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ORIGINAL PAPER

Urmia lake water depth modeling using extreme learning machine-improved grey wolf optimizer hybrid algorithm

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Abstract

Lake water level changes are relatively sensitive to the climate-born events that rely on numerous phenomena, e.g., surface soil type, adjacent groundwater discharge, and hydrogeological situations. By incorporating the streamflow, groundwater, evaporation, and precipitation parameters into the models, Urmia lake water depth is simulated in the current study. For this, 40 years of streamflow and groundwater recorded data, respectively collected from 18 and 9 stations, are utilized together with evaporation and precipitation data from 7 meteorological stations. Extreme learning machine (ELM) is hybridized with four different optimizers, namely artificial bee colony (ABC), ant colony optimization for continuous domains (ACOR), whale optimization algorithm (WOA), and improved grey wolf optimizer (IGWO). In the analysis, 13 various scenarios with multiple input combinations are used to train and test the employed models. The best scenarios are then opted based on the performance metrics which are applied to assess the accuracy of the methods. According to the results, the hybrid ELM-IGWO shows better performance compared to the ELM-ABC, ELM-ACOR, and ELM-WOA approaches. Results indicate that the groundwater and persistence of the lake water depth have effective roles in models while incorporating higher number of variables can lower the performance of the models. Statistical analysis showed a 62% improvement in the performance of ELM-IGWO in comparison to the ELM-WOA with regard to the root mean square error. The promising outcomes obtained in this study may encourage the application of the utilized algorithms for modeling alternative hydrological problems.

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1 Introduction

1.1 Background

Water can be considered as the most precious natural commodity on the biosphere (Vorosmarty et al. 2010), while its accessibility is seriously threatened by anthropogenic activities (Meybeck 2003). Lakes are vital components of the earth's hydrosphere, supplying not only the necessary freshwater for biota but also regulating the subtle indices of the climatic events (Adrian et al. 2009; Cretaux et al. 2016; Ma et al. 2010; Tong et al. 2016; Zhang et al. 2013, 2019). Likewise, Lake Urmia has been experiencing abrupt decline in the water level that pushes the environmental conditions to blink of a catastrophe (Nhu et al. 2020). For this, the atrophy in the lake has been addressed by the researchers (e.g., AghaKouchak et al. 2015; Jalili et al. 2016; Alborzi et al. 2018) from the different angels.

Water budget (WB) is a fundamental tool that can be used to assess the water gain and loss in the natural environment, and is essential in studying the hydrological cycle, and water quality in a hydrologic system (Healy et al. 2007). Thus, WB studies can evaluate the volume and the changes of the water content within a control volume that demands a diverse look at the spatial and temporal properties of the system.

1.2 Relevant literature review

Recently, numerous studies have been conducted to investigate the properties of the lake water level modeling (Myronidis et al. 2012; Sanikhani et al. 2015; Shafaei and Kisi 2016; Zaji et al. 2018). Likewise, to identify the causes of lake water level decline, Li et al. (2007) investigated the water balance and lake water changes at Lake Qinghai located in West China between 1959 and 2000. Ito et al. (2008) used the tank model and Darcy's law to evaluate the lake water budget in Lake Ikeda, Japan. Engel et al. (2015) modeled urbanization impacts on the water level of Lake Maxinkuckee in northern Indiana by applying the long-term hydrological impact assessment approach. Wang et al. (2018) studied the physical flexibility and spatial location of Poyang Lake and surveyed the connection between lake level and meteorological drought in the basin. Short et al. (2020) estimated two-century records of water level at Lake George, New South Wales, applying satellite imagery and the lake's bathymetry. Maihemuti et al. (2020) used temporal scaling of water fluctuations to model a lake water balance in Ebinur Lake employing a system dynamics model.

Owing to the robustness of artificial intelligence (AL) techniques for lake water level modeling, Çimen and Kisi (2009) used support vector machines (SVMs) and artificial neural network (ANN) to model monthly lake-level oscillations of Lake Van in Turkey. To evaluate the monthly change in water level in Lake Beysehir, five artificial intelligence models consisting of support vector regression (SVR), particle swarm optimization-artificial neural networks (PSO-ANN), radial basis neural networks (RBNN), multilayer perceptron (MLP), and adaptive network-based fuzzy inference system (ANFIS) were utilized by Buyukyildiz et al. (2014). Also, by predicting daily lake water level fluctuations, Yadav and Eliza (2017) utilized a boosted wavelet-support vector machine (WA-SVM) method using hydro-meteorological data for Loktak Lake (India). Ghorbani et al. (2018) forecasted the water level in Lake Egirdir (Turkey), and used a coupled method combining the firefly algorithm (FFA) with the multilayer perceptron (MLP) algorithm. Bonakdari et al. (2019) applied four methods of relevance vector machine (RVM), minimax probability machine regression (MPMR), extreme learning machine (ELM), and Gaussian process regression (GPR) to model lake-level oscillations in Lake Huron using archival data records. Long et al. (2019) used lake water level information to evaluate real-time multi-temporal water region data of Dongting Lake (China) by applying simple linear regression (SLR) and stepwise multiple linear regression (SMLR) methods.

Recently, the water level modeling of Lake Urmia has attracted great interest due to its critical role and gradual decrease in its water level. As examples from the relevant literature, Abbaspour et al. (2012) investigated the drying condition of Lake Urmia regarding climate change by utilizing a hydrodynamic model. They used meteorological and hydrological annual data as inputs. The obtained results indicated that the water level will continue to decline in the future. By simulating the basin, Hassanzadeh et al. (2012) applied system dynamics to decode different contributions associated with the hydrological cycle in the lake. It was evaluated that more than half of the Lake Urmia's reduction is due to alterations in influxes. As a result, they proposed that constructing dams can be accused of 25% of the change, while the rest of the decline in the lake is the outcome of alterations in precipitation over the lake and basin. Sima and Tajrishy (2013) determined the spatial figure of temperature over Lake Urmia. Arkian et al. (2016) explored climatic parameters to examine the unexpected reduction in the lake water level by applying data to four meteorological sites nearby Lake Urmia. Based on the obtained results, a serious diminishing trend in annual average temperature can be recognized since 1995. Dehghanipour et al. (2020) analyzed the impacts of lake water level reduction in terms of hourly time series over weather parameters attained from Urmia and Saqqez meteorological in Lake Urmia vicinity. The results showed that the climate parameters at Urmia station depict fewer fluctuations compared to the Saqqez station. Furthermore, climate conditions in local areas were affected by Urmia Lake despite of decreasing lake water level.

Recently, metaheuristic algorithms have become popular in modeling hydrological problems. Machine learning algorithms coupled with a metaheuristic algorithm generate much better results compared to standalone algorithms (Safari et al. 2020; Zhou et al. 2020; Mohammadi et al. 2021; Meshram et al. 2021). ELM has been used by means of different metaheuristic algorithms, and satisfactory results have been obtained. For example, Li et al. (2020) used ELM coupled with particle swarm optimization (PSO) to determine groundwater contamination sources. They showed that hybrid ELM was better than standalone ELM. Also, Wu et al. (2019) modeled daily reference evapotranspiration using bio-inspired metaheuristics optimized ELM. They used a genetic algorithm (GA), ant colony optimization (ACO), cuckoo search algorithm (CSA), and flower pollination algorithm (FPA).

2 Research objectives

In recent years, an increasing number of studies have been conducted on the modeling of water level of Lake Urmia based on hydrological and climatological data records.

However, most of the studies in the literature used data from limited number of stations in Urmia lake basin. This study used data collected from 34 stations located in Urmia lake basin. Most importantly, a few numbers of hydrological/meteorological parameters were considered for Urmia lake water level modeling in the literature. This study considered streamflow, precipitation, evaporation, and groundwater for Urmia lake water level modeling for enhancing the credibility of the developed models. On the other hand, although the satisfactory performance of hybrid ELM-based models has been reported in the literature in contrast to the standalone ELM method, the efficiency of various metaheuristic algorithms for improving the ELM approach is not examined in the relevant literature. Therefore, this study scrutinizes the implementation of different optimizers in a hybridization of standalone ELM algorithm. The predominant purpose of the present study is to improve the modeling accuracy of monthly lake water level at the study area. To this end, the performance of four relatively novel methods (ELM-ABC, ELM-ACOR, ELM-IGWO, ELM-WOA) is evaluated in terms of modeling lake water level over the 1974–2014-time period under 13 different scenarios, including the considered hydrology and climatic archival data records of Lake Urmia supplied from the Iranian Water Resources Management Company (IWRM Co).

2.1 Study area

Lake Urmia, situated in the semi-arid region of northwestern Iran with an endorheic basin spread across longitudinal and latitudinal geographic coordinates of 44° 50′ to 46°10′ N and 36° 45′ to 38°20′ E, respectively, was the second largest hyper saline lake in the world (Vaheddoost and Aksoy 2019; Dehghanipour et al. 2020). It is shared between West Azerbaijan and East Azerbaijan as the neighboring provinces in the Northwest of Iran. As seen in Fig. 1, Lake Urmia and its basin have been investigated by means of several stations in its vicinity. These are hydro-meteorological stations used for precipitation and evaporation records, while data records at groundwater wells and hydrometric stations were used to determine the groundwater level and streamflow to the lake which will be detailed later.

Having an area of approximately 52,000 km^2, Lake Urmia plays a key role in the livelihoods of about five million habitants across its basin (Dehghanipour et al. 2020). Due to the mountains that have surrounded the lake, the weather conditions in this region are severe and freezing. Thus, the temperature usually changes between 0 and − 20 °C in winter and reaches up to 40 °C in summer. Therefore, Lake Urmia is considered a vital asset for the region in terms of moderating the extreme climatic events (Kelts and Shahrabi 1986; Ghaheri et al. 1999; Alipour 2006). The mean annual

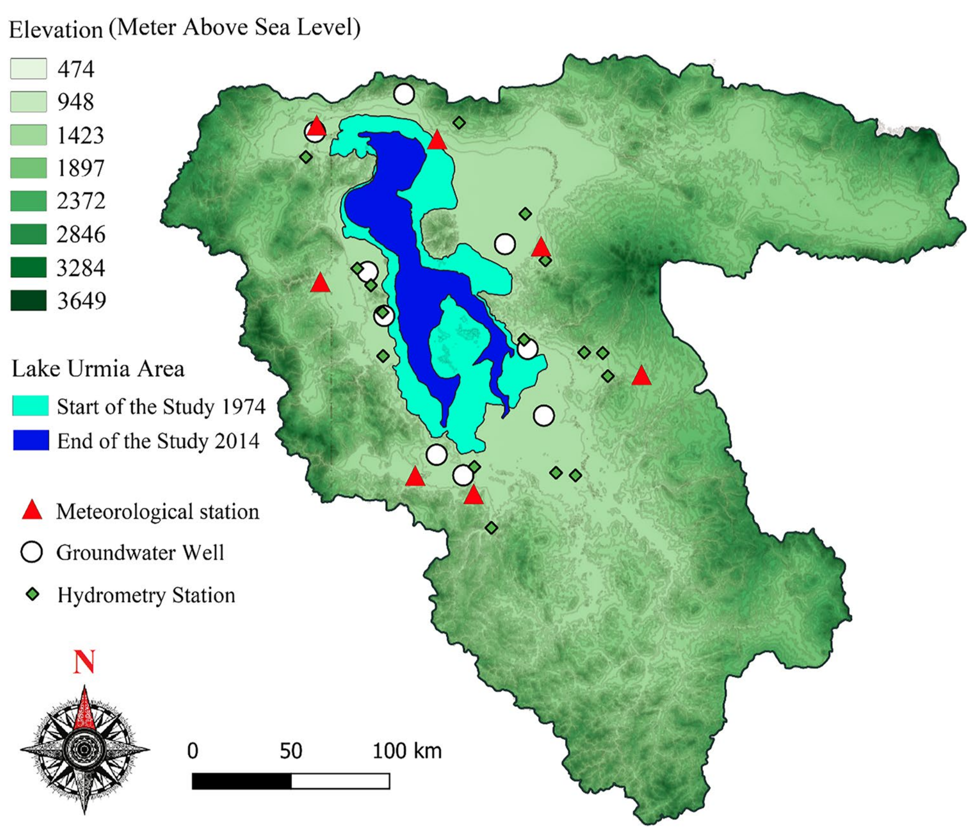

Fig. 1 Urmia lake and selected stations in the basin

precipitation is about 326 mm that is mostly in the form of rain in the lowlands and snow in the high altitudes (Vaheddoost and Aksoy 2017). As the lake is registered as a UNESCO Biosphere Reserve in 1977, and due to the importance of saving the lake, several researchers have drawn attention to it (e.g., Khazaei et al. 2019; Shadkam et al. 2016; Jeihouni et al. 2017; Arkian et al. 2016; Chaudhari et al. 2018; Khaki et al. 2018).

3 Material and methods

3.1 Data used

Hydrological and climatological data records of Lake Urmia are provided by the Iranian Water Resources Management Company (IWRM Co) up to year 2014. As depicted in Fig. 1, stations in the vicinity of the lake are selected. There was some data loss in the time series of the selected stations which was evaluated through data reconstruction using additive decomposition (Vaheddoost and Aksoy 2019). Afterward, the time series of the evaporation (*E*), precipitation (*P*), lake water depth (*L*), streamflow (*S*), and groundwater head (*G*) at the selected stations are utilized.

First, downstream hydrometric stations related to seventeen rivers discharging into the Lake Urmia are selected. However, Shirin Kandy station, which is on the Leylan River, is omitted from the examination process according to its short recorded historical data. Moreover, there are 156 hydrometric sites, from which the greatest downstream site was chosen for portraying each stream. Almost all the names for the downstream sites and connected streams along with the long-term average streamflow are shown in Table 1 (streamflow rates are ranged from the highest to the lowest). To obtain one single time series for *S*, the monthly average *S* of each site was altered into the monthly full volume and all of them were summarized together.

Table 2 The meteorological stations used in the analysis and the associated coverage area obtained by the Thiessen polygons (*P*, average monthly precipitation; *E*, average monthly evaporation)

Station	Area (km^2)	Coverage area (%)	*P* (mm)	*E* (mm)
Azarshahr	1227.72	23.78	18.19	143.73
Gharalar	1090.41	21.12	27.97	108.03
Sharafkhane	1052.24	20.38	21.19	95.03
Pole-Sorkh	1012.06	19.61	29.91	139.05
Peyghala	512.17	9.92	41.51	137.45
Abajalu-Sofla	265.21	5.14	22.73	95.25
Moghanjugh	2.34	0.05	26.94	126.52

Among 253 *P* and 67 *E* meteorological stations, as shown in Table 2, seven stations were opted. To select these stations, some aspects including their existence of *P* and *E* data through a long-term overlapping time, nearness to the lake water body, and the least missing data were considered. Moreover, the polygon of Thiessen was applied to compute the collaboration of each cite directly for both *P* and *E* from the surface of the lake. Table 2 shows *P* and *E* with their long-term average values, the region, and the comparable percentages through each station, and therefore, *E* and *P* were multiplied by the equivalent region and summarized to obtain the *P* and *E* time series in each station. Finally, *E* was multiplied by 0.76, which is a pan coefficient to incorporate the effect of salinity and open water environment on the Lake Urmia (WWA/Yekom 2005; Hashemi 2008). Additionally, after choosing *P* and *E*, the data associated with the groundwater wells are chosen based on the distance from the lake, high correlation coefficient with lake water level, and long recorded data with minimum missing data were considered. The time series of all parameters are given in Fig. 2 which depicts the time period of 1974 to 2014. Based on the trends and the data run, the decline in the lake water depth (*L*) can be compared to the declines in streamflow and precipitation. However, the evaporation showed a

Table 1 Discharge rate at the most downstream hydrometric stations on the selected river streams ending to the lake

River	Station	Streamflow (m^3/s)	River	Station	Streamflow (m^3/s)
Zarrineh	Miyandoab	40.24	Maraghe	Maraghe	2.32
Mahabad	Pole-Sorkh	8.69	Azarshahr	Azarshahr	1.49
Ghadar	Pole-Bahramloo	7.51	Ghala	Shishvan	1.25
Aji	Sarin-Dizaj	6.56	Leylan	Shirin-Kandy	1.05
Baranduz	Babarood	6.53	Zola Chay	Yalghuz-Aghach	0.99
Nazloo	Abajalu-Sofla	5.84	Ruzeh Chay	Ghojali-Aslan	0.86
Shahar Chay	Band	4.96	Dariyan	Dariyan	0.49
Sufi	Khormazard	4.81	Cheshmeh-Dul	Eslam-Abad	0.11
Simineh	Taze-Kand	2.48	Khorkhoreh	Tamar	0.04

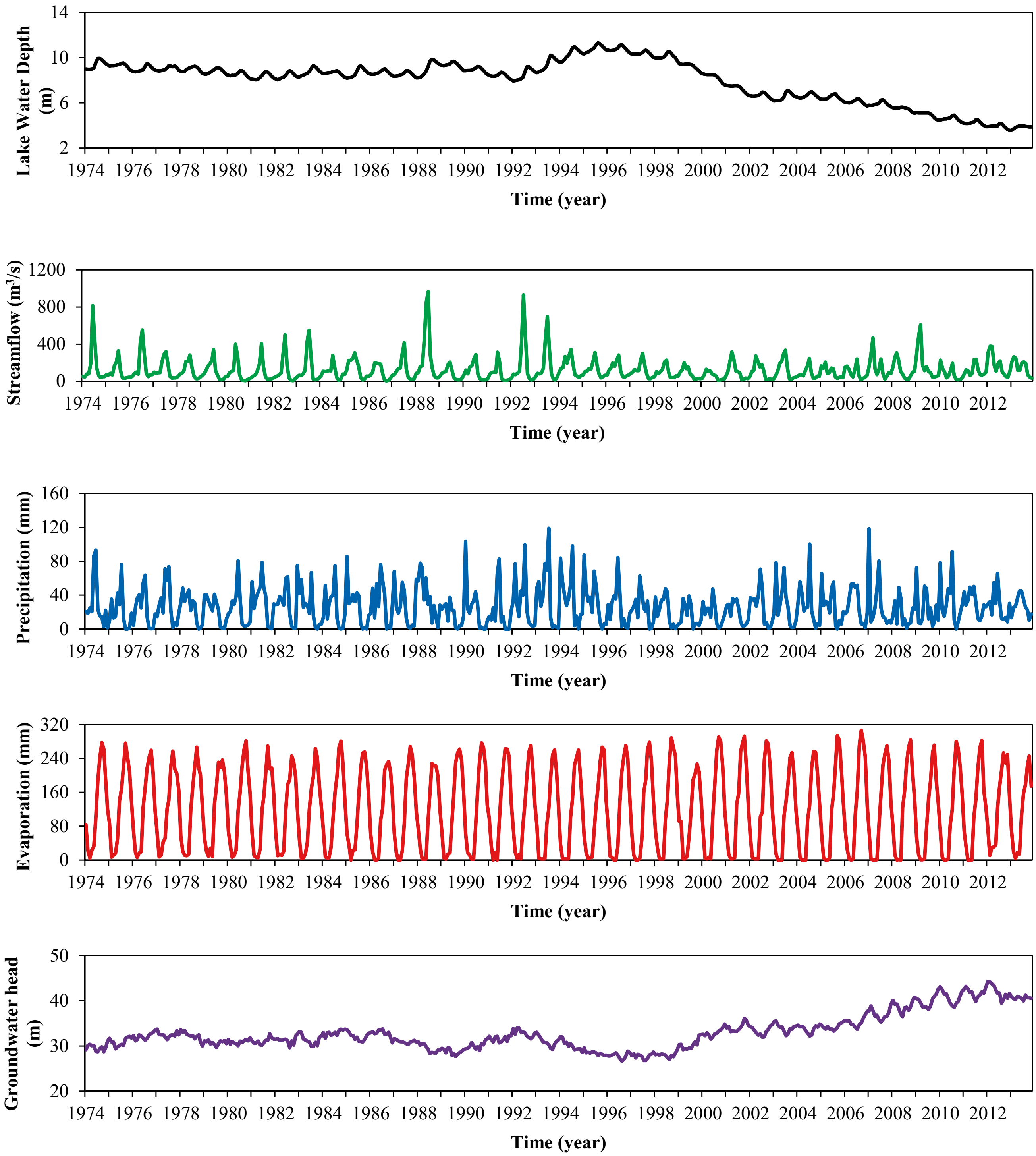

Fig. 2 Monthly time series of Urmia lake water level, precipitation, streamflow, evaporation, and groundwater level used in the modeling process at studied location (1974–2014)

cyclic behavior, while the effect of groundwater head was increasing due to the growth associated with the difference of lake water level and groundwater level in wells. Since the provided data were up to September 2014, recent decline occurred in lake water depth, streamflow, and precipitation could not be incorporated in the study. However, comparing to the recently conducted studies in the literature such as Zeynoddin et al. (2020) who used data from 1972 to 2003, this study used update data through considering more hydro-meteorological variables.

3.2 Model development assumptions and scenarios

To develop the lake water level models, several assumptions and scenarios are considered. First, assumptions are made to simplify the problem and reduce the dimensionality. Afterward, scenarios based on the reasonable interaction of dependent and independent variables are used to come across the best model. Likewise, the assumptions based on the preliminary study of Vaheddoost and Aksoy (2019) are considered as follows:

a. Lake is the control volume, and the hydro-meteorological events occurring in the basin can be neglected.
b. The independent variables which bring water to the lake water body are direct precipitation on the lake, streamflow, and groundwater discharge, while the independent variables, which take away the water from the lake, are evaporation and groundwater.
c. The provided data represents reality, and there is no major precision associated with the recorded data. However, the major changes after year 2014 can be applied to the data inventory in the future.
d. The hydrological relationship between variables does not change through the time.
e. The effect of the reported turn point in the late 1990s (Fathian and Vaheddoost 2021a, 2021b) can be lumped into the calibration stage as a permanent condition.
f. Selected predictors are and remain independent in time and space.

Scenarios were selected based on the spatio-temporal relationship between independent variables of which were thought to have a major impact on the lake water level. Accordingly, in Table 3, the potential scenarios used in this study are given.

Table 3 Considered scenarios for modeling

No	Inputs	Output
1	S_t, L_{t-1}	L_t
2	S_{t-1}, L_{t-1}	
3	S_{t-2}, L_{t-1}	
4	S_{t-2}, S_{t-1}, S_t, L_{t-1}	
5	P_t, E_t, L_{t-1}	
6	P_{t-1}, E_{t-1}, L_{t-1}	
7	G_t, L_{t-1}	
8	G_{t-1}, L_{t-1}	
9	G_{t-2}, L_{t-1}	
10	G_{t-3}, L_{t-1}	
11	G_{t-3}, G_{t-2}, G_{t-1}, G_t, L_{t-1}	
12	S_{t-2}, S_{t-1}, S_t, G_{t-3}, G_{t-2}, G_{t-1}, G_t, L_{t-1}	
13	S_{t-2}, S_{t-1}, S_t, P_{t-1}, P_t, E_{t-1}, E_t, G_{t-3}, G_{t-2}, G_{t-1}, G_t, L_{t-1}	

3.3 Description of utilized algorithms

3.3.1 Extreme learning machine

The single-hidden layer feed-forward neural network (SLFN) has a simple structure and quick convergence properties. SLFN is also used in statistical forecasting and trend analysis. SLFN has some drawbacks such as sluggish in the training speed and its responsivity to the learning pace. ELM is a new theory form where the relation weight is randomly calculated between the hidden layer and the input layer (Huang et al. 2004, 2006).

Huang et al. (2006) implemented the extreme learning machine algorithm as a revised configuration of a back-propagation perspective with an individual hidden layer. The ELM is easier to implement than the methods currently in use because the parameters for neurons in a hidden layer do not demand to be changed. One of the advantages of ELM is its higher learning speed compared to other machine learning techniques. The ELM method is applied because of its relatively fast learning speed and sufficient learning accuracy.

Figure 3 shows ELM structure and connections. ELM has three layers. Input layer *e* neurons, single-hidden layer *n* neurons, and output layer *m* neurons. Input layer weight and bias values are randomly created. The weights are trained between the output and the hidden layers. ELM can be expressed as follows:

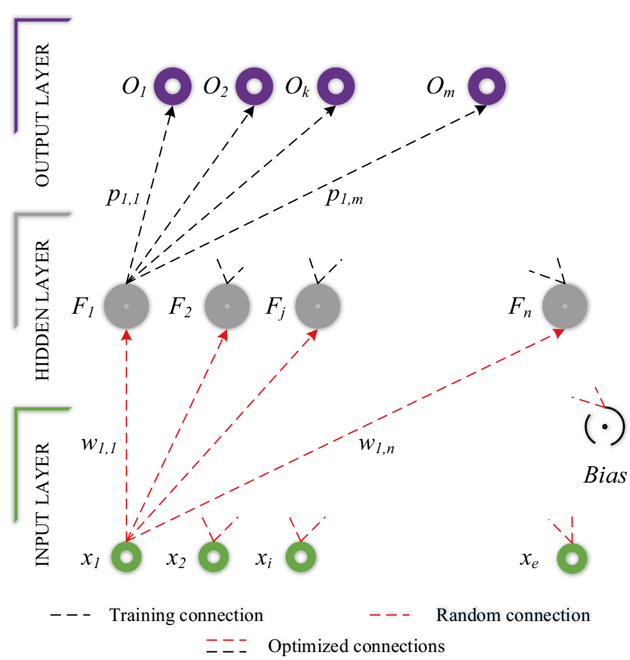

Fig. 3 Schematic view of ELM

$$\begin{pmatrix} F_1 \\ F_2 \\ \vdots \\ F_n \end{pmatrix}_T = \begin{pmatrix} f(\sum_{i=1}^{e} w_{i,1} x_i + b_i) \\ f(\sum_{i=1}^{e} w_{i,2} x_i + b_i) \\ \vdots \\ f(\sum_{i=1}^{e} w_{i,n} x_i + b_i) \end{pmatrix}_T \qquad f(x) = \frac{1}{1 + e^{-x}} \tag{1}$$

$$\begin{pmatrix} o_1 \\ o_2 \\ \vdots \\ o_m \end{pmatrix}_T = \begin{pmatrix} \sum_{j=1}^{n} p_{j,1} F_j \\ \sum_{j=1}^{n} p_{j,2} F_j \\ \vdots \\ \sum_{j=1}^{n} p_{j,m} F_j \end{pmatrix}_T \qquad \min_{\mathbf{P}} \boldsymbol{PF} - \boldsymbol{Y^T} \tag{2}$$

where P is output weight matrix, Y is the observed matrix, F is the hidden layer output matrix, f is the sigmoid function as activation function, and O is the simulated matrix. The solution of P is as follows:

$$P = F^{+} Y^{T} \tag{3}$$

where F^{+} is the Moore–Penrose generalized inverse of F.

3.3.2 Artificial bee colony (ABC)

An optimization algorithm that mimics the foraging behavior of honeybees was developed by Karaboga (2005). Each food source location in the ABC algorithm is in agreement with a potential answer to the search issue where the search cycle solutions are strengthened to find the global optimum. Initialized by a random population of food supply sources, the optimization technique is iterated before a termination condition is fulfilled. This period consists the employed, viewing, and scout bees' stages.

A swarm intelligence model involves the organizational activity of disparate individuals and produces a structure in which each part does its job better than any single part can. This is called group action and is an example of self-organization. Promoting constructive feedback, negative feedback, fluctuation, and various interactions are all the ways a system determines how to improve in the state. Individuals tend to favor states which occur frequently. The positive feedback will balance saturation and uncertainty, through negative feedback effects that cause repeated patterns to be overlooked. Swarms have a big opportunity for exploration and improvement. A person communicates with others and disperses knowledge of the entire swarm. A honeybee swarm is a model of an intelligent swarm which contains all the above properties. Foraging behavior is very critical since it keeps the colony intact. Overall, the hive bees massively enhance the collection of nectar.

Bees are usually categorized into working, onlooker, and scout bees. Working bees take the nectar to the hive. Aside from that, the onlooker bees are still conducting a quest for food sources. The onlooker bees are different from the scout bees in which the scouts detect new food sources through the use of external or internal stimulation, whereas the onlooker bees communicate the knowledge with the followers. This is something admirable in the interest of the onlooker bees because they determine the quality of food supply due to the quality of the employed bees' dances. This is a positive feedback system used for the beehive. When the flower has finished flowering, the bees abandon their jobs. Negative feedback holds the bees in place. A scout bee is seeking to discover the newest resources for fruit. In other words, due to the absence of supervision in the hive, bees interact with one another and share their experience by dancing to attract other bees to get farther and richer capital. Foragers are self-organizing agents (Kisi et al. 2012).

ABC algorithm is following six steps: (1) Initialization is the stage in which parameters are prepared. (2) Evaluating the population is the stage in which results are evaluated concerning fitness function. (3) Employed Bees Phase is the stage in which a regional scout is performed in the vicinity of each solution. (4) Onlooker Bees Phase is the stage in which profitability of the solutions is measured by onlookers. (5) Scout Bees Phase is the stage in which scout bees monitor all local search and decide whether it needs a new solution or not. (6) Memorize the finest food source discovered till the final standards are fulfilled.

3.3.3 Ant colony optimization for continuous domains (ACOR)

Ant colony optimization for continuous domains (ACOR) algorithm makes the use of artificial ants which cooperate in finding a good solution to the optimization problems as it applies to both discrete and continuous sets. There are specially engineered artificial ants that operate on a number of relatively simple agents (i.e., ants). This algorithm is based on the laws of statistics and uses a probability distribution for decision-making. In regard to searching for discrete problems, there are no objections. However, it has been documented that the algorithm is extended to solve continuous searches (Afshar et al. 2015; Dorigo et al. 2006).

The recent approach of Socha and Dorigo (2008) is analogous to the soul of algorithms based on ants. The vital concept in ACOR is to reduce cost, and improvement in ACOR will come from gradual measures. If the number of possible choices at each development stage grows, the likelihood of achieving a given outcome approaches a probability density function. Instead of collecting from a permissible set, the ant sampled the solution elements from the constant probability distribution function (PDF). Bi-modal PDF is defined with Gaussian kernel PDF, G^i, as the weighted total amount of numerous Gaussian functions $g_m{}^i(x)$:

$$G^i(x) = \sum_{m=1}^{t} \omega_m g_m^i(x) = \sum_{m=1}^{t} \omega_m = \frac{1}{\sigma_m^i \sqrt{2\pi}} e^{-\frac{\left(x-\mu_m^i\right)^2}{2\sigma_m^{i2}}} \tag{4}$$

where t is the number of single PDFs in which the Gaussian kernel PDF is constructed at the ith point, ω is the vector of the weights, σ is vectors of the standard deviations, and μ is the vectors of the means. For more detailed information, the interested readers can refer to Socha and Dorigo (2008) and Ghadimi and Ketabchi (2019).

3.3.4 The whale optimization algorithm (WOA)

Whale optimization algorithm (WOA) is a stochastic optimizer which has recently been introduced (Mirjalili and Lewis 2016). This optimization algorithm, inspired by nature, is based on the principle of hunting humpback whales with bubble-net feeding behavior. The search process of global optimum begins with a sequence of random solutions (candidate solutions) for the problem, like all population-based algorithms. It maximizes the satisfaction of an objective function. The key distinction of the WOA algorithm is the combination of the choices of rules to improve the candidate solutions. The prey at the humpback whale's target is regarded as the finest solution. The mathematical expression of reaching this prey is given in Eq. (5).

$$\vec{Y}(t+1) = \vec{Y}^*(t) - \vec{B} \times \left| \vec{C} \times \left(\vec{Y}^*(t) - \vec{Y}(t) \right) \right| \tag{5}$$

where $\vec{Y}$ indicates local solution, t indicates number of the iteration, $\vec{Y}^*$ indicates best solutions and updates in each solution, $\vec{B} = 2\vec{b} \times \vec{r} - \vec{b}$ and $\vec{C} = 2 \times \vec{r}$ are coefficient vectors, $\vec{r}$ is the random vector, and $\vec{b}$ is a vector which is decreased by repeated application of a linear from 2 to 0. There are several observations that the spiral-shaped path is existing around a pond by the whales circling around the food. This concurrent action is modeled through mathematical model given in Eqs. (6–7).

$$\vec{Y}(t+1) = \begin{cases} \vec{Y}^*(t) - \vec{B} \times \vec{D} & p < 0.5 \\ \vec{D}' \times e^{kl} \times \cos(2\pi l) + \vec{Y}^*(t) & p \geqslant 0.5 \end{cases} \tag{6}$$

$$\vec{D}' = \left| \vec{Y}^*(t) - \vec{Y}(t) \right| \tag{7}$$

where $\vec{D}'$ is the space between the hunt and the ith whale, l indicates a random number belonging to $[-1, 1]$, and k indicates a constant for the logarithmic motion flow to be determined. The probability (p) moves from one to another in a certain manner.

3.3.5 Improved grey wolf optimizer (IGWO)

The hunting strategies of wild wolves inspired the grey wolf optimizer algorithm. This algorithm is further developed by adding neighborhood information of individuals in the population (Mirjalili et al. 2014). Briefly, the GWO algorithm selects three leading wolves called α, β, and δ to be the best options in the search space to lead the remaining wolves (ω) to promising areas. Encircling, hunting, and invading the prey are three main processes for wolf behavior. The grey wolves are considered to encircling their prey in the mathematical form as given in Eq. (8).

$$Y(t+1) = Y_p(t) - B \times \left| C \times Y_p(t) - Y(t) \right| \tag{8}$$

where t is the number of iteration, Y_p is the prey placement, Y shows the place where the vector of a grey wolf exists, $C = 2 \times r_2$ and $B = 2 \times B \times r_1 - b(t)$ are the coefficient vectors, r_1, r_2 are random vectors in [0,1], the elements of the vector are linearly reduced by $b(t) = 2 - (2 \times t)/MaxIter$ formula. The way wolves hunt mathematically depends on the behavior of the three leading wolves (α, β, δ). Other wolves (ω) act according to these leading wolves. This behavior is expressed mathematically as follows:

$$\begin{aligned} Y_{i1}(t) &= Y_\alpha(t) - B_{i1} \times \left| C_1 \times Y_\alpha - Y(t) \right|, \\ Y_{i2}(t) &= Y_\beta(t) - B_{i2} \times \left| C_1 \times Y_\beta - Y(t) \right|, \\ Y_{i3}(t) &= Y_\delta(t) - B_{i3} \times \left| C_1 \times Y_\delta - Y(t) \right| \end{aligned} \tag{9}$$

where $Y_\alpha(t)$, $Y_\beta(t)$, and $Y_\delta(t)$ are the first three best solutions at iteration t, and B_{i1}, B_{i2}, and B_{i3} are calculated as in $B = 2 \times B \times r_1 - b(t)$,

$$Y(t+1) = \frac{Y_{i1}(t) + Y_{i2}(t) + Y_{i3}(t)}{3} \tag{10}$$

The attack process will continue until the prey is immobilized. So far, a classic GWO is performed. The attack process will continue until the prey is immobilized. The GWO algorithm has been updated with information from neighboring wolves, making it optimized powerful (Nadimi-Shahraki et al. 2021). In GWO, wolves lead α, β, and δ towards the spots of the search space that are auspicious to find the best answer to the problem. This action will result in the locally optimal solution being trapped. The lowering of demographic diversity and allowing GWO to collapse into the local optimum is another side effect. An enhanced grey wolf optimizer (IGWO) is proposed in this study to answer these questions. Three steps are used in the IGWO: initialization, movement, selection, and updating. Firstly, in the initialization stage, the distribution of the N wolves is located in the space between $[l_i]$ and $[u_j]$.

$$Y_{ij} = l_j + rand_j[0,1] \times (u_j - l_j) \tag{11}$$

where Y stored as a matrix pop in which the whole population of wolves as N rows and D columns ($i \in [1, N]$, $j \in [1, D]$). Secondly, in the movement stage, apart from GWO algorithm, the IGWO integrates additional techniques including dimension learning-based hunting (DLH) to optimize search performance. Each of the individual wolves is trained by its neighbor to be a possible leader candidate for the wolves (Nadimi-Shahraki et al. 2021).

Table 4 Initial parameters used in optimization algorithms (ABC, ACOR, IGWO, and WOA)

Algorithm	Quantity	Value
ABC	Maximum number of iterations	1000
	Boundary conditions	[− 1 1]
	Population size	30
	Number of onlooker bees	20
	Maximum acceleration	0.4
ACOR	Maximum number of iterations	1000
	Boundary conditions	[− 1 1]
	Population size	40
	Number of newly generated samples	40
	Intensification factor	0.1
	Deviation-distance ratio	1
IGWO	Number of the search agents	30
WOA	Number of the search agents	30

3.4 Establishment of hybrid models

In this study, weights and bias values of the ELM method are optimized using ABC, ACOR, IGWO, and WOA optimization algorithms. The most suitable neuron number and activation function are determined by making 100 trials for ELM. The most suitable number of neurons is found as 10 and sigmoid function as activation function. All data are re-scaled between − 1 and 1 through standardization. Afterward, the standardized data are separated into 70% training and 30% testing parts. After all the hyper-parameters were determined, the ELM algorithm was initiated. ELM weight and bias values are optimized applying the optimization parameters specified in Table 4. The root mean square error ($RMSE$) is used as a fitness function for all optimization algorithms. Figure 4 shows the hybridization process as a flowchart. The results obtained are interpreted through the help of different performance indexes. All algorithmic operations are done in Matlab 2018b environment.

3.5 Performance metrics

To appraise the performance of the developed models, several statistical indices were utilized, namely root mean square error ($RMSE$), mean absolute error (MAE), and coefficient of determination (R^2). These performance metrics have commonly been utilized in the preceding studies for the

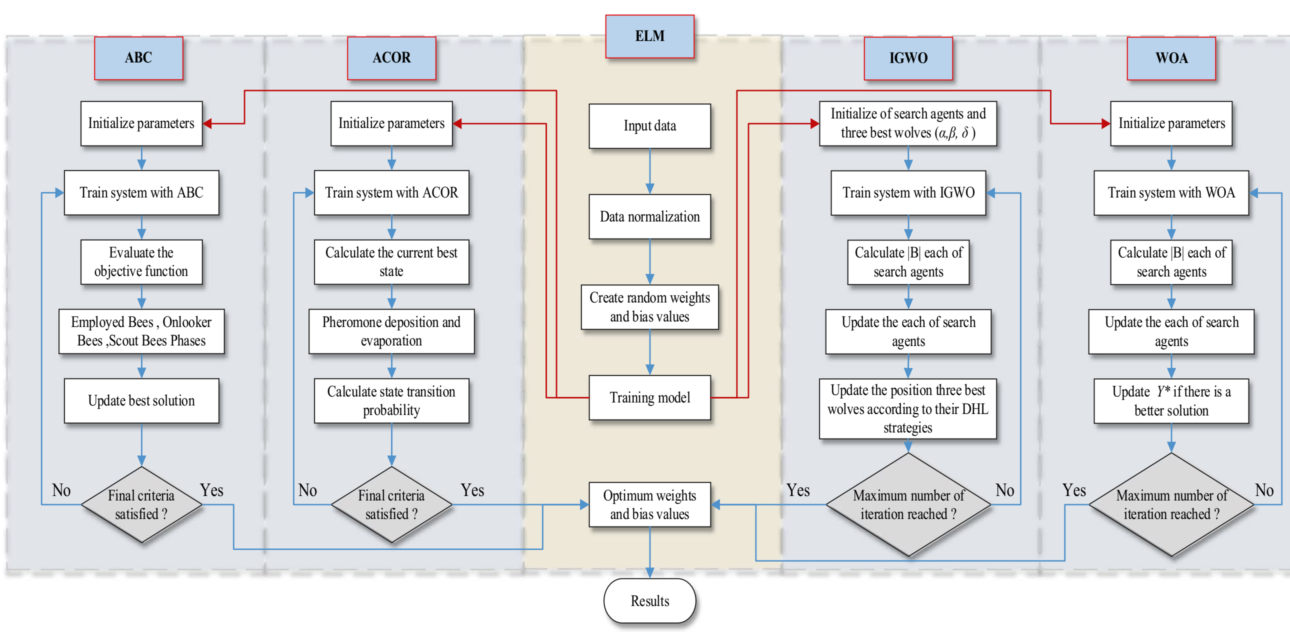

Fig. 4 The flowchart of the proposed hybrid methodology

evaluation aim in the AI methods (Harandizadeh et al. 2019; Chen et al. 2019; Xu et al. 2019). *RMSE* shows the disparity between the observed (O) and modeled (M) lake water level (L). Hence, a lower amount for *RMSE* and *MAE* indexes, and a higher amount for R^2 indicate the higher accuracy for any used methods. The subsequent equations are utilized to access the developed accuracy of the models.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (M_i - O_i)^2}{n}} \tag{12}$$

$$MAE = \frac{\sum_{i=1}^{n} |M_i - O_i|}{n} \tag{13}$$

$$R^2 = \left(\frac{\sum_{i=1}^{n} (M_i - \overline{M}_i)(O_i - \overline{O}_i)}{\sqrt{\sum_{i=1}^{n} (M_i - \overline{M}_i)^2 \sum_{i=1}^{n} (O_i - \overline{O}_i)^2}} \right)^2 \tag{14}$$

where M_i is the modeled lake water level (L) and O_i indicate the observed lake water level (L); M_i and O_i are average of M_i and O_i, respectively, and n the entire data number.

Beside the metrics mentioned above, a performance metric of $a10$-*index* has been applied to identify the strength of method reliability (Armaghani et al. 2019; Asteris et al. 2017, 2019; Ly et al. 2020; Apostolopoulou et al. 2020) introduced as follows:

$$a10 - index = \frac{m10}{M} \tag{15}$$

where M denotes the number of datasets and $m10$ is number of samples with observed/modeled amount is between 0.9 and 1.1. In this index ($a10$-*index*), the value of unity represents a perfect performance.

4 Results

In the current study, as mentioned earlier, several hydrological and climatological parameters including streamflow, precipitation, groundwater, and evaporation were applied to model the monthly lake water depth. Therefore, four optimization techniques, namely ABC, ACOR, IGWO, and WOA, are hybridized with the ELM method (i.e., ELM-ABC, ELM-ACOR, ELM-IGWO, and ELM-WOA). It is noteworthy that the input and output parameters are conceptualized under 13 different scenarios that are listed in Table 3. In each scenario, based on input combinations, the considered inputs lagged starting from 1 to 3 months for modeling monthly lake water level (i.e., L_t). For instance, scenario 13 indicates the fact that these inputs are applied to model the monthly L (i.e., S_{t-2}, S_{t-1}, S_t, P_{t-1}, P_t, E_{t-1}, E_t, G_{t-3}, G_{t-2}, G_{t-1}, G_t, L_{t-1}).

The ELM is hybridized using the optimization methods such as ABC, ACOR, IGWO, or WOA (i.e., ELM-ABC, ELM-ACOR, ELM-IGWO, and ELM-WOA) to model the lake water depth at the studied area with the input and output variables cited in Table 3. The coupling models have been constructed to improve the performance of single ELM to model the lake water depth. The obtained results for developed methods are given in Table 5 to show the values of statistical metrics acquired for the coupled methods. As a result, for the ELM-ABC coupled model, S7 was the best scenario which uses two inputs (i.e., G_t, L_{t-1}). Regarding the results given in Table 5, it can be seen that among 13 studied scenarios, ELM-ACOR provides better performance for S1. Besides, the results attained from ELM-ABC and ELM-IGWO methods during the test phase based on the performance metrics demonstrate that both methods provide almost the same results where S7 is found to be the best scenario. This might be on account of the connection of groundwater to the lake water depth. Table 5 reveals this fact that performance metrics including R^2 and $a10$ have almost the same performances in the testing stage for ELM-ABC model ($R^2 = 0.987$, $a10 = 1.000$) and ELM-IGWO method ($R^2 = 0.988$, $a10 = 1.000$).

Based on the obtained outcomes, for the ELM-WOA model, scenario 10 is the best scenario among the other scenarios utilized in this method for modeling monthly lake water level. Figure 5 graphically represents the scatter plots of the observed values versus modeled monthly lake water level during the test stage for developed models. To compare the obtained results in the current study, the hybrid ELM-IGWO method outperformed the other applied models consisting of boosted methods (i.e., ELM-ABC, ELM-ACOR, and ELM-WOA) due to the statistical metrics representing in Table 5. Moreover, the outcomes reveal that all the techniques produce more or less reasonable accuracies for modeling lake water level based on performance indexes utilized in the current study. Comparing the best performance of ELM-IGWO and ELM-WOA in terms of *RMSE* shows that the value of 0.261 for the ELM-WOA model reduces to 0.099 in ELM-IGWO model. It shows almost 62% improvement in accuracy of ELM-IGWO in contrast to the ELM-WOA model.

5 Discussion

As concluded, AI techniques are among commonly employed techniques for hydrological modeling problems, such as modeling monthly lake water depth. To increase the performance accuracy of lake water level models, the single ELM technique was coupled with four optimization techniques consisting of ABC, ACOR, IGWO, and WOA (i.e.,

Table 5 The statistical performances of the applied models under different scenarios

Scenarios	Training				Testing			
	R^2	*RMSE* (m)	*MAE* (m)	*a*10-index	R^2	*RMSE* (m)	*MAE* (m)	*a*10-index
ELM-ABC								
S1	0.990	0.120	0.093	1.000	0.982	0.127	0.098	1.000
S2	0.995	0.079	0.064	1.000	0.986	0.378	0.331	0.740
S3	0.991	0.110	0.088	1.000	0.986	0.181	0.115	1.000
S4	0.995	0.088	0.068	1.000	0.985	0.105	0.086	1.000
S5	0.988	0.127	0.098	1.000	0.979	0.218	0.180	0.958
S6	0.992	0.115	0.087	1.000	0.967	0.302	0.251	0.875
S7	0.983	0.145	0.113	1.000	0.987	0.168	0.146	1.000
S8	0.984	0.145	0.112	1.000	0.984	0.167	0.136	1.000
S9	0.983	0.146	0.112	1.000	0.983	0.265	0.233	0.865
S10	0.983	0.147	0.116	1.000	0.981	0.121	0.104	1.000
S11	0.984	0.144	0.112	1.000	0.987	0.189	0.166	1.000
S12	0.991	0.119	0.080	1.000	0.968	0.482	0.434	0.479
S13	0.969	0.213	0.168	0.997	0.945	0.425	0.357	0.615
ELM-ACOR								
S1	0.984	0.149	0.104	1.000	0.984	0.110	0.088	1.000
S2	0.994	0.088	0.069	1.000	0.978	0.253	0.216	0.938
S3	0.990	0.116	0.092	1.000	0.973	0.243	0.204	0.958
S4	0.988	0.138	0.099	0.977	0.980	0.203	0.177	1.000
S5	0.984	0.160	0.129	1.000	0.964	0.249	0.215	0.990
S6	0.988	0.142	0.097	0.997	0.961	0.280	0.232	0.885
S7	0.983	0.149	0.116	1.000	0.983	0.229	0.201	0.979
S8	0.984	0.147	0.114	1.000	0.986	0.214	0.189	0.990
S9	0.984	0.146	0.113	1.000	0.985	0.107	0.085	1.000
S10	0.983	0.148	0.114	1.000	0.979	0.122	0.103	1.000
S11	0.983	0.155	0.121	1.000	0.962	0.619	0.565	0.313
S12	0.975	0.185	0.138	0.997	0.937	0.251	0.207	0.938
S13	0.892	0.385	0.316	0.984	0.890	0.432	0.376	0.792
ELM-IGWO								
S1	0.990	0.116	0.087	1.000	0.985	0.173	0.148	1.000
S2	0.995	0.079	0.062	1.000	0.983	0.198	0.166	0.979
S3	0.991	0.111	0.090	1.000	0.986	0.326	0.296	0.854
S4	0.996	0.076	0.060	1.000	0.986	0.231	0.200	0.958
S5	0.991	0.110	0.080	1.000	0.988	0.179	0.150	0.990
S6	0.991	0.116	0.081	1.000	0.988	0.226	0.199	0.948
S7	0.984	0.147	0.113	1.000	0.988	0.099	0.078	1.000
S8	0.984	0.145	0.113	1.000	0.986	0.106	0.087	1.000
S9	0.984	0.147	0.115	1.000	0.983	0.157	0.133	1.000
S10	0.983	0.146	0.114	1.000	0.984	0.193	0.160	1.000
S11	0.984	0.141	0.109	1.000	0.981	0.333	0.305	0.833
S12	0.996	0.068	0.052	1.000	0.983	0.260	0.218	0.917
S13	0.997	0.063	0.046	1.000	0.973	0.164	0.128	0.979
ELM-WOA								
S1	0.976	0.184	0.129	0.997	0.971	0.408	0.371	0.719
S2	0.991	0.104	0.072	1.000	0.973	0.216	0.169	0.969
S3	0.953	0.393	0.301	0.966	0.986	1.009	0.986	0.073
S4	0.982	0.161	0.112	0.997	0.974	0.164	0.118	0.990
S5	0.970	0.410	0.320	0.942	0.903	1.389	1.338	0.042
S6	0.945	0.275	0.219	0.995	0.971	0.185	0.149	0.979

Table 5 (continued)

Scenarios	Training				Testing			
	R^2	*RMSE* (m)	*MAE* (m)	*a*10-index	R^2	*RMSE* (m)	*MAE* (m)	*a*10-index
S7	0.962	0.441	0.339	0.895	0.974	1.230	1.191	0.031
S8	0.978	0.172	0.133	1.000	0.981	0.417	0.383	0.552
S9	0.967	0.259	0.205	1.000	0.963	0.271	0.224	0.938
S10	0.962	0.258	0.212	1.000	0.984	0.261	0.240	1.000
S11	0.913	0.352	0.293	0.979	0.876	0.742	0.637	0.396
S12	0.961	0.224	0.174	0.997	0.931	0.789	0.690	0.292
S13	0.918	0.461	0.359	0.903	0.767	1.565	1.490	0.031

ELM-ABC, ELM-ACOR, ELM-IGWO, and ELM-WOA), and various input combinations were utilized in the current study. Additionally, effective variables consisting of *G*, *P*, *E*, and *S* are employed in the modeling lake water level (*L*) process. To this end, the outcomes are reasonable for modeling the lake water level. According to the attained results from modeling as explained in the previous section, the coupled ELM-IGWO is found superior to the ELM-ABC, ELM-ACOR, and ELM-WOA approaches.

The classical AI-based models and hybrid methods are utilized in the previous literature studies when modeling the meteorological and hydrological variables time series. Several studies are summarized to show the performance of AI-based techniques in the modeling of lake water level. For example, multi-linear regression (MLR), additive and multiplicative non-linear regression (ANLR and MNLR), and feed-forward back-propagation neural network (FFBP-NN) were superior to a decision tree (DT), generalized regression neural network (GR-NN), and radial basis function neural network (RBF-NN) by Vaheddoost et al. (2016) in forecasting monthly lake water level. Moreover, the newly coupled data intelligence methods based on the combination of MLP and whale optimization algorithm (WOA) are advanced for lake water modeling (Yaseen et al. 2020). Shiri et al. (2016) predicted water level using the ELM method, and the outcomes are in line with the present study in which the ELM approach can be a proper technique for modeling lake water depth. Referring to the current study, one scenario in each model had the best performing results due to the input combinations used in the modeling procedure of monthly lake water level. To this end, this represents that the models with fewer inputs can perform better even with one-month lagged data.

Further comparison of the models developed in this study to the earlier studies conducted in the literature is shown in Table 6. It must be noticed that, although some studies such as Kavehkar et al. (2011) and Shiri et al. (2016) utilized daily lake water level data, studies that used monthly data are listed in Table 6. On the other hand, several studies such as Razmkhah et al. (2016), Vaheddoost et al. (2016), and Boueshagh and Hasanlou (2019) analyzed Urmia lake water level fluctuations. Accordingly, there exist a few studies in the literature that modeled Urmia lake water level applying machine learning algorithms utilizing monthly hydro-meteorological data. As it is seen in Table 6, Mahsafar et al. (2017) utilized ANFIS method; Zeynoddin et al. (2020) applied ANFIS, generalized linear stochastic model (GLSM), SVM-FFA, MLP, genetic programming (GP), and gene expression programming (GEP); and Ehteram et al. (2021) utilized ANFIS-sunflower optimization (ANFIS-SO), ANFIS-FA, ANFIS-PSO, MLP-SO, MLP-FA, and MLP-PSO. The main deficiencies of studies available in the literature are utilizing data from limited number of stations and more importantly considering a few number of hydro-meteorological variables in the modeling. For instance as shown in Table 6, Mahsafar et al. (2017), Zeynoddin et al. (2020), and Ehteram et al. (2021) utilized data recorded from 24, 1, and 3 stations, while this study used data collected from 34 stations. Mahsafar et al. (2017) modeled Urmia lake water level considering streamflow, precipitation, and temperature variables. Zeynoddin et al. (2020) utilized only Urmia lake water level lagged data, and Ehteram et al. (2021) considered temperature and rainfall variables for Urmia lake water level modeling. However, this study incorporated much more variables in the modeling such as streamflow, precipitation, evaporation, and groundwater to promote the credibility of the developed models.

It has to be emphasized that the models which incorporate groundwater and lagged water depth variables give more accurate results where ELM-ABC and ELM-IGWO present their best performances in the S7 scenario. Therefore, the information provided by the groundwater head and lake water depth persistence is an essential predictor in the estimation of the lake water budget (WB). In addition, groundwater and surface water resources are interdepended systems across a variety of physiographic and climatic landscapes (Brunner et al. 2009; Owor et al. 2011; Shaw et al. 2013). Yet, the degree of interaction and the associated uncertainties demand discussion. Models that used a higher number of input parameters failed to accurately compute the lake water depth. Respectively, the course of dimensionality or parsimonious model development is also an important issue

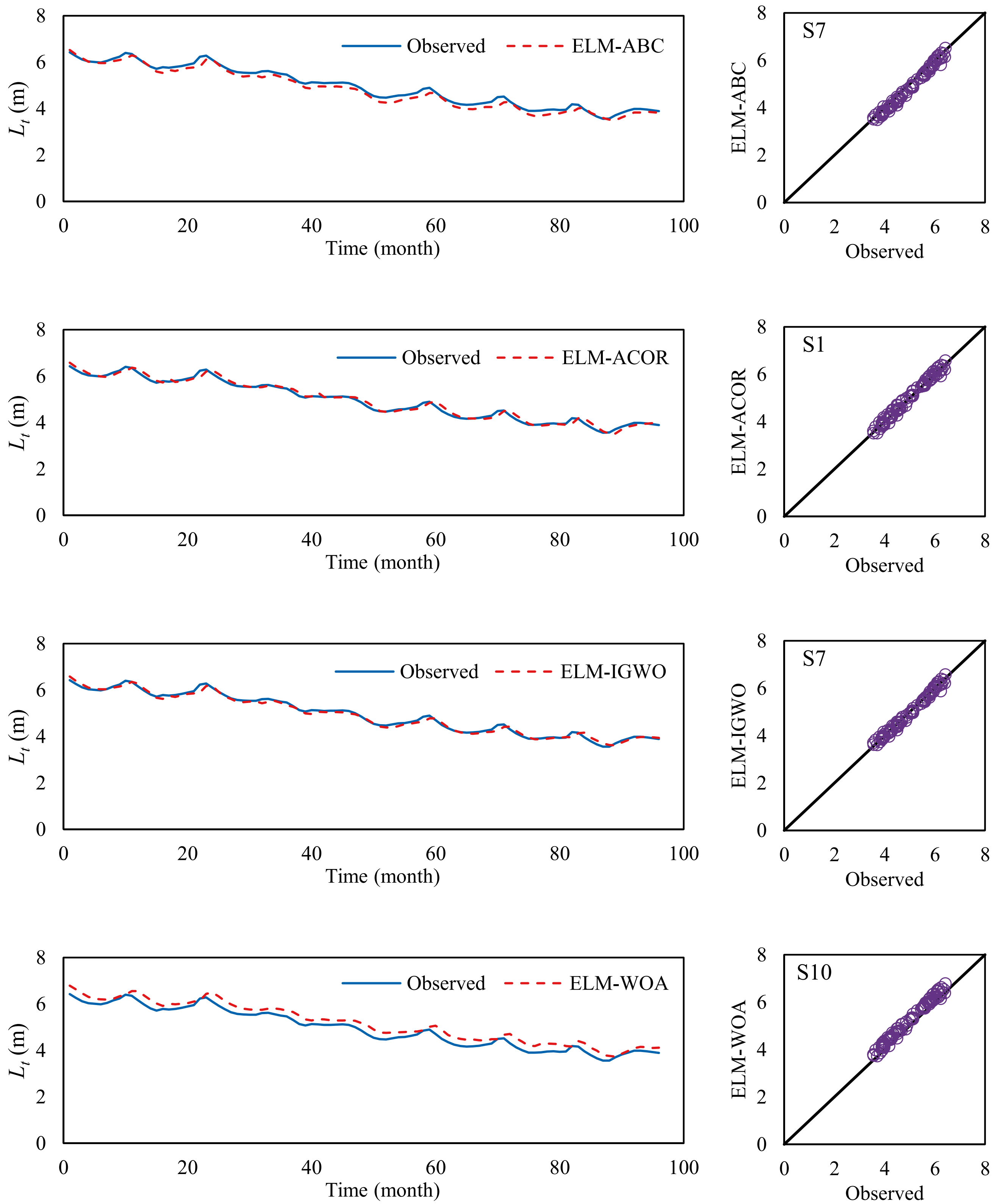

Fig. 5 ELM-ABC, ELM-ACOR, ELM-IGWO, and ELM-WOA models performance

Table 6 Comparison between the results of this study and several benchmark studies from the literature

Reference	Applied method	Best method	Performance		Variables used in modeling	Number of stations
			R^2	*RMSE* (m)		
This study	ELM-ABC ELM-ACOR ELM-IGWO ELM-WOA	ELM-IGWO	0.988	0.099	Streamflow Precipitation Evaporation Groundwater Lake water level	34
Ehteram et al. (2021)	ANFIS-SO ANFIS-FA ANFIS-PSO MLP-SO MLP-FA MLP-PSO	ANFIS-SO	0.920	1.92	Temperature Rainfall Lake water level	3
Zeynoddin et al. (2020)	GLSM SVM-FA ANN, MLP, GP, ANFIS, GEP	GLSM	0.995	0.069	Lake water level	1
Mahsafar et al. (2017)	ANFIS	-	0.85	0.41	Streamflow Precipitation Temperature Lake water level	24

to be considered in lake water budget models. Thus, incorporating a higher number of input parameters into the models' structure may increase the model complexity, and accordingly, the developed models fail to generate accurate results.

The current study was restrained to 3 months lags in modeling monthly lake water depth together with 13 scenarios and various input combinations of evaporation, precipitation, groundwater, lake water depth, and streamflow. For future works, researchers may consider the modeling with higher or lower lag times such as daily, weekly, seasonally, and annually. To this end, several hydro-meteorological parameters could be considered for lake water level modeling as a topic for future research direction. As the single ELM method was coupled with the ABC, ACOR, IGWO, and WOA optimization methods in this study, future works might consider the hybridization of ELM with alternative optimizers, consisting of gravitational search algorithm (GSA), firefly algorithm (FA), krill herd algorithm (KHA), and bat algorithm (BA).

6 Conclusions

In the present study, an extreme learning machine (ELM) integrated with the artificial bee colony (ABC), ant colony optimization for continuous domains (ACOR), whale optimization algorithm (WOA), and improved grey wolf optimizer (IGWO) has been adopted for the modeling of monthly lake water depth. The archival water depth data of Lake Urmia, between 1974 and 2014, are utilized. Hence, the recorded hydro-meteorological data including evaporation, precipitation, lake water level, streamflow, and groundwater level time series were employed. Afterward, the datasets with different input combinations under 13 various scenarios were trained and tested to define the best results in modeling monthly lake water level.

The outcomes have been evaluated by some statistical performance indices (i.e., R^2, *RMSE*, *MAE*, and *a*10) and optical indication criterion (i.e., scatter plot). A comparison of the hybrid ELM-ABC, ELM-ACOR, ELM-IGWO, and ELM-WOA techniques is performed to assess the modeling precision. The outcomes based on applied performance indexes demonstrated that the coupled ELM-IGWO was superior to its hybrid counterparts, namely ELM-ABC, ELM-ACOR, and ELM-WOA, in modeling monthly lake water level. Generally, coupled methods improved the performance precision of monthly lake water level modeling. The outcomes of the present study suggest that the artificial bee colony, ant colony optimization for continuous domains, whale optimization algorithm, and improved grey wolf optimizer are functional add-on tools for the precision of modeling ELM technique to model monthly lake water depth to be improved. It is also underlined that the groundwater head and the persistence in the lake water depth are the most effective variables in the estimation of the lake water depth, while the contributions of more variables not necessarily have a value-added effect on the performance of the models.

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Availability of data and material The data are available by the corresponding author upon request.

Code availability The codes are available by the corresponding author upon request.

Declarations

Ethics approval Not applicable.

Consent to participate Not applicable.

Consent for publication Not applicable.

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