Environmental Science and Pollution Research (2020) 27:44807–44819
https://doi.org/10.1007/s11356-020-10917-7

REVIEW ARTICLE

Lake water-level fluctuation forecasting using machine learning models: a systematic review

Senlin Zhu[1,2] · Hongfang Lu[3] · Mariusz Ptak[4] · Jiangyu Dai[2] · Qingfeng Ji[1]

Received: 3 July 2020 / Accepted: 17 September 2020 / Published online: 25 September 2020

Abstract
Lake water-level fluctuation is a complex and dynamic process, characterized by high stochasticity and nonlinearity, and difficult to model and forecast. In recent years, applications of machine learning (ML) models have yielded substantial progress in forecasting lake water-level fluctuations. This paper presents a comprehensive review of the applications of ML models for modeling water-level dynamics in lakes. Among the many existing ML models, seven popular ML model types are reviewed: (1) artificial neural network (ANN); (2) support vector machine (SVM); (3) artificial neuro-fuzzy inference system (ANFIS); (4) hybrid models, such as hybrid wavelet-artificial neural network (WA-ANN) model, hybrid wavelet-artificial neuro-fuzzy inference system (WA-ANFIS) model, and hybrid wavelet-support vector machine (WA-SVM) model; (5) evolutionary models, such as gene expression programming (GEP) and genetic programming (GP); (6) extreme learning machine (ELM); and (7) deep learning (DL). Model inputs, data split, model performance criteria, and model inter-comparison as well as the associated issues are discussed. The advantages and limitations of the established ML models are also discussed. Some specific directions for future research are also offered. This review provides a new vision for hydrologists and water resources planners for sustainable management of lakes.

Keywords Lakes · Water-level modeling · Stochasticity · Nonlinearity · Machine learning

Abbreviations

ADP	Absolute deviation percent
AI	Artificial intelligence
AIC	Akaike information criterion
ANFIS	Adaptive neuro-fuzzy inference system
ANN	Artificial neural network
AR	Autoregressive
ARMA	Autoregressive moving average
BNN	Bayesian neural network
CC	Correlation coefficient
DL	Deep learning
ELM	Extreme learning machine
ERM	Empirical risk minimization
ESN	Echo state network
FA	Firefly algorithm
FFNN	Feed-forward neural network
GAANN	Genetic algorithm artificial neural network
GEP	Gene expression programming

Responsible editor: Marcus Schulz

✉ Senlin Zhu
slzhu@nhri.cn

✉ Jiangyu Dai
jydai@nhri.cn

✉ Qingfeng Ji
qfji@yzu.edu.cn

Hongfang Lu
luhongfang_sci@126.com

Mariusz Ptak
marp114@wp.pl

[1] College of Hydraulic Science and Engineering, Yangzhou University, Yangzhou 225127, China

[2] State Key Laboratory of Hydrology-Water Resources and Hydraulic Engineering, Nanjing Hydraulic Research Institute, Nanjing 210029, China

[3] Division of Construction Engineering and Management, Purdue University, West Lafayette, IN 47907, USA

[4] Department of Hydrology and Water Management, Adam Mickiewicz University, Krygowskiego 10, 61-680 Poznan, Poland

GMDH	Group method of data handling
GP	Genetic programming
KGE	Kling–Gupta efficiency
LLNF	Local linear neuro-fuzzy
LMI	Legate and McCabe's index
LSTM	Long short-term memory
MA	Moving average
MAE	Mean absolute error
MAPE	Mean absolute percentage error
ML	Machine learning
MLPNN	Multilayer perceptron neural network
MLPNN-FA	Multilayer perceptron neural network coupled with firefly algorithm
MSE	Mean squared error
MSRE	Mean squared relative error
MS4E	Higher order mean squared error
NMSE	Normalized mean squared error
NRMSD	Normalized root mean squared deviation
NSC	Nash–Sutcliffe coefficient
NWN	Neural wavelet network
PSO	Particle swarm optimization
PSO-ANN	Artificial neural networks based on particle swarm optimization
R^2	Coefficient of determination
RAE	Relative absolute error
RBNN	Radial basis neural network
RF	Random forest
RL	Residual
RMAE	Relative mean absolute error
RMSE	Root mean squared error
RMSE	Relative root mean squared error
RNN	Recurrent neural network
RRSE	Root relative squared error
RT	Random tree
SBC	Schwarz Bayesian criterion
SCC	Squared correlation coefficient
SD	Standard deviation
SEP	Standard error prediction
SI	Scatter index
SRM	Structural risk minimization
SS	Skill score
SVM	Support vector machine
SVM-FA	Support vector machine coupled with firefly algorithm
SY	Similarity
VAF	Variance accounted for
WA	Wavelet analysis
WA-ANFIS	Hybrid wavelet-artificial neural fuzzy inference system
WA-ANN	Hybrid wavelet-artificial neural network
WA-MLPNN	Hybrid wavelet-multilayer perceptron neural network
WA-SVM	Hybrid wavelet-support vector machine
WDDFF	Wavelet data-driven forecasting framework
WI	Willmott's index of agreement
WL	Water level

Introduction

Lakes are important water sources on the earth. They play a significant role in domestic, industrial, and agricultural water supplies; regional flood control; and aquaculture, among others. Water level (WL) is one of the most important physical indicators of lakes/reservoirs, and its dramatic fluctuations may greatly impact lake ecosystems (Coops et al. 2003; Wantzen et al. 2008; Zohary and Ostrovsky 2011; Evtimova and Donohue 2016; Bakker and Hilt 2016), and cause serious consequences for regional flood control. For example, Evtimova and Donohue (2016) found that water-level fluctuations regulate the structure and functioning of natural lakes, and the study by Bakker and Hilt (2016) indicated that water-level fluctuations impact cyanobacterial blooms in lakes. It is, therefore, of great importance to have an accurate forecasting of water-level fluctuations in lakes.

Forecasting of water-level dynamics is a challenging task, as lake WL fluctuations are influenced by many factors, including meteorological, hydrological, and geological variables. The past decades witnessed the development and application of many mathematical models for WL forecasting in lakes, such as physically based models (Riley and Stefan 1988; Hostetler and Bartlein 1990; Muvundja et al. 2014), stochastic models (Şen et al. 2000; Aksoy et al. 2013), and system dynamic models (Hassanzadeh et al. 2012; Alifujiang et al. 2017). In recent decades, with the fast development of artificial intelligence (AI), there has been a boom of machine learning models in WL forecasting of lakes (Khan and Coulibaly 2006; Altunkaynak 2007; Çimen and Kisi 2009; Güldal and Tongal 2010; Kakahaji et al. 2013; Buyukyildiz et al. 2014; Das et al. 2016; Zaji et al. 2018; Zhu et al. 2020a).

The outcomes of the above studies are certainly encouraging, especially considering the fact that applications of machine learning models for the forecasting of WL in lakes are still at an early stage, when compared with the traditional approaches. At the same time, however, there also remain many questions and challenges, both in the implementation of the models and in the interpretation of the outcomes. For example, how to determine the input combinations to improve model reliability? How to split the available datasets to better capture water-level dynamics under the impact of climate change and influence of extreme events? Which model is more reliable? This is largely due to the fact that our knowledge of machine learning models is still very limited, as the concepts and methods are themselves fairly new and continue to be developed. These are currently leading to two different perceptions and activities: one is that there is a significant growth in the applications of machine learning models for water-level forecasting in lakes, and the other is that there is growing skepticism on the studies applying machine learning models for water-level forecasting in lakes and the reported outcomes. These contrasting perceptions necessitate a review of the available applications of machine learning models for WL forecasting in lakes, so that a better understanding and communication of the development of the methods, positive outcomes of their applications, and the challenges that still remain can be achieved.

In view of the above, the present study reviews the applications of machine learning models for WL forecasting in lakes. Because of their popularity and number of applications, seven ML model types are reviewed: (1) artificial neural network (ANN); (2) support vector machine (SVM); (3) artificial neuro-fuzzy inference system (ANFIS); (4) hybrid models by integration of wavelet analysis and artificial neural network, artificial neuro-fuzzy inference system, and support vector machine models; (5) evolutionary models (e.g., genetic programming (GP), gene expression programming (GEP)); (6) extreme learning machine (ELM); and (7) deep learning (DL). Among the challenges, how to determine the input combinations to improve model reliability and how to split the available datasets to better capture water-level dynamics under the impact of climate change and influence of extreme events are discussed.

The rest of this paper is organized as follows. "Machine learning models for lake water-level forecasting" section reviews the ML models. "Methodological aspects and the associated limitations" section discusses the methodological aspects and the associated limitations, such as the model inputs, data split for model evaluation, and model performance criteria. "Model evaluation and inter-comparison" section presents the advantages and disadvantages of the established ML models, and model inter-comparison. The major findings and future directions are summarized in "Conclusions and future directions" section.

Machine learning models for lake water-level forecasting

Up to date, many ML approaches have been promoted for modeling water levels in lakes. Table 1 presents a summary of the studies that have applied the ML models for lake WL forecasting. The ML models applied include (1) ANN; (2) SVM; (3) ANFIS; (4) hybrid models, such as hybrid WA-ANN model, hybrid WA-ANFIS model, hybrid WA-SVM model, SVM-FA, and MLPNN-FA; (5) evolutionary ML models, such as GP and GEP; (6) ELM; (7) DL; and (8) other models, such as RFs, RT, and GMDH. A brief description of these methods and their applications for WL forecasting in lakes is presented next.

Artificial neural network

Artificial neural network is a powerful computation tool. It has the capacity to solve complex nonlinear problems, which makes it attractive for applications in various fields, such as water temperature modeling (Piotrowski et al. 2015; Graf et al. 2019; Zhu et al. 2019a; Zhu et al. 2020b) and water quality predictions (Palani et al. 2008; Wu et al. 2014; Luo et al. 2019). Generally, an ANN model consists of the input, hidden, and output layers. Firstly, in the input layer, the input data are processed, and the weighted sum is computed; then, in the hidden layer, the data is further processed; finally, in the output layer, we get the results. The most popular ANN models are multilayer feed-forward neural network (FFNN) learned by backpropagation algorithm, radial basis neural network (RBNN), multilayer perceptron neural network (MLPNN), recurrent neural network (RNN), and Bayesian neural network (BNN).

ANNs have been widely employed to forecast lake water levels (see Table 1). For example, Altunkaynak (2007) used ANNs to forecast WL fluctuations in Lake Van, Turkey. The results show that the ANN model is more simple and reliable than the conventional methods, such as autoregressive (AR), moving average (MA), and autoregressive moving average (ARMA) models. Ondimu and Murase (2007) employed ANNs to model WL in Lake Naivasha, Kenya. The results indicated that the ANNs were able to forecast effectively the WL dynamics for the lake.

Support vector machine

Support vector machine has resilient conjectural statistical configuration, which makes it more robust in handling classification, regression, and forecasting problems (Suykens and Vandewalle 1999). The SVM models have also shown strong capability in adaptability, global optimization, and good generalization (Basudhar et al. 2012). The SVM model applies statistical learning theory and structural risk minimization hypothesis. It is a kernel-based model, developed by Cortes and Vapnik (1995), which can lessen the complexity and prediction error of the model. Kernels are special nonlinear functions created by nonlinear mapping, which allows the model to separate complicated hyperplanes. Proper selection of a kernel is the key to produce excellent model performance. The most common choices are linear, polynomial, radial basis, and sigmoid functions.

Similar to the ANN models, the SVM has also been widely used to model WL fluctuations in lakes (see Table 1). For example, Khan and Coulibaly (2006) applied the SVM model for WL prediction in Lake Erie. The results showed that the SVM exhibited innate advantages because it employs the structural risk minimization principle to format the cost functions, and it uses quadratic programming to optimize the

Table 1 Summary of studies applying machine learning models for forecasting of water levels in lakes

Reference	Temporal scale	Model	Model inputs	Performance evaluation criteria	Ratio of the testing data to total length of data
Khan and Coulibaly (2006)	Monthly	SVM, MLPNN	Water level	RMSE, CC	0.14
Altunkaynak (2007)	Monthly	ANN	Water level, rainfall	MAE, NSC	0.17
Altunkaynak and Şen (2007)	Monthly	ANFIS	Water level, rainfall	MAE	0.07
Ondimu and Murase (2007)	Monthly	MLPNN	Water level	MSE	0.06
Çimen and Kisi (2009)	Monthly	SVM, ANN	Water level	R^2, MSE, MAPE, NSC	0.20, 0.23
Yarar et al. (2009)	Monthly	ANN, ANFIS	Water level, evaporation, rainfall	R^2, MSE	0.24
Coulibaly (2010)	Monthly	RNN, BNN, ESN	Water level	CC, RMSE	0.21
Güldal and Tongal (2010)	Monthly	RNN, ANFIS	Water level, incoming runoff and discharge, rainfall, evaporation	RMSE, RMAE, AIC, SBC	0.13
Talebizadeh and Moridnejad (2011)	Monthly	MLPNN, ANFIS	Water level, inflow, evaporation, precipitation	CC, RMSE, MAE	0.36
Karimi et al. (2012)	Daily	GEP, ANFIS	Water level	R^2, RMSE, VAF	0.25
Kisi et al. (2012)	Daily	ANN, ANIFS, GEP	Water level	R^2, RMSE, SI, WI	0.15
Valizadeh et al. (2011, 2014), Valizadeh and El-Shafie (2013)	Daily	ANFIS	Water level, rainfall	CC, RMSE, MAE, MAPE	0.17
Hipni et al. (2013)	Daily	SVM, ANFIS	Water level, rainfall	RMSE, MAPE, MAE, CC	-
Kakahaji et al. (2013)	Monthly	MLPNN, LLNF	Water level, evaporation, rainfall, inflow	CC, RMSE, SY	0.38
Altunkaynak (2014)	Monthly	WA-ANFIS, WA-MLPNN	Water level	NSC, RMSE, MAE	0.34
Buyukyildiz et al. (2014)	Monthly	PSO-ANN, SVM, MLPNN, RBNN, ANFIS	Water level, inflow, rainfall, evaporation, outflow	R^2, RMSE, MAE, MSE	0.21
Khatibi et al. (2014)	Monthly	ANN, GEP	Water level	CC, MAPE, RMSE	0.20
Lan (2014)	Daily	SVM	Water level	RMSE, MAPE, SCC	-
Noury et al. (2014)	Yearly	SVM, NWN	Water level, rainfall, temperature, discharge	R^2, RMSE	0.24
Ashaary et al. (2015)	Daily	ANN	Water level	MSE	0.10
Kisi et al. (2015)	Daily	SVM-FA, GP, MLPNN	Water level	R^2, RMSE, CC	0.25
Seo et al. (2015)	Daily	WA-ANN, WA-ANFIS	Water level	R^2, NSC, WI, RMSE, MAE, MSRE, MS4E	0.25
Young et al. (2015)	Hourly	ANN	Water level, inflow and outflow discharges, rainfall	CC, RMSE, MAE, SS	0.50
Das et al. (2016)	Daily	FFNN, BNN	Water level	R^2, RMSE, MAE, NRMSD, CC	0.05-0.06
Li et al. (2016)	Daily	RF, ANN, SVM	Water level	R^2, RMSE, NSC	0.33
Shafaei and Kisi (2016)	Monthly	WA-SVM, WA-ANFIS	Water level	CC, RMSE, MAE	0.14
Shiri et al. (2017)	Daily	GP, ANN, ELM	Water level	R^2, CC, RMSE	0.25
Yadav and Eliza (2017)	Daily	WA-SVM	Water level, rainfall, evaporation, evapotranspiration	R^2, NSC, NMSE, RMSE	0.33
Yang et al. (2017)	Daily	RF, RBNN, RT,	Water level, temperature, rainfall, pressure, relative humidity, wind	RMSE, MAE, CC, RRSE, RAE	0.34
Ghorbani et al. (2018)	Monthly	MLPNN-FA	Water level	NSC, RMSE, MAE, WI	0.30

Table 1 (continued)

Reference	Temporal scale	Model	Model inputs	Performance evaluation criteria	Ratio of the testing data to total length of data
Liang et al. (2018)	Daily	SVM, DL	Water level, water inflow, rainfall	R^2, RMSE	0.27
Piasecki et al. (2018)	Monthly	ANN, WA-ANN	Water level, evaporation, rainfall	R^2, RMSE, MAE, MSE, MAPE	0.15
Zaji et al. (2018)	Daily	GMDH	Water level	R^2, RMSE, MAE, ADP, SEP, SD, SL	0.50
Hrnjica and Bonacci (2019)	Monthly	DL, FFNN	Water level	CC, RMSE	0.25
Zaji and Bonakdari (2019)	Daily	GP, GAANN	Water level	R^2, RMSE, MAE, ADP	0.50
Yaseen et al. (2020)	Monthly	MLPNN, RF	Water level	R^2, RMSE, NSC, WI, LMI	0.2
Zhu et al. (2020a)	Monthly	FFNN, DL	Water level	CC, RMSE	0.33

model, which leads to a global solution compared with the conventional ANN models, such as MLPNN. Çimen and Kisi (2009) used the SVM model for WL forecasting in Lake Van, Turkey, and found that the SVM-based model performed better than the ANN.

Artificial neuro-fuzzy inference system

Fuzzy logic models have proved to be a powerful tool in solving complex computational problems. They have the capability to deal with nonlinearity, uncertainty, and subjective data. The most widely applied fuzzy logic model is the adaptive neuro-fuzzy inference system (ANFIS). The ANFIS model is a multilayer feed-forward network, which utilizes a neural network learning algorithm. It has the capability to identify nonlinear boundaries and fuzzy logic to distinguish nonlinear equations and map the input–output space. It has the ability to achieve a highly nonlinear mapping. The stages of ANFIS consist of choosing the type of interfere system such as Mamdani, Sugeno, and Tsumoto; aggregation; and defuzzification (Karaboga and Kaya 2019).

The ANFIS models have been widely used to forecast water levels in lakes. For example, Altunkaynak and Şen (2007) used the ANFIS model for WL forecasting in Lake Van, Turkey. They obtained better forecasting results (lower absolute errors) with the Takagi–Sugeno fuzzy approach when compared with that with the autoregressive integrated moving average model. Yarar et al. (2009) compared the ANFIS and ANN models for WL forecasting in Lake Beysehir, Turkey, and found that the ANIFS model outperformed the ANN model. Kisi et al. (2012) applied the ANFIS model for WL forecasting in Lake Iznik in Western Turkey, and they obtained that the ANIFS model outperformed the ARMA model. Other studies that have applied the ANFIS models for WL forecasting in lakes include Güldal and Tongal (2010), Talebizadeh and Moridnejad (2011), Karimi et al. (2012), Valizadeh and El-Shafie (2013), Hipni et al. (2013), Buyukyildiz et al. (2014), and Seo et al. (2015).

Hybrid models

The hybrid models are the integration of wavelet analysis or optimization algorithms (e.g., firefly algorithm, particle swarm optimization) and ML models.

Wavelet analysis (WA) is capable of performing wavelet decomposition, denoising, and forecasting (Sang 2013). Wavelet analysis, as an excellent preprocessing tool, can solve the limitation of various AI models in handling nonstationary data. The WA-based hybrid model harbors the qualities of the WA and the AI model, but its performance is based on the selection of a competent mother wavelet and decomposition level (Graf et al. 2019). The mother wavelets that are most frequently used are Daubechies (levels 2, 4, 10) and Haar.

There are two common forms of wavelet analysis: (1) discrete wavelet analysis, which deals with discrete signals and decomposes the times series into subsignals at a specific wavelet and decomposition level (Daubechies 1988), and (2) continuous wavelet analysis, which deals with continuous signals and is applied for disclosing features of time series under multitemporal scales (Rioul and Duhamel 1992).

As summarized in Table 1, for WL forecasting using WA and AI, the hybrid models are WA-ANN (Altunkaynak 2014; Seo et al. 2015; Piasecki et al. 2018), WA-ANFIS (Altunkaynak 2014; Seo et al. 2015; Shafaei and Kisi 2016), and WA-SVM (Shafaei and Kisi 2016; Yadav and Eliza 2017).

Apart from WA, other models have also been coupled with AI for forecasting water levels in lakes. Examples include coupling of firefly algorithm (FA) or particle swarm optimization (PSO) with AI models, such as PSO-ANN in Buyukyildiz et al. (2014), SVM-FA in Kisi et al. (2015), and MLPNN-FA in Ghorbani et al. (2018). Firefly algorithm is based on a definite behavioral pattern (e.g., fireflies' flashing behavior). The FA has been proved to be a robust and efficient method to search global and local optima (Fister et al. 2013). Its coupling with AI models has been proved to be robust for WL forecasting in lakes as well (Kisi et al. 2015; Ghorbani et al. 2018).

Evolutionary machine learning models

Evolutionary ML models, such as GEP and GP, have been widely used in hydrological studies (Hashmi et al. 2011; Coulibaly 2004; Mehr et al. 2013; Mehr 2018). The GEP is a genetic algorithm (the same as GP). It uses populations of individuals, and selects them according to fitness. According to Ferreira (2001), the main advantages of the GEP method are (1) the chromosomes are simple entities and (2) the expression trees are exclusively the expression of their respective chromosomes.

Applications of the GEP and GP methods for lake WL forecasting are summarized in Table 1. Studies using these models include Karimi et al. (2012), Kisi et al. (2012, 2015), Khatibi et al. (2014), Shiri et al. (2017), and Zaji and Bonakdari (2019). For example, Karimi et al. (2012) compared the performance of the GEP and ANFIS models for daily WL forecasting in Urmieh Lake, Iran. The model intercomparison showed that the GEP outperformed the ANFIS and ARMA models. The results from these studies indicated that the GEP and GP models can be used to model water-level fluctuations in lakes with high accuracy.

Extreme learning machine

Extreme learning machine (ELM) method was firstly proposed by Huang et al. (2004, 2006). This model randomly selects the input weights, and analytically sets the output weights. The ELM method has a fast learning speed, and it is robust for computation as well. Because the ELM model analytically determines all the network parameters, indicating that it does not need many human interventions, it can work more efficient compared with the conventional algorithms.

Though the ELM models have been widely used in hydrological studies (Feng et al. 2016; Deo et al. 2016; Yadav et al. 2016; Rezaie-Balf and Kisi 2018; Zhu et al. 2019b), its application for lake WL forecasting is limited. To our knowledge, there has been only one study thus far (Shiri et al. 2017). In their study, Shiri et al. (2017) predicted the daily WL of the Urmia Lake, Iran, using ELM, GP, and ANN models, and the results showed that the ELM approach outperformed the GP and ANN models.

Deep learning

With the fast development of AI, deep learning (DL) models, such as the long short-term memory (LSTM), deep restricted Boltzmann machine, and stack Autoencoder, have been successfully applied in many studies (Fang et al. 2017; Shen et al. 2018). Among these DL methods, the LSTM is one type of advanced ANN network that includes feedback connections in its model architecture. Meanwhile, it consists of the memory blocks with self-connection (in the hidden layer), which can store the temporal state of the network.

Applications of the DL models for lake WL predictions (see Table 1) include those by Liang et al. (2018), Hrnjica and Bonacci (2019), and Zhu et al. (2020a). Liang et al. (2018) developed a LSTM-based DL model to forecast WL in Lake Dongting, China, and found that the LSTM model has better accuracy compared with the SVM model. Hrnjica and Bonacci (2019) compared the performance of the LSTM and FFNN models for monthly WL forecasting in Vrana Lake, Croatia, and the results showed that both model types can achieve satisfactory results. Zhu et al. (2020a) applied the LSTM and FFNN models for monthly WL predictions in 69 lakes in Poland, Central Europe, and the obtained results showed that the FFNN and LSTM (DL) models performed nearly the same for most of the lakes, with only marginal differences.

Other models

In addition to the models discussed above, some other models have also been used for lake WL forecasting. Such models include RFs and RT (Yang et al. 2017), and group method of data handling (GMDH) (Zaji et al. 2018), among others. As reported by these studies, such models have been proved to be able to forecast well the WL dynamics in lakes. For example, Yang et al. (2017) developed the RF model to forecast WL in Shimen Reservoir, Taiwan, and they found that the proposed time series forecasting model is feasible for forecasting water levels in the reservoir.

Methodological aspects and the associated limitations

In this section, the methodological aspects in the implementation of the above methods and the associated limitations are presented, such as the selection of model inputs, data split for model training and testing, and model performance criteria.

Model inputs

Most of the studies on lake WL forecasting have focused on daily or monthly lake WL dynamics (see Table 1). This is mainly due to the issue of data availability. To the best of our knowledge, only the studies by Noury et al. (2014) and Young et al. (2015) have analyzed other scales, i.e., yearly or hourly variations. For model inputs, all the studies have used the past WL information. Also, most of the studies have predicted WL fluctuations from the perspective of time series forecasting by using only the past WL information as model input (Khan and Coulibaly 2006; Ondimu and Murase 2007; Çimen and Kisi 2009; Coulibaly 2010; Karimi et al. 2012; Kisi et al. 2012; Altunkaynak 2014; Khatibi et al. 2014; Lan 2014; Seo et al. 2015; Ashaary et al. 2015; Kisi et al. 2015; Das et al. 2016; Li et al. 2016; Shafaei and Kisi 2016; Shiri et al. 2017; Ghorbani et al. 2018; Zaji et al. 2018; Hrnjica and Bonacci 2019; Zaji and Bonakdari 2019; Zhu et al. 2020a), rather than from the respect of water balance. For these studies, the optimal input combinations are usually determined by model trial and error.

Some studies have modeled the lake WL dynamics based on the concept of water balance. Therefore, in addition to the past WL information, they have also used inflow/outflow, rainfall, and evaporation as model inputs (Güldal and Tongal 2010; Talebizadeh and Moridnejad 2011; Kakahaji et al. 2013; Buyukyildiz et al. 2014; Young et al. 2015; Liang et al. 2018). Some other studies have used the past WL information and meteorological variables (e.g., rainfall, evaporation, temperature, evapotranspiration, pressure, relative humidity, wind) as model inputs (Altunkaynak 2007; Altunkaynak and Şen 2007; Yarar et al. 2009; Valizadeh et al. 2011, 2014; Valizadeh and El-Shafie 2013; Hipni et al. 2013; Noury et al. 2014; Yadav and Eliza 2017; Yang et al. 2017; Piasecki et al. 2018).

Modeling WL dynamics in lakes is a challenging task as it is influenced by many factors. From the point of view of water balance, lake WL dynamics are mainly modeled using inflow/outflow, rainfall, and evaporation conditions. Thus, these information should be used as model inputs when they are readily available. However, as summarized in Table 1, most of the current studies did not include meteorological variables and inflow/outflow conditions as model inputs, which may bring large uncertainties for the model results.

Data split for model training and testing

In hydrological time series forecasting, the raw data may be divided into three data sets: training, validation, and testing. The training dataset is used to fit the model; the validation dataset is used to adjust the parameters of the trained model, and the testing dataset is used to measure the performance of the trained model. However, only 11 of 39 publications on ML applications for lake WL forecasting have divided the data into three subsets (training, validation, and testing). The majority of the works (26/39) have split the available datasets into only two subsets: training and testing. Two studies (Hipni et al. 2013; Lan 2014) did not split the data for model evaluation. As summarized in Table 1, the ratio of the testing data ranges from 0.05 to 0.50.

Most of the studies on applications of ML methods for lake WL forecasting (listed in Table 1) have used sequential data for model evaluation. For example, in the study of Seo et al. (2015), the first 9-year data (2002–2010) was used for model training and the remaining 3-year data (2011–2013) was employed for model testing. This kind of data split may bring uncertainty for model evaluation. Further studies need to be conducted to evaluate the impact of data split scenarios on model performance.

Model performance criteria

For model performance evaluation criteria, as summarized in Table 1, the most commonly used indicators are the root mean squared error (RMSE), mean absolute error (MAE), correlation coefficient (CC), coefficient of determination (R^2), and Nash–Sutcliffe coefficient (NSC). Some other indicators, such as the mean squared error (MSE), mean absolute percentage error (MAPE), mean squared relative error (MSRE), normalized mean squared error (NMSE), and relative root mean squared error (RMSE), work in the way similar to RMSE and MAE.

In hydrological modeling, some new indicators are very popular. A typical example is the Kling–Gupta efficiency (KGE) (Gupta et al. 2009). The KGE is the decomposition of the MSE and NSC performance criteria, and the results have shown that it can improve model performance evaluation and identification (Gupta et al. 2009). Due to this, it has been widely used in hydrological modeling (Patil and Stieglitz 2015; Haas et al. 2016; Hirpa et al. 2018; Becker et al. 2019; Mathevet et al. 2020). However, for lake WL forecasting using ML models, the KGE criteria has never been used. It is highly suggested to employ these criteria in future studies.

Different ML models may have different number of parameters, such as the optimal number of hidden layers for ANN models, the number of rules for ANFIS models, and the learning rate and momentum for DL models. Thus, for model evaluation and inter-comparison, it is necessary to consider both the modeling errors and the independent parameters. The Akaike information criterion (AIC) and the Schwarz Bayesian criterion (SBC) are criteria of this kind (Akaike 1974; Schwarz 1978), which have been widely used for model evaluation and inter-comparison (Shabani et al. 2020; Singh and Najafi 2020; Yang et al. 2020; Wang et al. 2020). However, among the studies that have applied the ML methods for WL forecasting, there has been only one study that used these two criteria for model evaluation and inter-comparison (Güldal and Tongal 2010). To better evaluate the overall performance of each model, these criteria are highly recommended in future studies.

Model evaluation and inter-comparison

An examination of studies on lake water-level forecasting (see Table 1), especially studies that have compared ML models with traditional models, leaves little room for doubts on the superiority of the ML models over the traditional statistical methods (e.g., autoregressive, moving average, and autoregressive moving average models) in simulating lake water-level fluctuations. However, the question remains which category (e.g., ANN-based, SVM-based, ANFIS-based, evolutionary-based, hybrid models or DL-based) can be nominated as the best ML model in simulating lake water-level fluctuations. More investigative studies associated with this particular issue would lead to a definite and clear answer. Although the majority of researchers affirm the favorable results of all many types of ML models in simulating lake water-level fluctuations over the traditional methods based on model performance criteria, they do not unanimously present one specific model as the paramount one, which is hard to implement as we cannot request comparing all the ML models in one study. However, from the available studies (see Table 1), we can get some clues, as follows:

The superiority of the SVM

Khan and Coulibaly (2006) and Çimen and Kisi (2009) employed the SVM and MLPNN models for WL forecasting of Lake Erie in North America, and lakes Van and Egirdir in Turkey, respectively. They found that the SVM model outperformed the classic MLPNN model in simulating lake WL fluctuations. Hipni et al. (2013) compared the SVM and ANFIS models for WL forecasting in Klang Reservoir, Malaysia. The results indicated that the SVM is a superior model to the ANFIS, though the ANFIS model has been proved to outperform the ANN models in some other studies (Yarar et al. 2009; Güldal and Tongal 2010; Talebizadeh and Moridnejad 2011). Buyukyildiz et al. (2014) found that the SVM model outperformed the MLPNN, RBNN, and ANFIS models in forecasting the monthly WL change in Lake Beysehir (Turkey). The SVM is a relatively new ML algorithm based on the framework of structural risk minimization (SRM). The SRM has the ability of generalization, and it is preferable compared with the traditional empirical risk minimization (ERM) used in many conventional neural networks. Another advantage of the SVM over the ANN models is that it avoids the overfitting problems. The SVM model is trained using the quadratic programming with a global solution, and in this manner, it solves the problem of local minima suffered by the conventional neural networks (Çimen and Kisi 2009). In addition to the above studies, the capacity of the SVM model has also been proved in the study of Lan (2014), which applied the model for WL forecasting of Lake Poyang, China.

The superiority of the GP/GEP

One of the strong advantages of using the GP/GEP over the other ML models is in their abilities in producing explicit formulations of the relationship that rules the physical phenomenon. Additionally, they have higher model accuracy, and they have been well validated in many studies for lake WL forecasting. For example, Karimi et al. (2012) demonstrated that the GEP surpassed the ANFIS model for WL forecasting in Lake Urmieh, Iran; Kisi et al. (2012) found that the GEP approach performed better than the ANFIS and ANNs in predicting lake level dynamics in Lake Iznik, Turkey; Zaji and Bonakdari (2019) reported that the GP method outperformed the genetic algorithm artificial neural network (GAANN) in forecasting WL fluctuations in Lake Chahnimeh, Iran.

The superiority of the hybrid models

Integration of WA and ML models can help to improve the performance of ML models in hydrological modeling, which has been confirmed in a number of studies (Adamowski and Sun 2010; Adamowski and Chan 2011; Adamowski et al. 2012; Nourani et al. 2014; Belayneh et al. 2016; Graf et al. 2019; Zhu et al. 2019c, 2020b). For WL forecasting in lakes, the same conclusion can be drawn. For example, Altunkaynak (2014) and Seo et al. (2015) combined WA with the ANFIS and ANN models to predict WL fluctuations in Lake Michigan-Huron (USA), and Andong Reservoir (South Korea), respectively. The results revealed that the WA-ANFIS and WA-ANN models outperformed the stand-alone ANFIS and MLPNN models. Shafaei and Kisi (2016) integrated WA with ANFIS and SVM models and found that the integrated models yielded better precision in forecasting water levels in Lake Van (Turkey). Yadav and Eliza (2017) evaluated the performance of the WA-SVM model for WL forecasting in Lake Loktak (India), and found that WA could significantly improve the efficiency and accuracy of the SVM model. Piasecki et al. (2018) assessed the performance of the WA-ANN model for WL forecasting in a small glacial lake in Poland and reported that using WA as a preprocessing tool resulted in better predictions. The reason why the WA and ML integrated models performed better might be that the WA algorithm provided useful information of the original input time series by getting rid of the useless information (Adamowski and Chan 2011).

Though the WA and ML integrated models have been found to perform well for lake water-level forecasting, Quilty and Adamowski (2018) pointed out that some recent studies for the other hydrological time series incorrectly developed the hybrid WA and ML models. The major errors made by such studies, according to Quilty and Adamowski (2018) are (1) the use of future data as model input to the developed models, (2) inappropriate selection of the decomposition level and mother wavelet, and (3) not carefully partitioning the training and testing datasets. Without addressing the boundary conditions in applying WA, the studies incorrectly implemented the hybrid models, which led to better accuracy than what is realistically achievable. Quilty and Adamowski (2018) proposed a new forecasting framework, named wavelet data-driven forecasting framework (WDDFF), to avoid such errors. The WDDFF should be considered in future studies using hybrid WA and ML models.

In addition to WA, some other algorithms have also been coupled with the ML models for forecasting of lake WL dynamics, such as FA and PSO, which served to estimate the optimal parameters of the ML models. For example, Kisi et al. (2015) coupled FA with the SVM model to forecast lake WL dynamics in Lake Urmia (Iran), and found that the SVM-FA model performed better than GP and ANN models; Ghorbani et al. (2018) implemented the hybrid FA and MLPNN model for WL forecasting in Lake Egirdir (Turkey), and the results confirmed the robustness of the hybrid MLPNN-FA model over the standalone MLPNN model. The FA is a robust algorithm to estimate the optimal parameters of the ML models, and its coupling with the WA and ML integrated models is highly recommended for future studies: firstly, the WA is used as a pre-processing tool to denoising of the input data, which can solve the limitation of various AI models in handling nonstationary data; then, the ML models can be developed using the processed data as model inputs; finally, the FA is used to estimate the optimal parameters of the ML models, which can improve the model performance as well.

The superiority of the ELM

Extreme learning machine is an extension of the ANN model, and it is known as a fast-computational learning model, which has been certified as an online expert predictive system with great real-time application potential (Wang et al. 2013; Scardapane et al. 2014; Li et al. 2017). However, its application for lake water-level forecasting is limited (see Table 1). For a single hidden layer ELM model, the random initialization of weight of internal network during the learning process determines its efficiency; however, this framework can be a problem from a soft computing perspective, since the learning performance of the network can be affected by the single hidden layer, leading to inaccurate predictions. Therefore, efforts are being focused on the extension of the ELM model to a deep learning neural network model, where recurrent hidden layers are hosted in the feature space, thereby ensuring a better determination of the internal weight (Yu et al. 2015; Zeng et al. 2016). Their high accuracy and fast training/testing times have made them worth investigating for modeling water-level fluctuations in lakes.

Applicability of the DL

The DL models are highly recommended for hydrological and earth system studies (Shen et al. 2018). Shen et al. (2018) proposed to incubate the DL-powered hydrologic science advances as a research community. However, the applications of the DL models for lake WL forecasting are still very limited. Thus far, three studies (see Table 1) have used the LSTM-based DL model to forecast water levels in lakes (Liang et al. 2018; Hrnjica and Bonacci 2019; Zhu et al. 2020a).

The DL networks may include multiple processing layers to process data with multiple levels of abstraction. The DL models work well for large datasets; however, for smaller datasets, they are not that effective. The study of Zhu et al. (2020a) has clearly verified this point. In their study, monthly WL was predicted (35 years, 420 samples, small datasets), and the results showed that the DL model did not show significant superiority compared with the traditional ANN model (e.g., FFNN) for forecasting of lake WL. This has also been proved in other hydrological studies. For example, Gauch et al. (2019) found that tree-based models provide more accurate predictions on small datasets for streamflow prediction, while LSTM is superior given sufficient training data. However, for water-level forecasting with large datasets (e.g., daily timescale), the study of Liang et al. (2018) showed that the LSTM-based DL model has better accuracy compared with the SVM model for daily water-level prediction in Dongting Lake, China (daily data for 13 years). The above analysis suggests that the DL model is more effective for forecasting of lake WL with smaller temporal scale (e.g., daily timescale) with large datasets.

The other models

The other ML models, such as the RF model, have also shown their potentials in lake water-level forecasting. For example, the modeling results in Li et al. (2016) and Yang et al. (2017) confirmed that the RF model can be used as a robust tool for the prediction of lake water level. However, more work needs to be conducted to further test its efficiency.

Conclusions and future directions

Modeling of water levels in lakes is a very challenging issue with the possibility of diverse methodological approaches. Irrespective of the input data used (depending upon their availability), or mathematical methods, however, the primary objective of research on modeling lake water level is to provide possibly detailed and credible data on their course. According to the literature available, such a need is evident in different regions of the world, and concerns both groups of lakes and single lake. In many such regions, lakes are a key element of the environment that determines their attractiveness or economic development. As pointed out in the "Introduction" section, lake water level is an elementary parameter of lake ecosystems, and its dramatic fluctuation may cause a number of unpredictable effects. Therefore, it is necessary to forecast water-level fluctuations to allow for making optimal decisions at an appropriate moment in the scope of water management (e.g., through hydrotechnical regulations). Proper and sustainable lake management has gained particular importance due to increasingly frequently observed extreme climatic and hydrological events (droughts and floods). The possibility of mitigating of their effects requires detailed knowledge about the related hydrological processes (e.g., lake water-level dynamics).

This paper reviews the lake water-level forecasting works in the past decades. In total, seven main ML models are evaluated: ANN, SVM, ANFIS, hybrid models, evolutionary ML models, ELM, and DL. The pros and cons of the proposed ML models are discussed in detail. Model inputs, data split, model performance criteria, and model inter-comparison are analyzed.

Though great progress has been made on the applications of ML models to forecast water level in lakes, there are still many spaces for further investigations. The possible future directions include the following:

1. Evaluate the impact of data split scenarios on model performance
2. Use the criteria, such as KGE, AIC, and SBC for model evaluation
3. Employ the WDDFF as reference when using hybrid WA and ML models
4. Couple WA, FA, and ML models and test their efficiency
5. Evaluate the performance of the enhanced ELM models
6. Test the "breakeven point" when LSTM-based DL model begins to overtake the other models in length of the training Data.

Author contribution All the authors designed the research, performed the study, and wrote the paper.

Funding This work was jointly funded by the National Key R&D Program of China (2018YFC0407203) and China Postdoctoral Science Foundation (2018M640499).

Data availability Not applicable.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

References

Adamowski J, Chan HF (2011) A wavelet neural network conjunction model for groundwater level forecasting. J Hydrol 407:28–40
Adamowski J, Sun K (2010) Development of a coupled wavelet transform and neural network method for flow forecasting of non-perennial rivers in semi-arid watersheds. J Hydrol 390(1-2):85–91
Adamowski J, Chan HF, Prasher SO, Ozga-Zielinski B, Sliusarieva A (2012) Comparison of multiple linear and nonlinear regression, autoregressive integrated moving average, artificial neural network, and wavelet artificial neural network methods for urban water demand forecasting in Montreal, Canada. Water Resour Res 48(1): W01528
Akaike H (1974) A new look at the statistical model identification. In: Parzen E., Tanabe K., Kitagawa G. (eds) Selected Papers of Hirotugu Akaike. Springer Series in Statistics (Perspectives in Statistics). Springer, New York
Aksoy H, Unal NE, Eris E, Yuce MI (2013) Stochastic modeling of Lake Van water level time series with jumps and multiple trends. Hydrol Earth Syst Sci 17:2297–2303
Alifujiang Y, Abuduwaili J, Ma L, Samat A, Groll M (2017) System dynamics modeling of water level variations of Lake Issyk-Kul, Kyrgyzstan. Water 9(12):989
Altunkaynak A (2007) Forecasting surface water level fluctuations of Lake Van by artificial neural networks. Water Resour Manag 21(2):399–408
Altunkaynak A (2014) Predicting water level fluctuations in Lake Michigan-Huron using wavelet-expert system methods. Water Resour Manag 28(8):2293–2314
Altunkaynak A, Şen Z (2007) Fuzzy logic model of lake water level fluctuations in Lake Van, Turkey. Theor Appl Climatol 90(3-4): 227–233
Ashaary NA, Wan Ishak WH, Ku-Mahamud KR (2015) Forecasting the change of reservoir water level stage using neural network. In Proc. of the 2nd International Conference on Mathematical Sciences and Computer Engineering (ICMSCE 2015) (pp. 5-6)
Bakker ES, Hilt S (2016) Impact of water-level fluctuations on cyanobacterial blooms: options for management. Aquat Ecol 50(3):485–498
Basudhar A, Dribusch C, Lacaze S, Missoum S (2012) Constrained efficient global optimization with support vector machines. Struct Multidiscip Optim 46(2):201–221

Becker R, Koppa A, Schulz S, Usman M, aus der Beek T, Schüth C (2019) Spatially distributed model calibration of a highly managed hydrological system using remote sensing-derived ET data. J Hydrol 577:123944

Belayneh A, Adamowski J, Khalil B, Quilty J (2016) Coupling machine learning methods with wavelet transforms and the bootstrap and boosting ensemble approaches for drought prediction. Atmos Res 172:37–47

Buyukyildiz M, Tezel G, Yilmaz V (2014) Estimation of the change in lake water level by artificial intelligence methods. Water Resour Manag 28(13):4747–4763

Çimen M, Kisi O (2009) Comparison of two different data-driven techniques in modeling lake level fluctuations in Turkey. J Hydrol 378(3-4):253–262

Coops H, Beklioglu M, Crisman TL (2003) The role of water-level fluctuations in shallow lake ecosystems–workshop conclusions. Hydrobiologia 506(1-3):23–27

Cortes C, Vapnik V (1995) Support-vector networks. Mach Learn 20(3): 273–297

Coulibaly P (2004) Downscaling daily extreme temperatures with genetic programming. Geophys Res Lett 31(16)

Coulibaly P (2010) Reservoir computing approach to Great Lakes water level forecasting. J Hydrol 381(1-2):76–88

Das M, Ghosh SK, Chowdary VM, Saikrishnaveni A, Sharma RK (2016) A probabilistic nonlinear model for forecasting daily water level in reservoir. Water Resour Manag 30(9):3107–3122

Daubechies I (1988) Orthonormal bases of compactly supported wavelets. Commun Pure Appl Math 41:909–996

Deo RC, Samui P, Kim D (2016) Estimation of monthly evaporative loss using relevance vector machine, extreme learning machine and multivariate adaptive regression spline models. Stoch Env Res Risk A 30(6):1769–1784

Evtimova VV, Donohue I (2016) Water level fluctuations regulate the structure and functioning of natural lakes. Freshw Biol 61(2):251–264

Fang K, Shen C, Kifer D, Yang X (2017) Prolongation of SMAP to spatiotemporally seamless coverage of continental US using a deep learning neural network. Geophys Res Lett 44(21):11030–11039

Feng Y, Cui N, Zhao L, Hu X, Gong D (2016) Comparison of ELM, GANN, WNN and empirical models for estimating reference evapotranspiration in humid region of Southwest China. J Hydrol 536: 376–383

Ferreira C (2001) Gene expression programming: a new adaptive algorithm for solving problems. Complex Syst 13(2):87–129

Fister I, Fister I Jr, Yang XS, Brest J (2013) A comprehensive review of firefly algorithms. Swarm Evol Comput 13:34–46

Gauch M, Mai J, Lin J (2019) The proper care and feeding of CAMELS: how limited training data affects streamflow prediction. arXiv preprint arXiv:1911.07249

Ghorbani MA, Deo RC, Karimi V, Yaseen ZM, Terzi O (2018) Implementation of a hybrid MLP-FFA model for water level prediction of Lake Egirdir, Turkey. Stoch Env Res Risk A 32(6):1683–1697

Graf R, Zhu S, Sivakumar B (2019) Forecasting river water temperature time series using a wavelet–neural network hybrid modelling approach. J Hydrol 578:124115

Güldal V, Tongal H (2010) Comparison of recurrent neural network, adaptive neuro-fuzzy inference system and stochastic models in Eğirdir Lake level forecasting. Water Resour Manag 24(1):105–128

Gupta HV, Kling H, Yilmaz KK, Martinez GF (2009) Decomposition of the mean squared error and NSE performance criteria: implications for improving hydrological modelling. J Hydrol 377(1-2):80–91

Haas MB, Guse B, Pfannerstill M, Fohrer N (2016) A joined multi-metric calibration of river discharge and nitrate loads with different performance measures. J Hydrol 536:534–545

Hashmi MZ, Shamseldin AY, Melville BW (2011) Statistical downscaling of watershed precipitation using gene expression programming (GEP). Environ Model Softw 26(12):1639–1646

Hassanzadeh E, Zarghami M, Hassanzadeh Y (2012) Determining the main factors in declining the Urmia Lake level by using system dynamics modeling. Water Resour Manag 26(1):129–145

Hipni A, El-shafie A, Najah A, Karim OA, Hussain A, Mukhlisin M (2013) Daily forecasting of dam water levels: comparing a support vector machine (SVM) model with adaptive neuro fuzzy inference system (ANFIS). Water Resour Manag 27(10):3803–3823

Hirpa FA, Salamon P, Beck HE, Lorini V, Alfieri L, Zsoter E, Dadson SJ (2018) Calibration of the Global Flood Awareness System (GloFAS) using daily streamflow data. J Hydrol 566:595–606

Hostetler SW, Bartlein PJ (1990) Simulation of lake evaporation with application to modeling lake level variations of Harney Malheur Lake, Oregon. Water Resour Res 26(10):2603–2612

Hrnjica B, Bonacci O (2019) Lake level prediction using feed forward and recurrent neural networks. Water Resour Manag 33(7):2471–2484

Huang GB, Zhu QY, Siew CK (2004) Extreme learning machine: a new learning scheme of feedforward neural networks. IEEE Int Joint Conf Neural Netw 2:985–990

Huang GB, Zhu QY, Siew CK (2006) Extreme learning machine: theory and applications. Neurocomputing 70:489–501

Kakahaji H, Banadaki HD, Kakahaji A, Kakahaji A (2013) Prediction of Urmia Lake water-level fluctuations by using analytical, linear statistic and intelligent methods. Water Resour Manag 27(13):4469–4492

Karaboga D, Kaya E (2019) Estimation of number of foreign visitors with ANFIS by using ABC algorithm. Soft Comput 24:7579–7591. https://doi.org/10.1007/s00500-019-04386-5

Karimi S, Shiri J, Kisi O, Makarynskyy O (2012) Forecasting water level fluctuations of Urmieh Lake using gene expression programming and adaptive neuro-fuzzy inference system. Int J Ocean Climate Syst 3(2):109–125

Khan MS, Coulibaly P (2006) Application of support vector machine in lake water level prediction. J Hydrol Eng 11(3):199–205

Khatibi R, Ghorbani MA, Naghipour L, Jothiprakash V, Fathima TA, Fazelifard MH (2014) Inter-comparison of time series models of lake levels predicted by several modeling strategies. J Hydrol 511: 530–545

Kisi O, Shiri J, Nikoofar B (2012) Forecasting daily lake levels using artificial intelligence approaches. Comput Geosci 41:169–180

Kisi O, Shiri J, Karimi S, Shamshirband S, Motamedi S, Petković D, Hashim R (2015) A survey of water level fluctuation predicting in Urmia Lake using support vector machine with firefly algorithm. Appl Math Comput 270:731–743

Lan Y (2014) Forecasting performance of support vector machine for the Poyang Lake's water level. Water Sci Technol 70(9):1488–1495

Li B, Yang G, Wan R, Dai X, Zhang Y (2016) Comparison of random forests and other statistical methods for the prediction of lake water level: a case study of the Poyang Lake in China. Hydrol Res 47:69–83

Li Y, Zhang S, Yin Y, Xiao W, Zhang J (2017) A novel online sequential extreme learning machine for gas utilization ratio prediction in blast furnaces. Sensors 17(8):1847

Liang C, Li H, Lei M, Du Q (2018) Dongting lake water level forecast and its relationship with the three gorges dam based on a long short-term memory network. Water 10(10):1389

Luo W, Zhu S, Wu S, Dai J (2019) Comparing artificial intelligence techniques for chlorophyll-a prediction in US lakes. Environ Sci Pollut Res 26(29):30524–30532

Mathevet T, Gupta H, Perrin C, Andréassian V, Le Moine N (2020) Assessing the performance and robustness of two conceptual rainfall-runoff models on a worldwide sample of watersheds. J Hydrol 585:124698

Mehr AD (2018) An improved gene expression programming model for streamflow forecasting in intermittent streams. J Hydrol 563:669–678
Mehr AD, Kahya E, Olyaie E (2013) Streamflow prediction using linear genetic programming in comparison with a neuro-wavelet technique. J Hydrol 505:240–249
Muvundja FA, Wüest A, Isumbisho M, Kaningini MB, Pasche N, Rinta P, Schmid M (2014) Modelling Lake Kivu water level variations over the last seven decades. Limnologica 47:21–33
Nourani V, Baghanam AH, Adamowski J, Kisi O (2014) Applications of hybrid wavelet–artificial intelligence models in hydrology: a review. J Hydrol 514:358–377
Noury M, Sedghi H, Babazedeh H, Fahmi H (2014) Urmia lake water level fluctuation hydro informatics modeling using support vector machine and conjunction of wavelet and neural network. Water Res 41(3):261–269
Ondimu S, Murase H (2007) Reservoir level forecasting using neural networks: Lake Naivasha. Biosyst Eng 96(1):135–138
Palani S, Liong SY, Tkalich P (2008) An ANN application for water quality forecasting. Mar Pollut Bull 56(9):1586–1597
Patil SD, Stieglitz M (2015) Comparing spatial and temporal transferability of hydrological model parameters. J Hydrol 525:409–417
Piasecki A, Jurasz J, Adamowski JF (2018) Forecasting surface water-level fluctuations of a small glacial lake in Poland using a wavelet-based artificial intelligence method. Acta Geophys 66(5):1093–1107
Piotrowski AP, Napiorkowski MJ, Napiorkowski JJ, Osuch M (2015) Comparing various artificial neural network types for water temperature prediction in rivers. J Hydrol 529:302–315
Quilty J, Adamowski J (2018) Addressing the incorrect usage of wavelet-based hydrological and water resources forecasting models for real-world applications with best practices and a new forecasting framework. J Hydrol 563:336–353
Rezaie-Balf M, Kisi O (2018) New formulation for forecasting streamflow: evolutionary polynomial regression vs. extreme learning machine. Hydrol Res 49(3):939–953
Riley MJ, Stefan HG (1988) MINLAKE: a dynamic lake water quality simulation model. Ecol Model 43(3-4):155–182
Rioul O, Duhamel P (1992) Fast algorithms for discrete and continuous wavelet transforms. IEEE Trans Inf Theory 38(2):69–586
Sang YF (2013) A review on the applications of wavelet transform in hydrology time series analysis. Atmos Res 122:8–15
Scardapane S, Comminiello D, Scarpiniti M, Uncini A (2014) Online sequential extreme learning machine with kernels. IEEE Trans Neural Netw Learning Syst 26(9):2214–2220
Schwarz G (1978) Estimating the dimension of a model. Ann Stat 6(2):461–464
Şen Z, Kadioğlu M, Batur E (2000) Stochastic modeling of the Van Lake monthly level fluctuations in Turkey. Theor Appl Climatol 65(1-2):99–110
Seo Y, Kim S, Kisi O, Singh VP (2015) Daily water level forecasting using wavelet decomposition and artificial intelligence techniques. J Hydrol 520:224–243
Shabani S, Pourghasemi HR, Blaschke T (2020) Forest stand susceptibility mapping during harvesting using logistic regression and boosted regression tree machine learning models. Global Ecol Conserv 22:e00974
Shafaei M, Kisi O (2016) Lake level forecasting using wavelet-SVR, wavelet-ANFIS and wavelet-ARMA conjunction models. Water Resour Manag 30(1):79–97
Shen C, Laloy E, Elshorbagy A, Albert A, Bales J, Chang FJ, Ganguly S, Hsu KL, Kifer D, Fang Z, Fang K (2018) HESS Opinions: incubating deep-learning-powered hydrologic science advances as a community. Hydrol Earth Syst Sci 22(11):5639–5656
Shiri J, Shamshirband S, Kisi O, Karimi S, Bateni SM, Nezhad SHH, Hashemi A (2017) Prediction of water-level in the Urmia Lake using the extreme learning machine approach. Water Resour Manag 30(14):5217–5229
Singh H, Najafi MR (2020) Evaluation of gridded climate datasets over Canada using univariate and bivariate approaches: implications for hydrological modelling. J Hydrol 584:124673
Suykens JA, Vandewalle J (1999) Least squares support vector machine classifiers. Neural Process Lett 9(3):293–300
Talebizadeh M, Moridnejad A (2011) Uncertainty analysis for the forecast of lake level fluctuations using ensembles of ANN and ANFIS models. Expert Syst Appl 38(4):4126–4135
Valizadeh N, El-Shafie A (2013) Forecasting the level of reservoirs using multiple input fuzzification in ANFIS. Water Resour Manag 27(9):3319–3331
Valizadeh N, El-Shafie A, Mukhlisin M, El-Shafie AH (2011) Daily water level forecasting using adaptive neuro-fuzzy inference system with different scenarios: Klang Gate, Malaysia. Int J Phys Sci 6(32):7379–7389
Valizadeh N, El-Shafie A, Mirzaei M, Galavi H, Mukhlisin M, Jaafar O (2014) Accuracy enhancement for forecasting water levels of reservoirs and river streams using a multiple-input-pattern fuzzification approach. Sci World J 2014:432976
Wang H, Qian G, Feng XQ (2013) Predicting consumer sentiments using online sequential extreme learning machine and intuitionistic fuzzy sets. Neural Comput & Applic 22(3-4):479–489
Wang Y, Duan L, Liu T, Li J, Feng P (2020) A non-stationary standardized streamflow index for hydrological drought using climate and human-induced indices as covariates. Sci Total Environ 699:134278
Wantzen KM, Rothhaupt KO, Mörtl M, Cantonati M, László G, Fischer P (2008) Ecological effects of water-level fluctuations in lakes: an urgent issue. In Ecological effects of water-level fluctuations in lakes (pp. 1-4). Springer, Dordrecht
Wu W, Dandy GC, Maier HR (2014) Protocol for developing ANN models and its application to the assessment of the quality of the ANN model development process in drinking water quality modelling. Environ Model Softw 54:108–127
Yadav B, Eliza K (2017) A hybrid wavelet-support vector machine model for prediction of lake water level fluctuations using hydro-meteorological data. Measurement 103:294–301
Yadav B, Ch S, Mathur S, Adamowski J (2016) Estimation of in-situ bioremediation system cost using a hybrid extreme learning machine (ELM)-particle swarm optimization approach. J Hydrol 543:373–385
Yang JH, Cheng CH, Chan CP (2017) A time-series water level forecasting model based on imputation and variable selection method. Comput Intell Neurosci 2017:8734214
Yang X, Magnusson J, Huang S, Beldring S, Xu CY (2020) Dependence of regionalization methods on the complexity of hydrological models in multiple climatic regions. J Hydrol 582:124357
Yarar A, Onucyıldız M, Copty NK (2009) Modelling level change in lakes using neuro-fuzzy and artificial neural networks. J Hydrol 365(3-4):329–334
Yaseen ZM, Naghshara S, Salih SQ, Kim S, Malik A, Ghorbani MA (2020) Lake water level modeling using newly developed hybrid data intelligence model. Theor Appl Climatol 141:1285–1300. https://doi.org/10.1007/s00704-020-03263-8
Young CC, Liu WC, Hsieh WL (2015) Predicting the water level fluctuation in an alpine lake using physically based, artificial neural network, and time series forecasting models. Math Probl Eng 2015:708204
Yu W, Zhuang F, He Q, Shi Z (2015) Learning deep representations via extreme learning machines. Neurocomputing 149:308–315
Zaji AH, Bonakdari H (2019) Robustness lake water level prediction using the search heuristic-based artificial intelligence methods. ISH J Hydraulic Eng 25(3):316–324

Zaji AH, Bonakdari H, Gharabaghi B (2018) Reservoir water level forecasting using group method of data handling. Acta Geophys 66(4):717–730

Zeng Y, Xu X, Shen D, Fang Y, Xiao Z (2016) Traffic sign recognition using kernel extreme learning machines with deep perceptual features. IEEE Trans Intell Transp Syst 18(6):1647–1653

Zhu S, Heddam S, Nyarko EK, Hadzima-Nyarko M, Piccolroaz S, Wu S (2019a) Modeling daily water temperature for rivers: comparison between adaptive neuro-fuzzy inference systems and artificial neural networks models. Environ Sci Pollut Res 26(1):402–420

Zhu S, Heddam S, Wu S, Dai J, Jia B (2019b) Extreme learning machine-based prediction of daily water temperature for rivers. Environ Earth Sci 78(6):202

Zhu S, Hadzima-Nyarko M, Gao A, Wang F, Wu J, Wu S (2019c) Two hybrid data-driven models for modeling water-air temperature relationship in rivers. Environ Sci Pollut Res 26(12):12622–12630

Zhu S, Hrnjica B, Ptak M, Choiński A, Sivakumar B (2020a) Forecasting of water level in multiple temperate lakes using machine learning models. J Hydrol 585:124819

Zhu S, Ptak M, Yaseen ZM, Dai J, Sivakumar B (2020b) Forecasting surface water temperature in lakes: a comparison of approaches. J Hydrol 585:124809

Zohary T, Ostrovsky I (2011) Ecological impacts of excessive water level fluctuations in stratified freshwater lakes. Inland Waters 1(1):47–59