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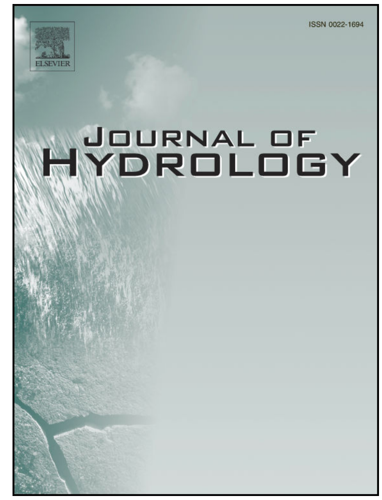

Research papers

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Forecasting of water level in multiple temperate lakes using machine learning models

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Abstract

Due to global climate change and growing population, fresh water resources are becoming more vulnerable to pollution. Protecting fresh water resources, especially lakes and the associated environment, is one of the key challenges faced by policy makers and water managers. Lake water level is an important physical indicator of lakes, and its fluctuation may significantly impact lake ecosystems. Therefore, reliable forecasting of lake water level is vital for a proper assessment of the health of lake ecosystems and their management. In this study, two machine learning models, including feed forward neural network (FFNN) and Deep Learning (DL) technique, were used to predict monthly lake water level. The two models were employed for one month ahead forecasting of lake water level in 69 temperate lakes in Poland. The results show that both the FFNN and the DL models performed generally well for forecasting of lake water level of the 69 lakes, with only marginal differences. The results also indicate that the DL model did not show significant superiority over the traditional FFNN model; indeed, the FFNN model slightly outperformed the DL model for 33 of the 69 lakes. These results seem to suggest that traditional machine learning models may just be sufficient for forecasting of lake water level when they are properly trained. The outcomes of the present study have important implications for water level forecasting and water resources management of lakes, especially from the perspective of machine learning models and their complexities.

Keywords: Lake water level forecasting; Deep Learning; Neural networks; Feed forward neural networks; Long short-term memory; Time series forecasting

1. Introduction

Lakes are valuable natural resources on the earth, playing a significant role on economic and societal development. Lake water level (WL) is an important physical indicator of lakes, and its fluctuations may significantly impact lake ecosystems (Coops et al., 2003; Zohary and Ostrovsky, 2011; Ptak et al., 2017). For example, Zohary and Ostrovsky (2011) found that at moderate WL fluctuation levels in lakes, littoral habitats and biota were affected, and with further disturbance levels, ecosystem destabilization symptoms (such as weakening of keystone species, proliferation of nuisance and invasive species, loss of biodiversity, and increased internal nutrient loading) were observed. It is, therefore, of great significance to study water level fluctuations in lakes.

Mathematical models are powerful tools to model and forecast water level fluctuations in lake systems. During the past several decades, a wide variety of models have been developed, from very simple statistical models (Aksoy et al., 2013; Khatibi et al., 2014) to highly complex physically-based hydrodynamic models (Kebede et al., 2006; Huang et al., 2010). The physically-based hydrodynamic models, which are complex in general, need a bunch of data as model inputs, such as lake bathymetry, inflow and outflow conditions, and a complete set of meteorological variables (e.g., air temperature, precipitation, wind). This makes their application impractical for areas with limited data. This limitation has also led to the development and applications of machine learning models for WL forecasting due to their relatively minor data requirements as inputs (Kisi et al., 2015; Li et al., 2016; Shiri et al., 2016).

In recent decades, various types of machine learning models have been developed and applied in hydrological and environmental studies (Afan et al., 2015; Yaseen et al., 2016, 2019; Hameed et al., 2017; Sulaiman et al., 2018; Ghorbani et al., 2018; Zhu et al., 2018, 2019; Sanikhani et al., 2019). As for the forecasting of lake water level, several traditional and classic model types have been assessed, such as artificial neural networks (ANNs) (Altunkaynak, 2007; Yarar et al., 2009; Buyukyildiz et al., 2014), adaptive neuro fuzzy inference systems (ANFIS) (Yarar et al., 2009; Güldal and Tongal, 2010; Kisi et al., 2012), and extreme learning machines (ELM) (Shiri et al., 2016; Bonakdari et al., 2019), among others. With the development of artificial intelligence, deep learning (DL) methods (e.g., the long short-term memory (LSTM) recurrent neural network (RNN), deep restricted Boltzmann machine, stack Autoencoder) have been successfully applied for hydrological time series forecasting, such as flow forecasting (Sahoo et al., 2019), prediction of water level of the combined sewer overflow structure (Zhang et al., 2018a), rainfall-runoff simulation (Hu et al., 2018), water table depth prediction in agricultural areas (Zhang et al., 2018b), and daily reservoir inflow forecasting (Li et al., 2016), among others.

Deep Learning networks allow computational models composed of multiple processing layers to learn representations of data with multiple levels of abstraction, and these networks simulate the way the human brain works. Among the DL networks, the long short-term memory (LSTM) recurrent neural network (RNN) is a type of advanced ANN approach, which involves feedback connections in the model architecture (Zhang et al., 2018a). While it has found many applications in other areas of hydrology, its applications for lake water level forecasting are very limited. To our knowledge, only three studies have employed the Deep Learning models for lake water level forecasting (Güldal and Tongal, 2010; Liang et al., 2018; Hrnjica and Bonacci, 2019). Güldal and Tongal (2010) applied the recurrent neural network for water level forecasting in the Eğirdir Lake in Turkey, and compared the results with those obtained using adaptive neuro-fuzzy inference system and stochastic models. Liang et al. (2018) applied the LSTM model for forecasting the water level in the Tongding Lake, China, and found that the LSTM model outperformed the support vector machine (SVM) method. Hrnjica and Bonacci (2019) developed the LSTM and the feed forward neural network (FFNN) models to forecast the water level in the Vrana Lake, Croatia. They found that the LSTM and FFNN models performed better than the time series methods, such as nonlinear regression, exponential smoothing, and autoregressive integrated moving average (ARMA) model.

The outcomes of the above studies are certainly encouraging regarding the suitability and effectiveness of the DL models for lake water level forecasting. However, a definitive conclusion and generalization on the performance of DL models is difficult to make, since each of the above studies has focused on only one specific lake: the Eğirdir Lake by Güldal and Tongal (2010), the Tongding Lake by Liang et al. (2018), and the Vrana Lake by Hrnjica and Bonacci (2019). Therefore, whether the DL model can also perform well, and better than other models, in forecasting water levels at multiple lakes in a region remains a relevant and key question. This provides the motivation for the present study.

To address the above question, in this study, we applied the DL model for water level forecasting at 69 lakes in Poland. We analyzed long-term monthly WL data (at least 31 years) from each of these lakes. The results obtained using the DL model were also compared with those obtained from the widely used FFNN model, to check its superiority. The methods we employed in the present study were the same as that of Hrnjica and Bonacci (2019). However, there was a major difference between the two studies in the way the analysis was done. Hrnjica and Bonacci (2019) used the data from one lake and, hence, the data used was limited. In the present study, we trained the data from multiple lakes and then used the model for WL forecasting for multiple lakes. This allowed better evaluation of the models, since we had a large dataset. The outcomes were expected to provide useful information on the robustness of the DL models for WL forecasting in lakes. Further, since the present study was the first attempt to apply the DL models for forecasting water level in as many as 69 Polish lakes, the outcomes could provide new avenues for lake modeling and management in Poland. Additionally, the forecasting results of monthly lake water level would provide guideline for different agencies to facilitate lake water management, such as water supply, the regulation of ecological water level for lakes, and flood-control for the lake watershed.

2. Materials and Methods

2.1 Study area and data

In the present study, water level forecasting of multiple lakes in Poland was attempted. Due to the impact of the last glaciation (Weichselian), which occurred about 12000 years ago, most lakes in Poland are located in the northern part (Czernecki and

Ptak, 2018, Fig. 1). These lakes have and continue to important water resources for economic and social development in Poland, including water supply for domestic, industrial, agricultural, and recreational uses (Ptak et al., 2018).

Insert Figure 1 here

In this study, water level data from 69 lakes were used. The morphologies of these lakes are summarized in Table S1. As seen, these lakes have diverse morphologies. For instance, the mean water depth ranges from 1.0 m to 17.7 m, and the lake area varies from 1.1 km^2 and 114.9 km^2.

In Poland, lake water level is measured at 7 am daily, by the Institute of Meteorology and Water Management, National Research Institute (IMGW-PIB). Daily observed WL data were available from 1984 to 2018 (35 years) for 42 lakes. For the other 27 lakes, daily observed WL data were available from 1984 to 2014 (31 years). The IMGW-PIB has followed strict procedures for lake WL measurements to assure data quality. More detailed information on these data and their quality can be found in https://www.imgw.pl/instytut/imgw-obserwator.

The daily observed data were averaged to obtain monthly data, for the modeling studies. Thus, for 42 lakes, there are 420 monthly WL data points (35 years), and for the other 27 lakes, there are 372 monthly WL data points (31 years). Fig. 2 presents the time series of the monthly WL data of 8 lakes, as examples: Śniardwy, Wigry, Wdzydze, Sępoleńskie, Sławianowskie, Studzieniczne, Selmet Wlk, and Rospuda.

Insert Figure 2 here

2.2 Feed forward neural network (FFNN)

Artificial neural network was inspired by the human brain and neurons. A typical ANN model consists of several sets: input variables (x_i), weight factors (w_i), bias term (b_0), and activation function (a) (Zhu et al., 2019; Graf et al., 2019). With these inputs, the output of an ANN model y can be represented as:

$$y = a(\sum_{i=1}^{n} x_i w_i + b_0) \quad (1)$$

The feed forward neural network (FFNN) is a widely used ANN model. In this network, information moves only in the forward direction, from the input layer, through the hidden layer, and finally to the output layer. In the input layer, the number of neurons is determined by the number of input variables; in the output layer, the number of neurons is determined by the number of output variables; the optimal number of neurons in the hidden layer is generally determined by a trial and error method (Graf et al., 2019). The FFNN model is developed by connecting the above neurons into one network. Since each neuron can produce a simple decision, the FFNN model must consist of many neurons in order to establish a network that can find solutions to real-world problems (Burgsteiner, 2006; Bartolini et al., 2011). The three layers of the FFNN are fully connected, since every neuron from one layer is connected to every neuron in the next layer.

2.3 Recurrent neural network (RNN)

The widely used FFNN models are usually built on the fact that data has no order when fed into the network. Thus, the output of the ANN depends only on the input features. Consequently, for data where the sequence of data is important, specifically when the data is recorded in time, simple feed-forward ANN might not handle it (Jiang, 2009; Nourani, 2009). One of the solutions for such kind of problems is to develop the recurrent neural network (RNN). The RNN was first introduced by Hopfield (1982), and was later popularized when the backpropagation algorithm was improved (Pineda, 1987). The concept of the RNN model is depicted in Fig. 3 (top). Here, $x_1, x_2, \ldots, x_t$ are model inputs, and $h_1, h_2, \ldots, h_t$ are model outputs. As seen, the RNN contains cycles, indicating that the current state of the network relies on the data from the current network as well as the outputs produced by the previous network.

Insert Figure 3 here

A particular problem with RNN is the vanishing or exploding gradient (Bengio et al., 1994). In the vanishing gradient problem, updates of weights are proportional to the gradient of the error. In most cases, the gradient value is vanishingly small, which results in the corresponding weight to be constant and stops the network from further training. The exploding gradient problem refers to the opposite behavior, where the updates of weights (gradient of the cost function) become large in each backpropagation step. In both cases (vanishing and exploding), the error propagation through the network is not constant. The solution to the above-mentioned problems is found in the specific design of the RNN, called *long short-term memory* (LSTM) (Hochreiter and Schmidhuber, 1997). The LSTM is a special RNN, which can provide a constant error flow. This requires a special network design. The LSTM consists of the memory blocks with self-connection defined in the hidden layer that have the ability to store the temporal state of the network. Besides the memorization, the LSTM cell has special multiplicative units, called *gates*, which control the information flow. Each memory block consists of the input gate (i_t) (which controls the flow of the input activations into a memory cell) and the output gate (o_t) (which controls the output flow of the cell activation). In addition, the LSTM cell also contains the forget gate (f_t) (which filters the information from the input (x_t) and the previous output) and decides which one should be remembered or forgotten and dropped.

The LSTM cell with activation layers (input, output, forget gates, and the cell, connected with peephole connections) is shown in Fig. 3 (bottom). Here, x_t is the input, f_t is the forget gate, i_t is the input gate, $\hat{c}_t$ is the cell update, C_t is the cell state, o_t is the output gate, and h_t is the output.

2.4 Deep learning (DL)

Recently, Deep Learning (DL) technique has become very popular and has been applied in various fields. The DL technique has found widespread applications in some fields, such as image and speech recognition, processing of computer vision and natural language (Noda et al., 2015; Oyedotun and Khashman, 2017). Applications of the DL technique in hydrologic, climate, and environmental sciences have started to emerge only very recently (Fang et al., 2017; Shen, 2018; Reichstein et al., 2019; Hrnjica and Mehr, 2020), but are gaining significant momentum at the current time. Despite their state of infancy, such DL model-based studies have provided encouraging results, with generally more reliable and accurate predictions for water-related processes. Consequently, the DL technique is being increasingly recommended for forecasting environmental time series, especially for its ability to provide robust and scalable solutions (Shen, 2018; Shen et al., 2018).

The DL technique is essentially based on ANN. However, it differs from the traditional FFNN in terms of the number and types of hidden layers. The DL defines a deep learning network (DLN), consisting of two or more hidden layers. The hidden layers can be of different structure, type or dimension, depending on the complexity of the problem. The DLN may contain one or more of the following layers:

- Normalization layer: It normalizes the data before it gets into another layer. It can be placed at the beginning or in the interior of the network. Data normalization is an important step in DL, and it helps to remove the dimensional differences in the input data and improve the prediction ability (Zhu et al., 2019). In this study, the widely used Z-score method (Heddam, 2016; Zhu et al., 2019) was used (Fig. 4).
- Encoding/Decoding layer: This layer is part of the Autoencoders network. The autoencoder network represents a set of layers mostly used for dimensionality reduction and feature extraction.
- Convolution layer: This layer is used as feature transformation, and

dimensionality reduction as a part of the subnetwork usually called Convolutional Network.

- Recurrent neural network layer: This layer can be of LSTM, Gated Recurrent Unit (GRU) or classic RNN layer based on recurrent neural network. In this study, the widely used LSTM layer (Liang et al., 2018; Hrnjica and Bonacci, 2019) was used (Fig. 4).
- Dropout layer: It is a special layer for preserving overfitting in the network. It is widely used in DL (Wu and Gu, 2015). It can be placed between any two layers in the DL network.
- Dense layer: It is a fully connected feed-forward network layer. In this layer, all activation neurons/units are connected to all the inputs, and the information is passed to the next layer.

The DL model proposed in this study consisted of different layers: Normalization, Encoding, LSTM, Dropout, and Dense layers (Fig. 4).

Insert Figure 4 here

2.5 Model structure

In the present study, we lumped the data from the above 69 lakes in Poland into one dataset. For the two models, the whole dataset was divided into two parts: one part for model training, and the other for model testing. For each lake, the data was trained separately. The training dataset consisted of 280 monthly water level values for each lake (almost 2/3rd), and the remaining data of each lake were used as the testing dataset (almost 1/3rd) (Hrnjica and Bonacci, 2019). Model input was the water levels of the previous two months, and model output was the water level of the month for which forecasting was to be made. After model training and testing, the modelling results were reconstructed for each lake. The workflow of data preparation, multivariate time series construction into data frame machine learning ready dataset, and data frame deconstruction into time series for each lake using the DL model is presented in Fig. 5. The same procedure was followed for the construction of the FFNN model.

Insert Figure 5 here

Data preparation, model training, and evaluations were performed using ANNdotNET, a deep learning tool on the .NET platform (Hrnjica, 2018). The ANNdotNET implements the machine learning engine based on Cognitive Toolkit (CNTK), a deep learning framework developed by Microsoft Research (Yu et al., 2014).

For the FFNN and DL models, the number of iterations was fixed to 10000, and the early stopping criterion was used by saving models for every 25 epochs. The internal parameters of the models were determined by trial and error, and the criterion was to minimize the modeling error. For LSTM, cells per layer were 150; for FFNN, neurons per layer were 150. For both models, Adam learner was used; the learning rate was set as 0.01; momentum value was set as 0.85; squared error (SE) was used as the loss function; relative mean squared error (RMSE) was used as the evaluation function; and minibatch size was set as 75. The source codes, model data and model structure files can be found in Github: https://github.com/bhrnjica/69lakes.

2.6 Model performance measures

In this study, model accuracy was assessed with two evaluation measures: the relative root mean squared error ($\overline{\mathrm{RMSE}}$) and the coefficient of correlation (R). These are given by:

$$\overline{RMSE} = \sqrt{\frac{1}{P}\sum_{i=1}^{P}(O_i - M_i)^2}/O_m \quad (2)$$

$$R = \left[\frac{\frac{1}{P}\sum(O_i - O_m)(M_i - M_m)}{\sqrt{\frac{1}{P}\sum_{i=1}^{P}(O_i - O_m)^2}\sqrt{\frac{1}{N}\sum_{i=1}^{P}(M_i - M_m)^2}}\right] \quad (3)$$

where P is the total number of data points, O_i is the measured lake water level and M_i is the forecasted lake water level, and O_m and M_m are, respectively, the average values of O_i and M_i. The reason we used $\overline{\mathrm{RMSE}}$ in this study is that it would be easier to assess model performance with large datasets between multiple lakes, since these lakes may have quite different annual average lake water levels.

3. Results and Discussion

The variation of the model error (RMSE: relative mean squared error) for all the lakes against the number of iterations is presented in Fig. 6. As seen, the RMSE values decreased with the increase in the number of iterations, and tended to be stable after about 8000 iterations. When the training process was completed, the best model was selected and the results were evaluated. The results from the FFNN and DL models are presented next.

Insert Figure 6 here

DL model: Table S2 also presents the lake water level forecasting results obtained using the FFNN model for the training and testing datasets. In the training period, the $\overline{\text{RMSE}}$ values varied between 1.21% (Lake Raduńskie Górne) and 23.31% (Lake Charzykowskie), with an average value of 5.25%; and the R values ranged between 0.45 (Lake Drużno) and 0.98 (Lake Lednica), with an average value of 0.82. In the testing period, the model performed better with lower $\overline{\text{RMSE}}$ values. The $\overline{\text{RMSE}}$ values ranged from 0.73% (Lake Raduńskie Górne) to 15.75% (Lake Charzykowskie), with an average value of 4.56%; and the R values varied between 0.31 (Lake Łebsko) and 0.97 (Lake Lednica), with an average value of 0.80.

In the training period, the $\overline{\text{RMSE}}$ values for 63 of the 69 lakes (91.3%) were found to be less than 10% and for 43 of the 69 lakes (62.3%) were less than 5%. The R values for 51 of the 69 lakes (73.9%) were greater than 0.8 and for 28 of the 69 lakes (40.6%) were greater than 0.9. In the testing period, the $\overline{\text{RMSE}}$ values for 65 of the 69 lakes (94.2%) were less than 10% and for 49 of the 69 lakes (71.0%) were less than 5%. The R values for 45 of the 69 lakes (65.2%) were greater than 0.9 and for 25 of the 69 lakes (36.2%) were greater than 0.9. These results indicate that the forecasting results from the DL model were generally good for most of the 69 lakes studied here. Fig. 8, for example, presents the time series comparison of the observed water level values and the DL-modeled water level values for eight selected lakes for which the DL model performed better than that for the other lakes: Śniardwy, Wigry, Wdzydze, Ińsko, Sławianowskie, Leleskie, Mikołajskie, and Lednica.

Insert Figure 8 here

Comparing the forecasting results obtained from the FFNN and DL models (Table S2 and Figures 9 and 10), it was found that, for most of the lakes, the two models performed nearly the same, with only marginal differences. This observation was similar to that reported in the study by Hrnjica and Bonacci (2019), which compared the DL and FFNN models for lake water level forecasting in the Vrana Lake, Croatia. The spatial distributions of $\overline{\text{RMSE}}$ and R indicated that, for the two models, model errors were heterogeneous spatially. The obtained results in the spatial system showed no evident similarities in the regional system (e.g., in reference to climatic regions, as is the case, for example, in the case of water temperature or ice phenomena (Ptak et al., 2018, 2019)). The situation was caused by the stronger influence of the local conditions on the course of water levels, as confirmed by earlier studies (Plewa et al., 2018; Wrzesiński et al., 2018).

The present results indicated that the DL model did not show any significant superiority over the traditional FFNN model for lake water level forecasting. This is, even more clearly shown in Figures 11 and 12 using the box and histogram plots. Indeed, the FFNN model slightly outperformed the DL model for 33 of the 69 lakes, while the DL performed slightly better than the FFNN model for 7 of the 69 lakes; for the remaining 29 lakes, the two models performed almost equally. However, from the point view of its overall performance, we can conclude that the DL model is a suitable and effective model to forecast lake water level fluctuations.

Insert Figure 9 here

Insert Figure 10 here

Insert Figure 11 here

Insert Figure 12 here

The generally accurate results obtained from the two models indicate that using the WL information from the past to estimate WL in the future is reliable. This has also been proved in a number of previous studies on lake WL modeling (e.g., Altunkaynak, 2007; Yarar et al., 2009; Güldal and Tongal, 2010; Kisi et al., 2012; Buyukyildiz et al., 2014; Shiri et al., 2016; Bonakdari et al., 2019). Therefore, for the study area, the modeling results can be used to: (1) inform water supply, as water availability is determined by lake water level; and (2) provide guidelines for flood-control and lake management.

With these encouraging results, it is also important to note that, for some lakes, both the DL model and the FFNN model performed poorly in water level forecasting.

This is exemplified by Lake Charzykowskie, and also several other cases: Roś, Białe Augustowskie and Rajgrodzkie. For Lake Charzykowskie, as seen in Table S2, both models have higher $\overline{\mathrm{RMSE}}$ values (>22% in the training period and >15% in the testing period), even though the R values are greater than 0.8. The poor performance of both the models may have been mainly due to the model input used. For instance, for both models, water level information during the previous two time periods (i.e. months) were used as model input for forecasting of water level at the current time period (i.e. month). In the case of those lakes, however, due to the effect of anthropogenic activity, frequent water level fluctuations were observed. Lake Charzykowskie is fed by the Brda River (mean flow rate 11.0 m^3 s^{-1}, station Swornegacie). On some selected sections of the river, artificial clearing of its channel is necessary to facilitate water flow (otherwise the surrounding areas would be flooded), affecting the water level fluctuation dynamics. Another factor is a weir located in Mylof, regulating the water level in the river depending on the needs of the local power plant. Lake Roś is located below the system of the Great Masurian Lakes – the largest river-lake system in Poland connected with canals, and artificially regulated. Water levels are determined by the operation of the Karwnik dam closing the entire hydrographic system to the south. Lake Białe Augustowskie is an important part of the Augustów Canal – a waterway already exploited for almost two centuries, where the water level is regulated by a system of weirs and dams. In the case of Lake Rajgrodzkie, Chrzanowski (1995) emphasized its role as a retention reservoir used as a source of water for irrigation of the Kuwasy peatland. Therefore, the sole use of information on water level as input data for the model may be insufficient to capture the water level dynamics. Further research is required to verify and confirm this.

Key information in this scope, as evidenced in the cited examples, should particularly cover local conditions, especially since it is now difficult to find lakes not impacted by humans in terms of water level fluctuations. They are regulated directly on the water outflow from the lake (weirs, floodgates on the outflow), or hydrotechnical works are conducted in their vicinity. As reported by several studies on water level fluctuations in Polish lakes (Wrzesiński and Ptak, 2016; Plewa et al., 2018; Wrzesiński et al., 2018; Nowak and Ptak, 2019), it is the processes occurring in the catchment, and not climatic factors (which are obviously important, but constitute a background for activities undertaken by humans), that are primarily responsible for the dynamics of water level fluctuations in lakes.

Nowak and Ptak (2018a) described a situation where a floodgate renovated in 2010, located on the outflow from Lake Powidzkie, along with high precipitation in the period, contributed to the prolongation of the occurrence of high water levels. In the case of Lake Wierzchowo, hydrotechnical infrastructure was the primary element determining the course of water levels. Due to the increased frequency of local floods, the lake dam was abandoned, which considerably changed the current water level regime and conditions related to the course of water levels (Ptak, 2015a). Cieśliński (2016) described a case of coastal Lake Jamno, where the construction of a floodgate contributed to a reduction of the amplitude of water level fluctuations in the lake by an order of 30–40 cm annually. According to Dorożyński and Skowron (2002), in the case of Lake Gopło, as a result of melioration works, the water level permanently decreased by more than 3 m. Moreover, situations where water level regulation caused complete disappearance of lakes are numerous (Ptak, 2015b, 2017). The above examples point to a broad range of adaptation of lakes with artificially regulated water level fluctuations.

From the perspective of the observed climate changes, it will be important to have detailed knowledge on the possibilities of conducting water management in reference to natural lakes, constituting easily available water reservoirs. Activities undertaken by the governmental agencies in Poland aim at an increase in water retention, and lakes constitute the key element of the programme. In the case of only one administrative region (Wielkopolskie Voivodeship), it is estimated that damming of lakes will result in an increase in water resources by approximately 33008 million m^3 (www.wzmiuw.pl). Therefore, the results from the present study may prove to facilitate making decisions concerning hydrotechnical infrastructure on lakes, and in a further perspective shaping water resources. It is a situation requiring relatively fast and universal solutions, considering among others the overgrowing and shallowing of lakes (Choiński et al., 2014, 2016).

The territory of Poland is among the least abundant in water in Europe. Due to this, extensive activities have been undertaken aimed at prolongation of water retention in the environment. One of the primary elements potentially rapidly retaining water resources are lakes and the possibility of their damming (Nowak and Ptak, 2018b). The results obtained from the present study will permit better modelling of water level fluctuations, which is key for conducting proper water management on particular lakes.

Importantly, the knowledge can provide the basis for future planning of potential regulation works.

4. Conclusions

In this study, two machine learning models, including the traditional Feed forward neural network (FFNN) model and the Deep Learning (DL) model, were used for forecasting time series of monthly water level in lakes. The two models were applied to water level data from 69 temperate lakes in Poland. The results from this study led to the following conclusions:

(1) The FFNN and DL models performed generally well for lake water level forecasting, indicating the successful application of the FFNN and DL models for multivariate times series forecasting.

(2) The FFNN and DL models performed nearly the same for most of the lakes, with only marginal differences.

(3) The DL model did not show any significant superiority over the traditional FFNN model for lake water level forecasting.

(4) For lake water level forecasting, using the traditional machine learning models maybe sufficient when such models are well calibrated.

The results from the present study have important implications for research on water level forecasting in lakes, especially from the viewpoint of employing Deep Learning methods. Although the FFNN and DL models used in this study generally performed well, further improvements are still needed. For some lakes, both the FFNN model and the DL model produced poor results, which may have been induced by the model input used in this study. Many other influencing factors, such as meteorological variables, inflow to lakes, and water withdrawal from lakes often significantly impact water level fluctuations in these lakes. It is important to properly consider these variables and refine the models to achieve more reliable outcomes. We will address this in our future studies.

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Figure captions

Figure 1. Locations of the 69 lakes in Poland considered in this study. The detailed characteristics of these lakes are listed in Table S1 (breakline- maximum range of the Vistulian Glaciation).

Figure 2. Monthly lake level time series for eight lakes, as examples: (a) Śniardwy; (b) Wigry; (c) Wdzydze; (d) Sępoleńskie; (e) Sławianowskie; (f) Studzieniczne; (g) Selmet Wlk; and (h) Rospuda.

Figure 3. Schematic representation of the recurrent neural network (top) and the structure of the long short-term memory (LSTM) cell (bottom) : $x_1, x_2,...,x_t$ are model inputs; $h_1, h_2,...,h_t$ are model outputs; f_t is the forget gate; i_t is the input gate; $\hat{c}_t$ is the cell update; C_t is the cell state; and o_t is the output gate.

Figure 4. Network configuration of the deep learning model (the long short-term memory (LSTM)) used in this study: x_i is the input; z is the normalized value of the input (the Z-score method was used); and h_i is the output.

Figure 5. Workflow of data preparation, multivariate time series construction into data frame machine learning ready dataset, and data frame deconstruction into time series of the 69 lakes: TS is time series; and t_1-t_n are input variables.

Figure 6. Model error (RMSE: root mean squared error) vs number of iterations for the training and testing datasets.

Figure 7. Comparison of the observed and modeled (testing period) lake level time series for eight of the studied lakes of the feed forward neural network model: (a) Śniardwy; (b) Wigry; (c) Wdzydze; (d) Ińsko; (e) Sławianowskie; (f) Leleskie; (g)

Mikołajskie; and (h) Lednica.

Figure 8. Comparison of the observed and modeled (testing period) lake level time series for eight of the studied lakes of the long short-term memory recurrent neural network model: (a) Śniardwy; (b) Wigry; (c) Wdzydze; (d) Ińsko; (e) Sławianowskie; (f) Leleskie; (g) Mikołajskie; and (h) Lednica.

Figure 9. Spatial distribution of the two measures (relative root mean squared error (RMSE) and coefficient of correlation (R)) for the feed forward neural network (FFNN) model.

Figure 10. Spatial distribution of the two measures (relative root mean squared error (RMSE) and coefficient of correlation (R)) for the long short-term memory (LSTM) model.

Figure 11. Comparison of the model performance between the feed forward neural network (FFNN) and long short-term memory (LSTM) models using the box plots. Two measures: relative root mean squared error (RMSE) and coefficient of correlation (R).

Figure 12. Comparison of the model performance between the feed forward neural network (FFNN) and long short-term memory (LSTM) models using the histogram plots for the model testing period. Two measures: relative root mean squared error (RMSE) and coefficient of correlation (R).

Figure 1

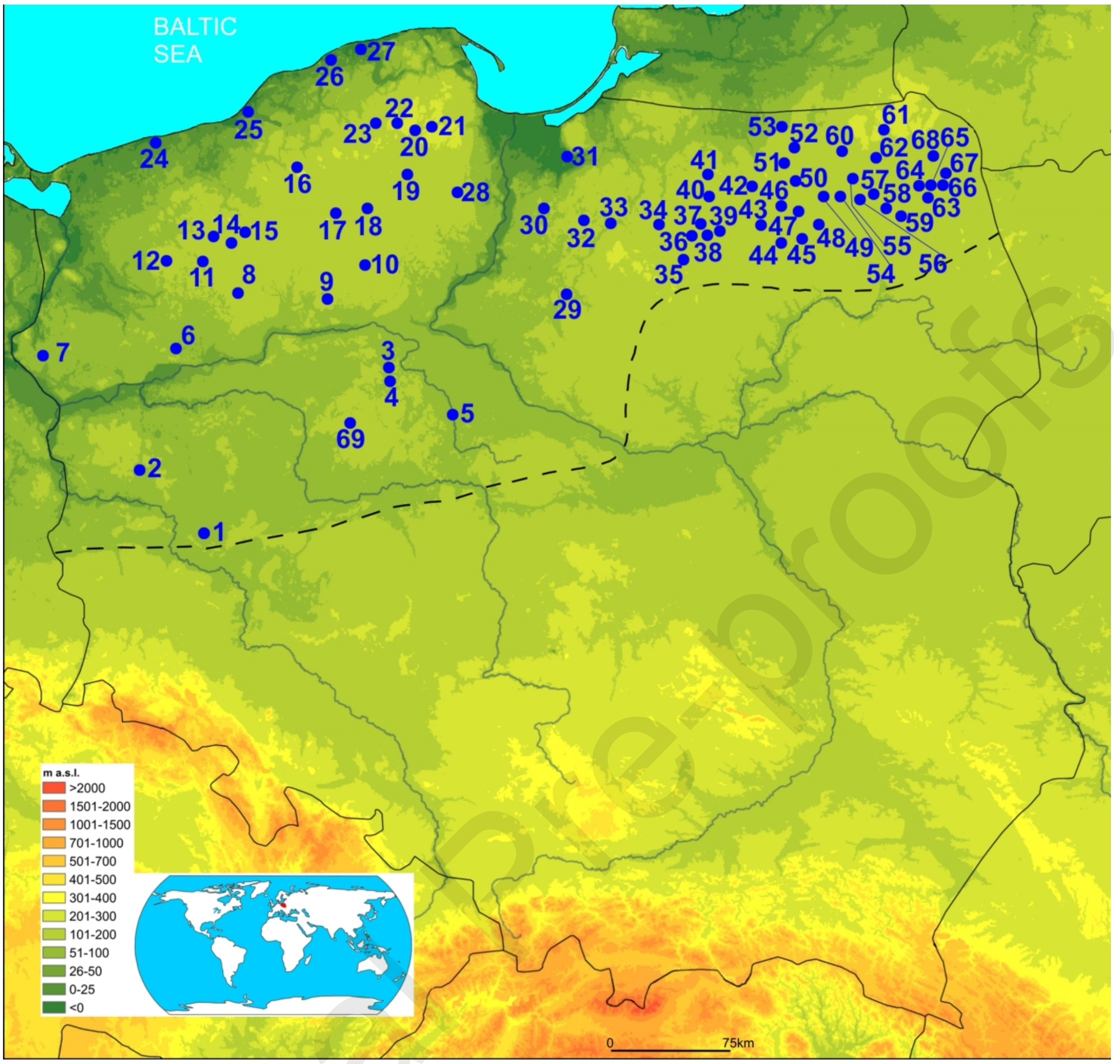

BALTIC SEA
m a.s.l.
>2000
1501-2000
1001-1500
701-1000
501-700
401-500
301-400
201-300
101-200
51-100
26-50
0-25
<0
0
75km

Figure 2

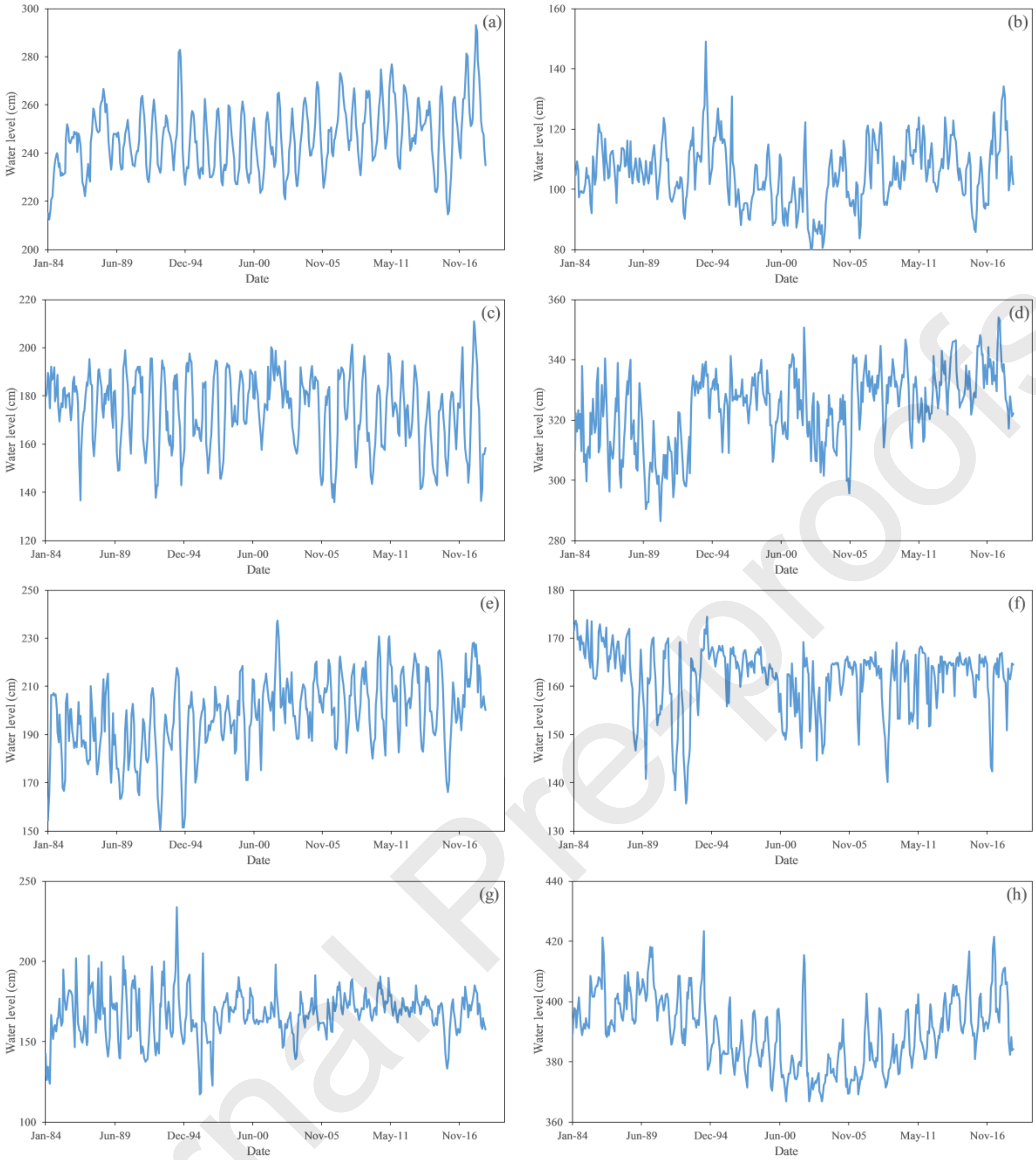

(a)
(b)
(c)
(d)
(e)
(f)
(g)
(h)
Water level (cm)
Date
Jan-84
Jun-89
Dec-94
Jun-00
Nov-05
May-11
Nov-16

Figure 3

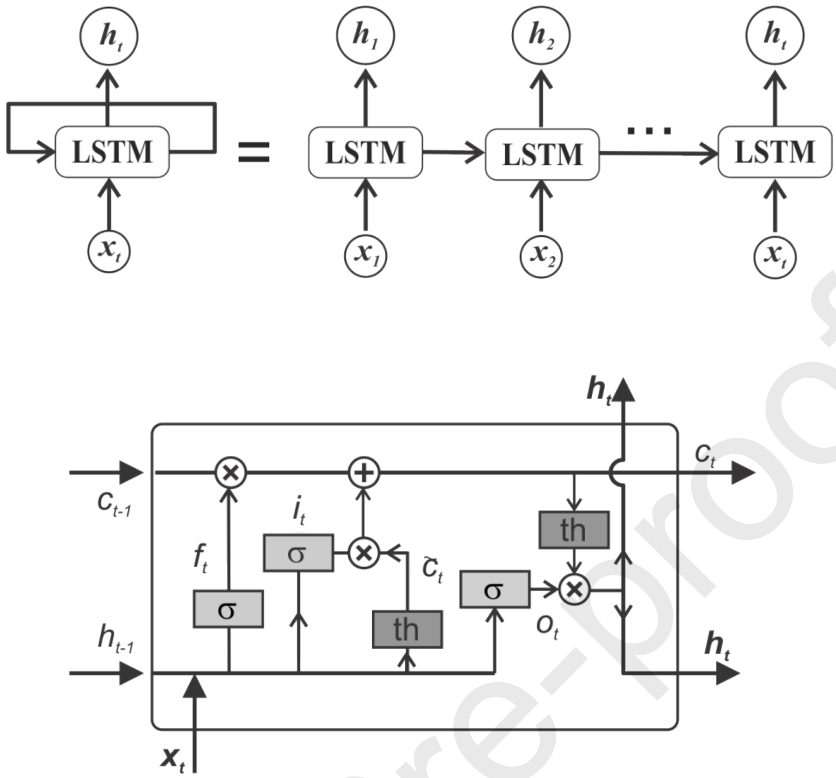


Figure 4

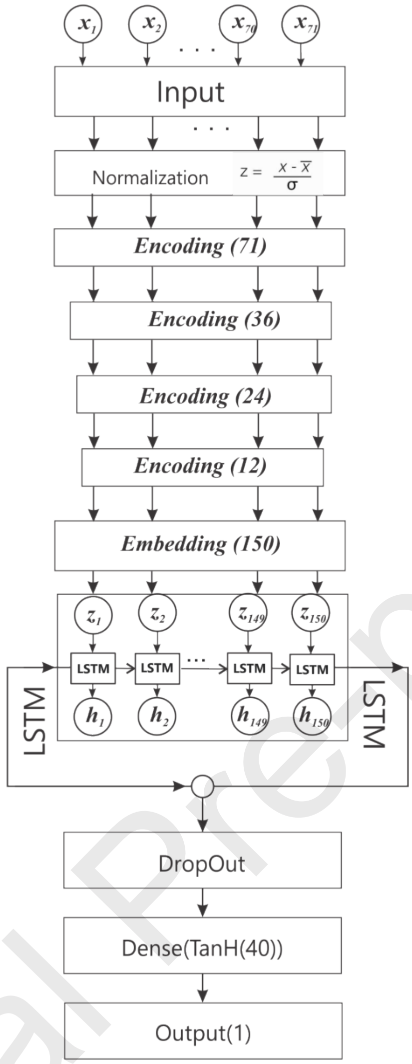

x_1
x_2
x_{70}
x_{71}
Input
Normalization
$z = \frac{x - \bar{x}}{\sigma}$
Encoding (71)
Encoding (36)
Encoding (24)
Encoding (12)
Embedding (150)
z_1
z_2
z_{149}
z_{150}
LSTM
LSTM
LSTM
LSTM
h_1
h_2
h_{149}
h_{150}
LSTM
LSTM
DropOut
Dense(TanH(40))
Output(1)

Figure 5

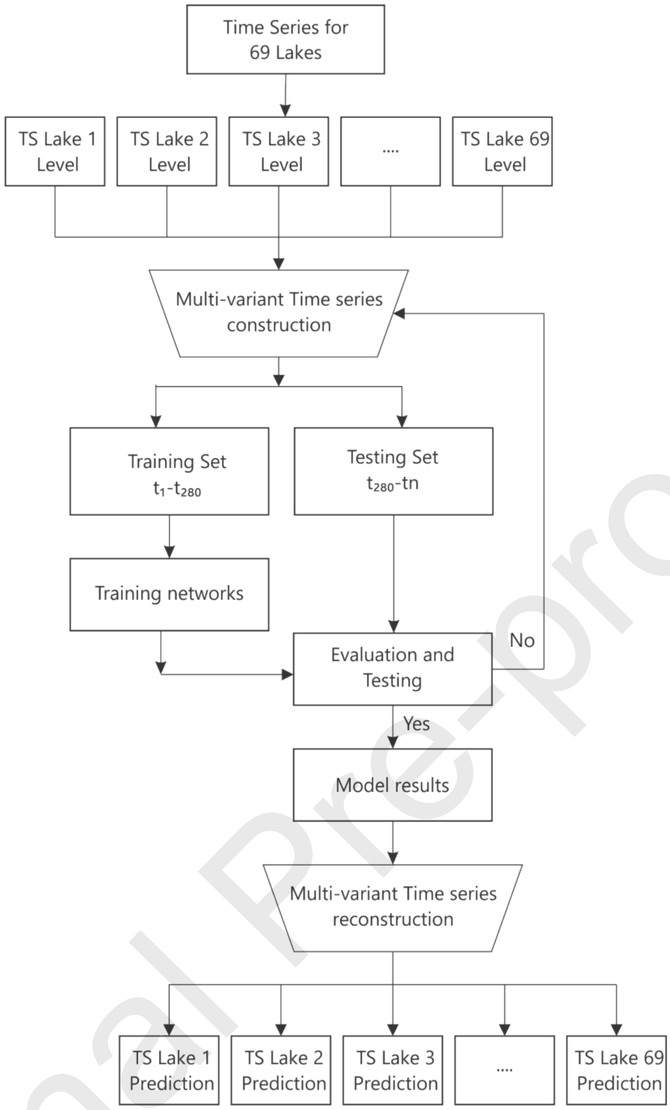

Time Series for 69 Lakes
TS Lake 1 Level
TS Lake 2 Level
TS Lake 3 Level
....
TS Lake 69 Level
Multi-variant Time series construction
Training Set t_1-t_{280}
Testing Set t_{280}-tn
Training networks
Evaluation and Testing
No
Yes
Model results
Multi-variant Time series reconstruction
TS Lake 1 Prediction
TS Lake 2 Prediction
TS Lake 3 Prediction
....
TS Lake 69 Prediction

Figure 6

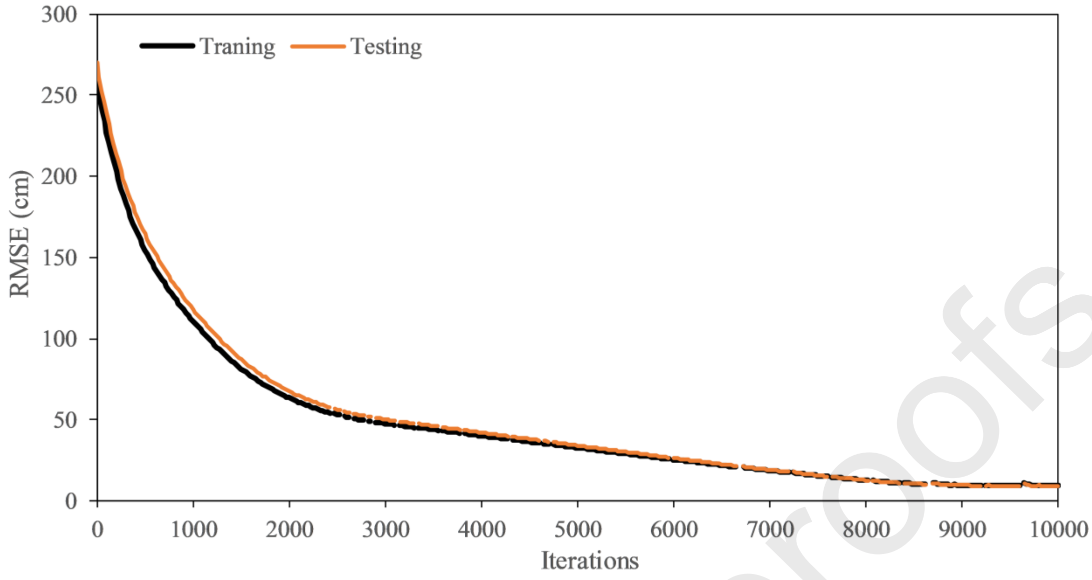

Traning
Testing
RMSE (cm)
Iterations
0
50
100
150
200
250
300
0
1000
2000
3000
4000
5000
6000
7000
8000
9000
10000

Figure 7

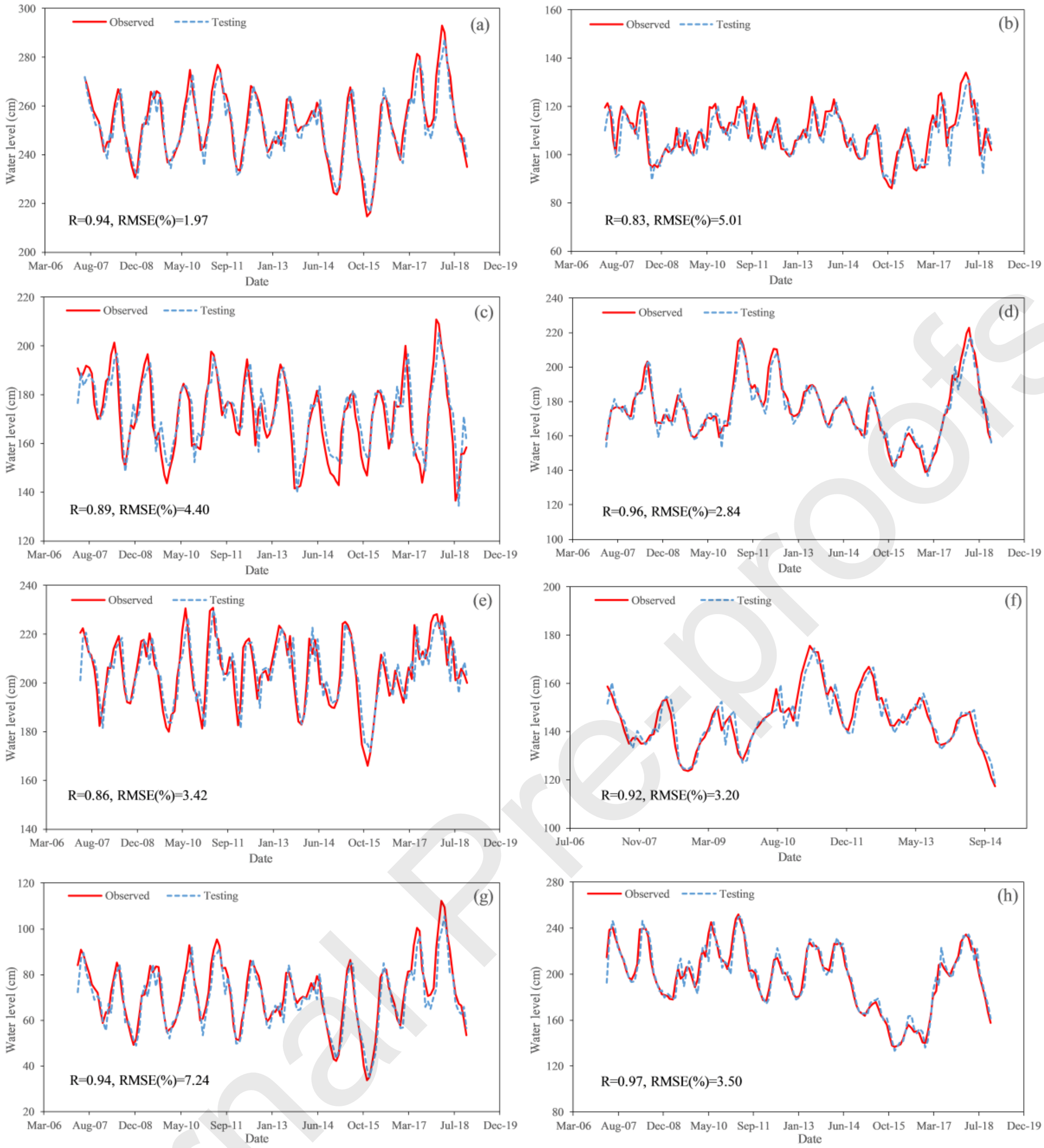
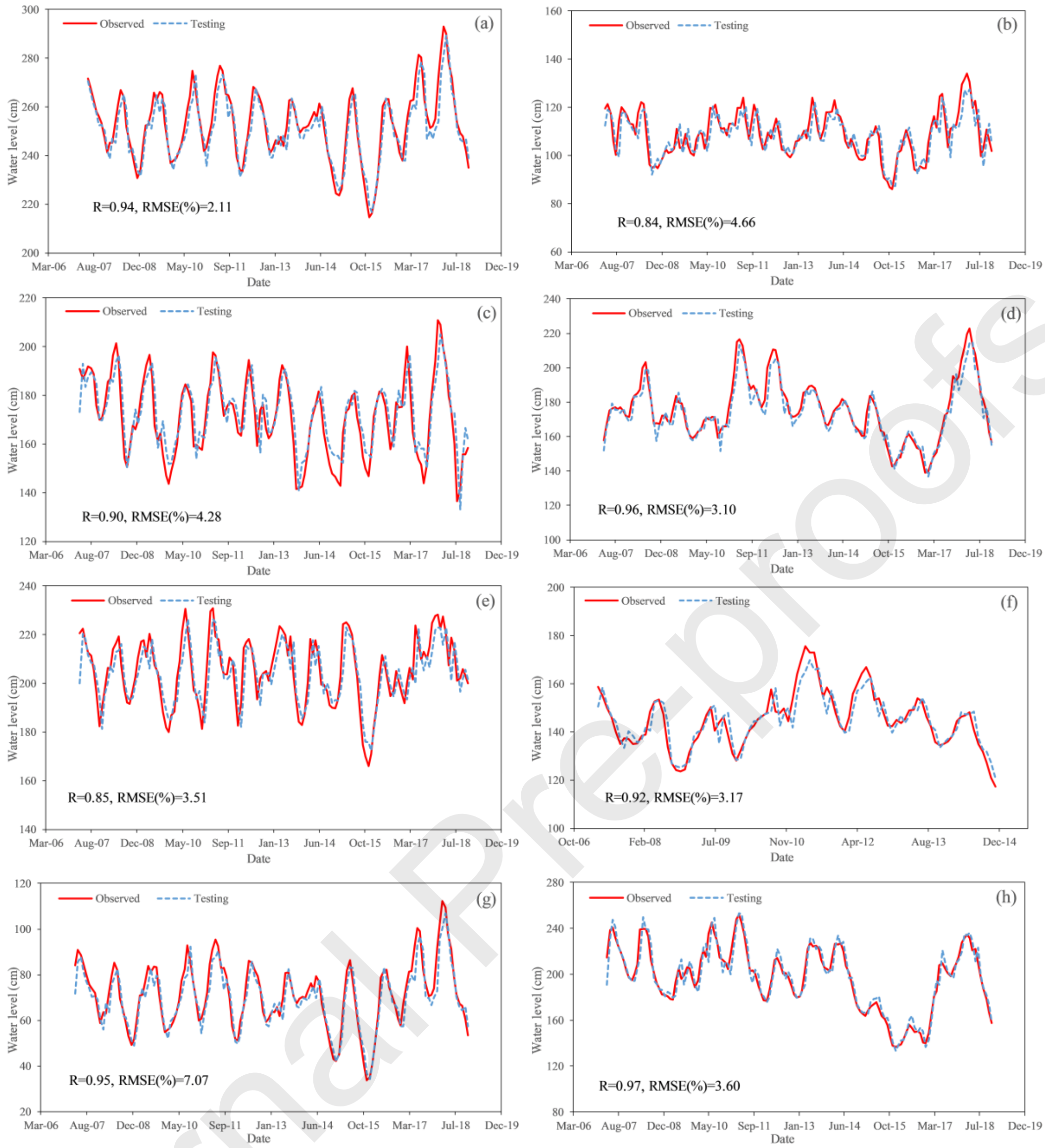

Observed
Testing
(a)
R=0.94, RMSE(%)=1.97
(b)
R=0.83, RMSE(%)=5.01
(c)
R=0.89, RMSE(%)=4.40
(d)
R=0.96, RMSE(%)=2.84
(e)
R=0.86, RMSE(%)=3.42
(f)
R=0.92, RMSE(%)=3.20
(g)
R=0.94, RMSE(%)=7.24
(h)
R=0.97, RMSE(%)=3.50
Water level (cm)
Date
Mar-06 Aug-07 Dec-08 May-10 Sep-11 Jan-13 Jun-14 Oct-15 Mar-17 Jul-18 Dec-19
Jul-06 Nov-07 Mar-09 Aug-10 Dec-11 May-13 Sep-14

Figure 8



Observed
Testing
(a)
R=0.94, RMSE(%)=2.11
(b)
R=0.84, RMSE(%)=4.66
(c)
R=0.90, RMSE(%)=4.28
(d)
R=0.96, RMSE(%)=3.10
(e)
R=0.85, RMSE(%)=3.51
(f)
R=0.92, RMSE(%)=3.17
(g)
R=0.95, RMSE(%)=7.07
(h)
R=0.97, RMSE(%)=3.60
Water level (cm)
Date

Figure 9

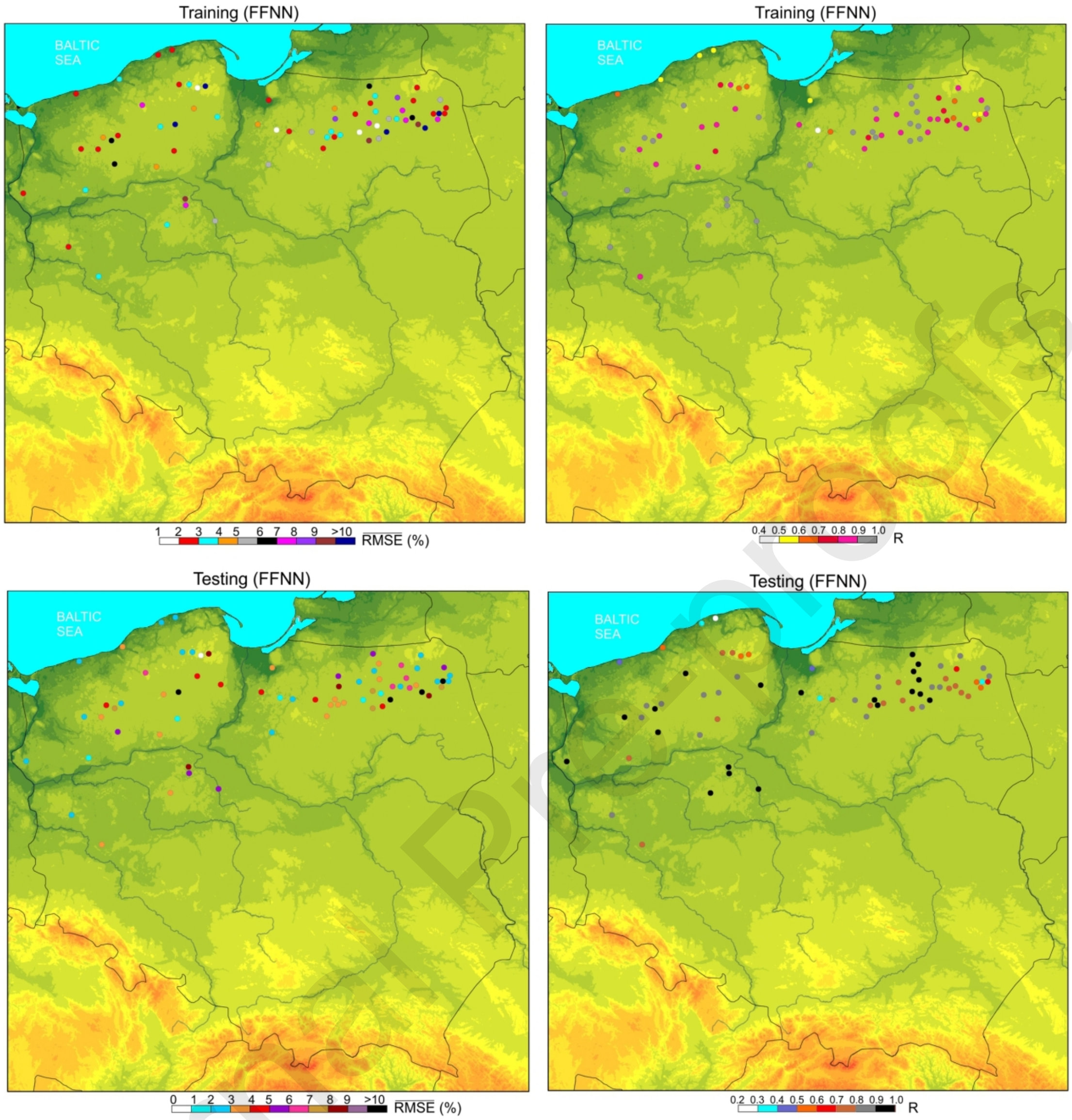

Training (FFNN)
BALTIC SEA
1 2 3 4 5 6 7 8 9 >10 RMSE (%)
Training (FFNN)
BALTIC SEA
0.4 0.5 0.6 0.7 0.8 0.9 1.0 R
Testing (FFNN)
BALTIC SEA
0 1 2 3 4 5 6 7 8 9 >10 RMSE (%)
Testing (FFNN)
BALTIC SEA
0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1.0 R

Figure 10

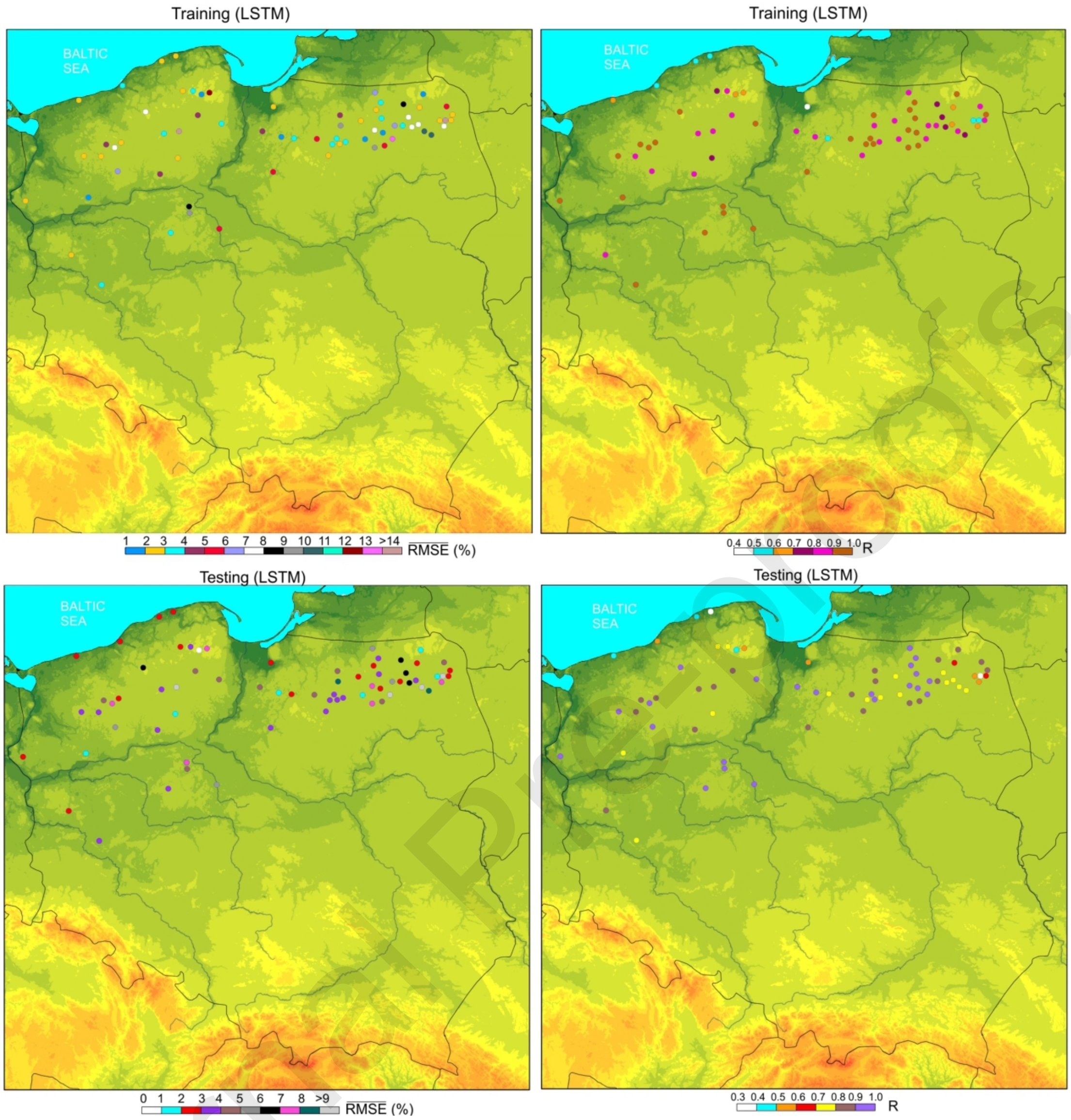
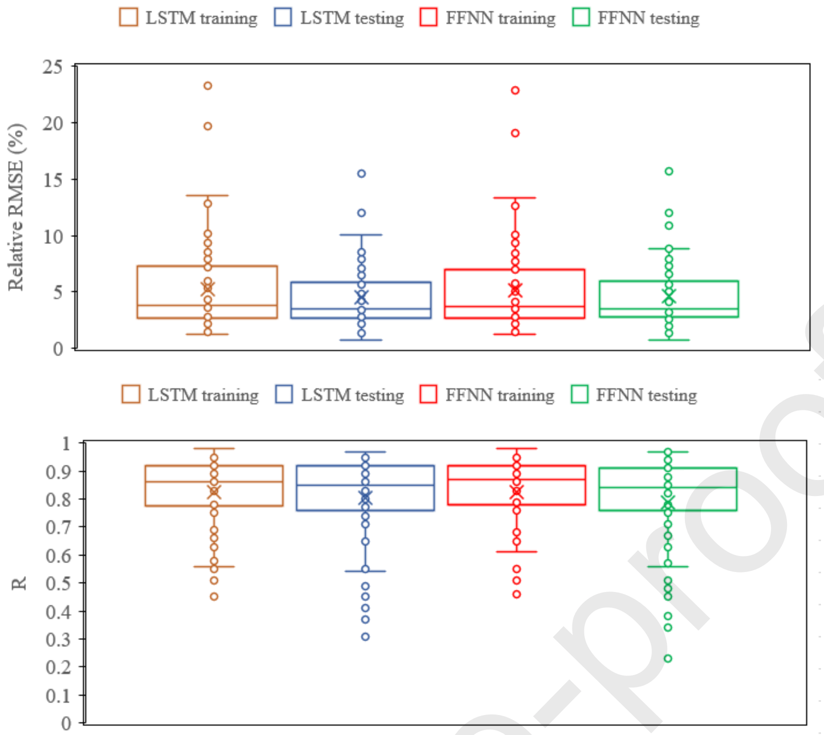
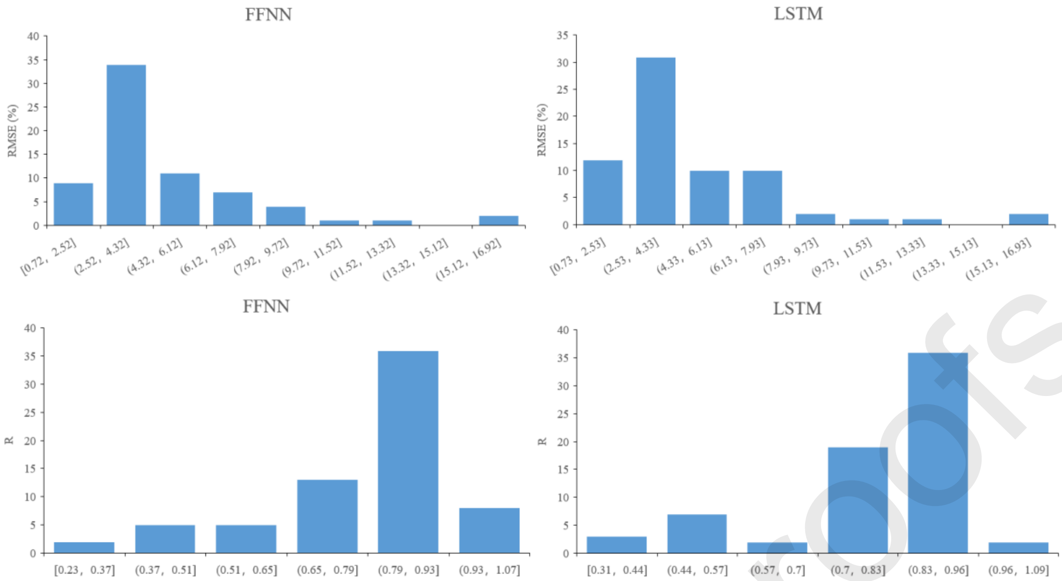

Training (LSTM)
BALTIC SEA
1 2 3 4 5 6 7 8 9 10 11 12 13 >14 RMSE (%)
Training (LSTM)
BALTIC SEA
0.4 0.5 0.6 0.7 0.8 0.9 1.0 R
Testing (LSTM)
BALTIC SEA
0 1 2 3 4 5 6 7 8 >9 RMSE (%)
Testing (LSTM)
BALTIC SEA
0.3 0.4 0.5 0.6 0.7 0.8 0.9 1.0 R

Figure 11



LSTM training
LSTM testing
FFNN training
FFNN testing
Relative RMSE (%)
25
20
15
10
5
0
LSTM training
LSTM testing
FFNN training
FFNN testing
R
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0

Figure 12


FFNN
LSTM
RMSE (%)
[0.72，2.52]
(2.52，4.32]
(4.32，6.12]
(6.12，7.92]
(7.92，9.72]
(9.72，11.52]
(11.52，13.32]
(13.32，15.12]
(15.12，16.92]
[0.73，2.53]
(2.53，4.33]
(4.33，6.13]
(6.13，7.93]
(7.93，9.73]
(9.73，11.53]
(11.53，13.33]
(13.33，15.13]
(15.13，16.93]
R
[0.23，0.37]
(0.37，0.51]
(0.51，0.65]
(0.65，0.79]
(0.79，0.93]
(0.93，1.07]
[0.31，0.44]
(0.44，0.57]
(0.57，0.7]
(0.7，0.83]
(0.83，0.96]
(0.96，1.09]

CRediT author statement

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Senlin Zhu: Supervision, Funding Acquisition, Conceptualization, Methodology, Project Administration, Investigation, Software, Writing – Original Draft, Writing – Review & Editing. **Bahrudin Hrnjica:** Software, Conceptualization, Writing – Review & Editing. **Mariusz Ptak:** Data analysis, Conceptualization, Writing – Review & Editing. **Adam Choiński:** Data analysis, Conceptualization, Writing – Review & Editing. **Bellie Sivakumar**: Supervision, Writing – Review & Editing.

Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: