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Forecasting of monthly average lake levels of Lake Michigan with artificial neural networks

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ABSTRACT

Forecasting of water level at various time intervals using historical record series is important in water resource management and related engineering. Similarly, a reliable estimation of water level change is required in drought and flood hydrology studies. In this study, Lake Michigan between 1981-2020 was modeled with 3 different Artificial Neural Networks (ANNs) using monthly average water level data. These are Multilayer ANN, Radial Based ANN, and Generalized ANN models. Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and Coefficient of Determination (R^2) were used as comparison criteria. When the results were compared, the lowest error rate and the highest coefficient of determination were seen in the 12 inputs of the MANN model (MAE= 0.0342, RMSE= 0.0435, R^2= 0.9906).

Introduction

Anthropogenic climate change, which has emerged especially in the last century and affects the whole earth, also has important effects on lakes. Temperature increases due to climate change also increase open surface evaporation in lakes with a larger surface area than other surface fresh water sources. Changing temperatures bring along the need for more water consumption. The use of water resources to provide more water than normal, due to both agricultural water needs and water needs in cities, causes the capacity of water reserves such as lakes to decrease or disappear [1]. Changes in lake level can lead to erosion, destruction of wetlands, changes in bird, fish and plant populations, increase or decrease in micro-organisms in the lake, and destruction of habitats. The main causes of changes in the decreasing level of lakes in many parts of the world have been associated with various anthropogenic factors such as changes in ground cover and land use, urbanization, increased agricultural and animal water needs, excessive use of the resources that feed [2-7]. In water resources engineering, estimating the water level at certain intervals according to the past records plays an important role for the continuity and feasibility of the planning. ANN is an information processing technology inspired by the working principle of the human brain. Neurons form a network system by connecting to each other in various ways, and these networks have features such as learning and memorizing the relationship between data. The main element of ANNs are mathematical functions. They evolve with the architecture of the network structure. ANNs are structures that reveal the relationship between input and output behaviorally [8-9]. In his study in 2004, Yarar tried to successfully predict the water level changes of Beyşehir Lake in Konya with various parameters and different training algorithms of MANN [10]. Abu Salam, in his study in 2018, used 10-year flow data from the Dibis dam in Iraq to make level estimation with ANN models and compared it with real measurements [11]. Çubukçu, in this study in 2019, it has been tried to predict the changes in sea level by six different Artificial Neural Networks (ANN's) training algorithms and Multiple Linear Regression (MLR) methods. Levenberg-Marquardt is faster and has a better accuracy than the other training algorithms in modeling sea level [12]. In his study in Damla 2020, he created the estimation model of the water level of Yalova Gökçe Dam for 2019 using ANN. The input parameters were; Basin precipitation and evaporation values, dam water discharges, leachate amount, dam water level are the measurements and dam water level the flow rate of Sellimandıra stream, which is effective in the formation used as. As a result, while the average dam water level estimated by the Levenberg-Marquardt training function in 2019 was 73.77 meters, the actual average water level in the dam was 72.13 meters, thus giving successful results [13]. The occurrence of such hydrological events depends on many parameters, so it can be difficult to predict and model. The literature shows that ANN can be applied, but the study on its comparison is quite limited.

In this study, 3 different types of ANNs were modeled using monthly average water level data of Lake Michigan in the US between 1981 and 2020. These are Generalized Regression, Multilayer, Radial Based ANN models. In modeling, the oldest 2/3 of the data number was used in the training phase, and the most recent 1/3 was used in the testing phases. The main reason for choosing this field of study is that the data is continuous and accessible.

Material and Method

Material

Lake Michigan is the only Great Lake entirely contained within the United States. The lake is surrounded by the states of Michigan, Wisconsin, Illinois, and Indiana. The Straits of Mackinac connect Lake Superior to Lake Huron, allowing the two lakes to function as one large body of water. The statistical information of the data is given in Table 1. According to Table 1; There are 480 pieces of data. The mean of these data is 176,479 m, the standard deviation is 0.432. Physical characteristics of Lake Michigan are given in Table 2.

Table 1. Statistical information

Criteria	Value
Average	176.479
Standard error	0.020
Standard Deviation	0.432
Kurtosis	-0.783
Distortion	0.178
The biggest	175.570
Smallest	177.500
Total	84710.040
Number	480

Figure 1. Study area [14]

Table 2. Physical characteristics [14]

Data	Value
Length	494 km
Breadth	190 km
Elevation	176 m
Depth	85 m aver; 281 m max
Volume	4,918 km^3
Water surface area	57,753 km^2
Drainage basin area	118,095 km^2
Shoreline length	2,639 km
Outlet	Straits of Mackinac to Lake Huron
Retention or replacement time	62 years
Population	12+ million

Method

ANNs perform learning processes with the help of examples, that is, it can be defined as the machine-transferred version of the learning mechanism of humans by experience. This learning mechanism, unlike what is known, brings the computational feature to the computer by using the ability to adapt to the environment, to adapt, to work according to past experiences or incomplete information in times of uncertainty. In ANNs, various pre-processes are applied to the inputs and outputs of the network cells, and the training process of the data that is included in the ANN cycle and trained can become more efficient. In this study, 3 different ANN models were used. First of all, one of the most widely used ANN models, MANN is an input layer, at least one-cell intermediate It consists of a layer and an output layer. Second, Radial-based ANN model of neuron cells in the nervous system seen in humans. Finally, the generalized regression neural network uses back propagation, requires no iterative training, and predicts any function between the input and output vectors. For detailed information [15-18] can be examined.

Application

In modeling, 320 of 480 data were used in training phase and 160 in testing phase. Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and Coefficient of Determination (R^2) were used as comparison criteria. Related equations are given in Equation 1-3 below.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|Z_e - Z_o\right| \quad (1)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Z_e - Z_o)^2} \quad (2)$$

$$R^2 = \left(\frac{N*(\sum Z_o * Z_e) - (\sum Z_o)*(\sum Z_e)}{\sqrt{(N*\sum Z_o^2) - (\sum Z_e)^2 * (N*\sum Z_e^2) - (\sum Z_e)^2}}\right)^2 \quad (3)$$

In the equations, "Ze" and "Zo" show the estimated and observed elevation values and "N" represents the amount of data. Training and test results are given in Table 3. In the table, the models with the lowest RMSE and MAE, and the highest models in R^2 are colored closer to red.

Table 3. Training Results and Test Results

Criteria	Methods	Inputs											
		1	2	3	4	5	6	7	8	9	10	11	12
RMSE (Training)	MANN	0.0651	0.0454	0.0421	0.0452	0.0448	0.0440	0.0444	0.0408	0.0417	0.0397	0.0396	0.0408
	GRNN	0.0632	0.0384	0.0260	0.0403	0.0288	0.0389	0.0310	0.0395	0.0314	0.0249	0.0463	0.0394
	RBANN	0.0649	0.0444	0.0444	0.0426	0.0424	0.0419	0.0418	0.0433	0.0426	0.0434	0.0426	0.0414
MAE (Training)	MANN	0.0525	0.0362	0.0328	0.0352	0.0349	0.0344	0.0346	0.0329	0.0330	0.0316	0.0314	0.0323
	GRNN	0.0507	0.0301	0.0194	0.0310	0.0206	0.0293	0.0224	0.0301	0.0235	0.0175	0.0364	0.0298
	RBANN	0.0524	0.0353	0.0347	0.0328	0.0332	0.0329	0.0332	0.0342	0.0339	0.0345	0.0336	0.0326
R^2 (Training)	MANN	0.9727	0.9867	0.9886	0.9869	0.9871	0.9875	0.9873	0.9893	0.9888	0.9899	0.9899	0.9893
	GRNN	0.9743	0.0301	0.9957	0.9897	0.9947	0.9905	0.9939	0.9903	0.9939	0.9961	0.9869	0.9905
	RBANN	0.9729	0.9873	0.9873	0.9883	0.9884	0.9887	0.9888	0.9880	0.9883	0.9879	0.9883	0.9890
RMSE (Test)	MANN	0.0743	0.0502	0.0471	0.0480	0.0499	0.0484	0.0481	0.0516	0.0503	0.0449	0.0436	0.0435
	GRNN	0.0761	0.0683	0.0823	0.0859	0.0926	0.0994	0.1051	0.1095	0.1125	0.1190	0.1236	0.1283
	RBANN	0.0722	0.0482	0.0521	0.0486	0.0451	0.0447	0.0461	0.0467	0.0469	0.0497	0.0487	0.0451
MAE (Test)	MANN	0.0575	0.0388	0.0365	0.0377	0.0387	0.0371	0.0369	0.0407	0.0399	0.0355	0.0344	0.0342
	GRNN	0.0593	0.0523	0.0626	0.0653	0.0715	0.0772	0.0820	0.0867	0.0891	0.0954	0.1012	0.1059
	RBANN	0.0561	0.0380	0.0393	0.0376	0.0345	0.0345	0.0354	0.0367	0.0359	0.0388	0.0374	0.0352
R^2 (Test)	MANN	0.9723	0.9875	0.9886	0.9887	0.9884	0.9891	0.9888	0.9877	0.9880	0.9902	0.9904	0.9906
	GRNN	0.9712	0.9775	0.9672	0.9663	0.9617	0.9563	0.9512	0.9479	0.9438	0.9342	0.9290	0.9216
	RBANN	0.9735	0.9880	0.9867	0.9884	0.9899	0.9901	0.9893	0.9893	0.9892	0.9880	0.9881	0.9898

Results

When we look at the tables in general, it is seen that all models can make very good predictions regardless of the training and test parts. According to the training results, the algorithm that trains the best with the least error and the highest coefficient of determination GRNN (10 input) RMSE= 0.0249, OMH=0.0175, R^2=0.9961. For the training pieces the best method is GRNN, then MANN and RBANN respectively. However, according to the test results, the best training algorithm is MANN. It is seen that it gives the best result in 12 inputs RMSE= 0.0435, OMH=0.0342, R^2=0.9906. For the test pieces the best method is MANN, then RBANN and GRNN respectively.

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