0.038	0.986	0.046	0.036	0.983
		3	0.044	0.034	0.988	0.045	0.036	0.984
		4	0.044	0.034	0.988	0.045	0.035	0.984
		5	0.041	0.031	0.990	0.042	0.033	0.986
		6	0.041	0.031	0.990	0.042	0.034	0.986
		7	0.038	0.029	0.991	0.042	0.033	0.986
		8	0.038	0.029	0.991	0.042	0.033	0.986
		9	0.037	0.029	0.991	0.047	0.035	0.983
		10	0.038	0.029	0.991	0.043	0.035	0.985
		11	0.038	0.030	0.991	0.043	0.034	0.985
		12	0.043	0.033	0.988	0.043	0.034	0.985

In the Table 4, the most successful result in the test phase was obtained in 8 inputs. The scatter plot of the best method is given in Figure 12.

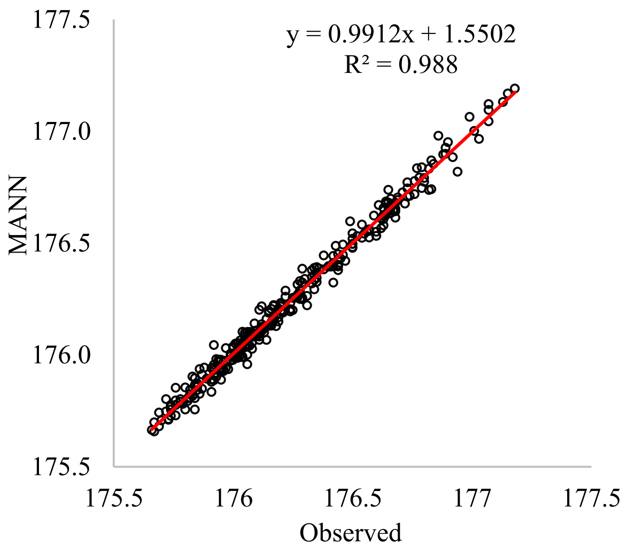

Figure 12. Scatter plot

When the values in the graph are examined, it is seen that the results obtained using the MANN model are compatible with the water level data of the observed lake, and the graph equation approaches the y=x line, and the R^2 value is 0.988. The variation of these estimates in the time series is shown in Figure 13.

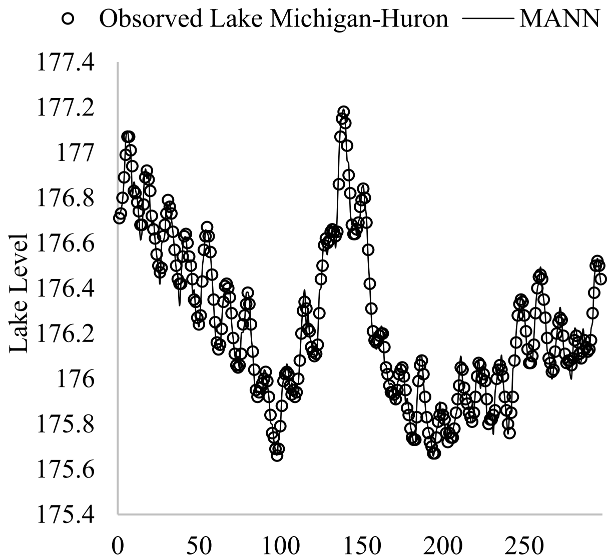

Figure 13. Timeline graph of test data

Figure 13 shows the estimates of test data for the M1 package. MANN appears to capture the highs and lows of the test data well.

4. Discussion

In a study conducted by Çubukçu et al. in 2021 on the estimation of the monthly average water levels of Lake Michigan, data between 1981 and 2021 were used and studied with three different artificial neural network models. These models are multilayer ANN, radial basis

ANN and generalized ANN models. RMSE, MAE and R^2 were used as comparison criteria. In general, it was seen that all models gave good results, but according to the test results, the best training algorithm was seen as multilayer ANN, giving the best results in 12 inputs. (MAE= 0.0342, RMSE= 0.0435, R^2= 0.9906). The best method was found to be MANN, RBANN and GRNN, respectively (Çubukçu et al. 2021).

Çalım conducted a study in 2008 on the estimation of dam reservoir elevation using artificial neural networks. ANN models were used in the study. When the results obtained using ANN are compared with the results obtained with different methods before, it is concluded that ANN models perform better than the classical methods used in the past (Çalım, 2008).

In a study conducted by Dikbaş and Fırat in 2005, a comparison of POM and ANN models was made in three-dimensional hydrodynamic modeling in lakes. When the results obtained with both models were compared, it was seen that the methods had advantages and disadvantages compared to each other. ANN requires previously obtained observation results and calculations, while POM does not. In addition, ANN achieves results in a much shorter time than POM. As a result, it can be recommended to use the artificial neural network method in certain sections and studies that require many detailed calculations (Dikbaş and Fırat, 2005).

In a study conducted by Demir in 2021, the water level changes of Lake Michigan were examined using MARS, M5-tree and LSSVR methods. These three models have gone through training and testing phases. RMSE, MAE and R^2 were used as evaluation criteria. In the study, 80% of the data was used in the training phase and the remaining 20% in the testing phase. The data period of the study is between 1918 and 2020. Data deferred up to 8 months were used as the input set. When the results were examined, it was seen that better results were obtained with the MARS method (RMSE=0.0359, MAE=0.0288, R^2=0.9922). In addition, it was stated that the periodicity effect increased the model performance. (Demir, 2022).

In a study conducted by Özaydın in 2009, the estimation of the water reservoir level of Eskişehir badger dam was studied. In this study, artificial neural networks and ARMAX model were used as methods and these two models were compared with each other. Data from January 1973 to December 2006 were used. As a result of the analyzes made, it has been seen that the results obtained with artificial neural networks are closer to the truth than the results obtained with the ARMAX method (Özaydın, 2009).

In 2009, a study was conducted by Yarar and Onuçyıldız on the determination of water level changes in Beyşehir Lake with artificial neural networks. In this study, data belonging to the years 1962-1990 were used. The data between 1962-1985 was used for training, and the data between 1985-1990 was used for testing. As a method, back propagation multilayer ANN model was chosen due to its widespread use and 3 different algorithms, Levenberg-Marquardt, One-Step Secant and Scaled Matched Gradient, were used. The smallest error 0.056285 was obtained for the 1 hidden layer, 7 hidden nodes and 500 epochs in the Scaled Matching Gradient model from these three different models. The data obtained by ANN models were compared with the data obtained by classical methods, and it was concluded that the use of ANN models would be beneficial in estimating the water level of Beyşehir Lake (Yarar and Onuçyıldız, 2009).

In 2010, a study was conducted on the use of artificial neural networks in river flow prediction. The Blue Nile River in Sudan was chosen as the study area. Four different ANN models were used in the study. The common feature of the four selected models was that they had a multi-layer perceptron structure. All four models use the precipitation index as a common input. ANN1 only uses this common input, while ANN2 and ANN3 use seasonal precipitation expectation or seasonal flow expectation as additional input. ANN4 uses both the seasonal flow forecast and the seasonal precipitation forecast. When the results are examined, it is seen that the ANN4 model gives the most successful result (highest R^2). The results of the study show that the selection of appropriate inputs in the ANN model directly affects the success of the model (Shamseldin, 2010).

The methods used in this study and the findings obtained are compatible and supportive with the performances obtained in previous studies in the literature.

5. Conclusion

In this study, using the monthly average lake water level data of Lake Michigan-Huron between 1918 and 2021, predictions were made with different ANN methods and the results were compared. In the study, 75% of all data were used in the training phase and 25% in the testing phase. At this stage, four different combinations of training (75%) and testing (25%) were tried. Mean Absolute Error (MAE), Root Mean Square Error (RMSE), coefficient of determination (R^2) were used as evaluation criteria. The results are as follows:

- When the Tables 2-4 obtained with 3 different models are examined, it is seen that all models do very well in the training and testing stages, seem to make predictions.
- When the training results are compared, after GRANN (RMSE=0.000012, R^2=0.9998), which has the least error with the evaluation criteria, are MANN (RMSE=0.0337, R^2=0.9914) and RBANN (RMSE =0.0386, R^2=0.9910), respectively.
- According to the test results, the model algorithm that gives the most successful result is RBANN (RMSE=0.0381, R^2=0.9881). Best result in 7 entries seems to give. The best method for the testing phase is RBANN, MANN, and GRANN, respectively.

As a result, it is thought that the use of ANN algorithms will be useful in estimating the Michigan-Huron lakes water level.

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Author contributions

Mehmet Fehmi Yıldız: Data supply, Writing-Original Draft Preparation, Revision.
Vahdettin Demir: Investigation, Methodology, Software, Revision.

Conflicts of interest

There is no conflict of interest between the authors.

Statement of Research and Publication Ethics

Research and publication ethics were complied with in the study.

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