Predicting Water Level Fluctuations in Lake Van Using Hybrid Season-Neuro Approach

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Abstract: Predicting water level fluctuations in a lake is crucial in terms of sustainable water supply planning, flood control, management of water resources, shoreline maintenance, sustainability of ecosystem, and economic development. This study developed a new predictive model based on the season algorithm (SA) and multilayer perceptron (MP) methods to improve prediction accuracy and extend water-level lead-time prediction. For the first time, the additive season algorithm (ASA) was used as an alternative data preprocessing technique for predicting water levels, and its performance was compared with that of wavelet transform (WT). The prediction accuracy and longer lead-time predictions were improved by the hybrid additive season algorithm–multilayer perceptron (ASA-MP) model. The results indicated that the hybrid additive season algorithm–multilayer perceptron model can be used to predict monthly water levels accurately with up to a 12-month lead time. The combined wavelet–multilayer perceptron (W-MP) model can be used to predict monthly water levels up to 6 months in advance with good agreement, whereas the standalone multilayer perceptron (MP) model can be used to predict the water levels up to 2 months in advance. The combined additive season algorithm–multilayer perceptron model outperformed the W-MP and standalone MP models based on the mean squared error (MSE) and the Nash-Sutcliffe coefficient of efficiency (CE) as performance evaluation criteria. As opposed to the ASA, the WT method has serious drawbacks and complicated mathematical processes. Furthermore, the prediction performance of the W-MP model was not satisfactory. The results of this study indicated that the ASA-MP model outperformed the W-MP model at all lead times. This implies that the season algorithm can effectively eliminate periodicity and trend cycles from original data better than the wavelet transform. In addition, the MP model should be combined with a preprocessing technique for more-accurate and longer lead-time predictions. **DOI: 10.1061/(ASCE)HE.1943-5584.0001804.**

Author keywords: Additive decomposition model; Lake Van; Water level fluctuations; Wavelet; Perceptron; Season algorithm; Prediction.

Introduction

Fluctuations of lake water level can directly affect the hydrological aspects and ecology in its basin and surroundings (Coops et al. 2003; Leira and Cantonati 2008; Webb 2008). The seasonal water level fluctuations of a lake reflect the annual hydrological cycle in the watershed. Rising water levels may make water resources management difficult to operate, affect plant and animal lives in lakeside and cause coastal erosion and inundation of agricultural and settlement areas (Meadows et al. 1997). High water levels can also alter the intensity of the erosion in the shoreline and produce new layers on the lake bottom. In addition, excessive changes at the lake level induce a wet formation zone surrounding the lake area. On the other hand, decreasing water levels may cause adverse effects on the water supply and on living creatures in the region and generate stressful conditions for fish and other aquatic species. Lake level variations may also affect commercial transport and human recreational activities. However, water level changes can serve as a proxy for climate change in the lake watershed. Large economic losses occur as a result of excessive variations in lake water levels. For this reason, this problem has become an important issue in hydrological studies. Khan and Coulibaly (2006) used a support vector machine (SVM) to predict monthly water levels of Lake Erie up to 12 months ahead. The SVM model was compared with the multilayer perceptron (MP) and seasonal autoregressive (SAR) models. They found that the results of the SVM model were slightly better than the prediction values of MP and SAR models. Altunkaynak (2007) developed an artificial neural network (ANN) model to predict monthly water level fluctuations in Lake Van. He found that the ANN model performed very well when rainfall and consecutive water levels were used as inputs into the ANN model. Coulibaly (2010) used an echo state network (ESN) model, which is a reservoir computing method for long-term prediction of lake water levels. Coulibaly compared the results with recurrent neural network (RNN) and Bayesian neural network (BNN) prediction values. It was found that the ESN model can be used to predict average water levels up to a lead time of 10 months, whereas RNN provides accurate results for lead times between 8 and 12 months. Coulibaly also reported that the dynamical reservoir approach of the ESN model and its restricted learning capability makes it easier to train, thus reducing the computational cost, which proves that ESN is a practical alternative tool for improved lake level forecasting. Kakahaji et al. (2013) developed two linear methods, namely autoregressive with exogenous input (ARX) and Box-Jenkins (B1), and two nonlinear intelligent models, the multilayer perceptron (MP) and local linear neuro-fuzzy (LLNF), for predicting water levels of Lake Urmia. They found that the MP and LLNF models provide accurate monthly water level predictions and outperform other models, except when there is limited data access, because intelligent methods need more data for training purposes. Buyukyildiz et al. (2014) developed models using five different artificial intelligence methods, namely an artificial neural network

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based on particle swarm optimization (PSO-ANN), ε-support vector machine (ε-SVR), multilayer artificial neural networks (MLPs), radial basis neural networks (RBNNs), and adaptive network-based fuzzy inference system (ANFIS), to estimate the water level of Lake Beyşehir by using monthly inflow-lost flow (I), precipitation (P), evaporation (E), outflow (O), and their combinations as inputs. The results obtained from the ε-SVR model were the most accurate. The ANFIS, MLP, and RBNN methods performed close to the ε-SVR model, but the PSO-ANN method was not successful for lake level prediction. Altunkaynak (2014) developed combined wavelet–fuzzy (W-Fuzzy) and wavelet–multilayer perceptron (W-MP) models for forecasting lake water level fluctuations. Altunkaynak tested the developed models' ability to predict monthly water level fluctuations of Lakes Michigan and Huron for lead times of 1, 3, 6, 9, and 12 months. The W-Fuzzy and W-MP models predicted the water levels accurately. Kisi et al. (2015) developed a model that predicts daily lake levels based on a support vector machine using the firefly algorithm (FA). Shiri et al. (2016) used the extreme learning machine (ELM) method for daily water level prediction of Lake Urmia, which was used by Huang et al. (2004) to develop two predictive models for 1- and 7-day prediction times. They compared their results with genetic programming (GP) and ANN techniques. They found that performance of the ELM method was better than that of the GP and ANN techniques for 1-day prediction. However, at 7 days, the ELM and ANN methods were better than the GP model, and the ANN technique slightly outperformed the ELM model. Shafaei and Kisi (2016) developed three conjunction models by integrating wavelet with support vector regression, adaptive neuro-fuzzy inference system, and autoregressive moving average (ARMA) models to predict monthly lake level fluctuations. They compared these model results with individual SVR, ANFIS and ARMA model values. The wavelet conjunction models, namely wavelet-SVR (W-SVR), wavelet-ANFIS (W-ANFIS), and wavelet-ARMA (W-ARMA), performed better than the individual models. They also reported that predicted lake level fluctuation values of the W-SVR model were slightly more accurate than those of the other conjunction models. Yadav and Eliza (2017) used discrete wavelet transform (DWT) and SVM methods to develop a combined W-SVM model to predict daily water levels of Loktak Lake. They compared combined W-SVM model results with individual SVM model values up to a lead time of 20 days. The combined W-SVM model had higher efficiency for all lead times. A number of studies have predicting water levels in Lake Van (Altunkaynak et al. 2003; Altunkaynak 2007; Altunkaynak and Şen 2007). Almost all of these studies used conventional parametric time series modeling techniques without combination with preprocessing methods such as Fourier, Walsh, and wavelet transforms, and so forth. The discrete wavelet transform is known to be an effective preprocessing method to remove trend and seasonality components from original data, and is used for decomposition of the original data into wavelets to improve prediction accuracy for short lead times. In addition to the complicated mathematical procedures involved, DWT has three main drawbacks (Fernandes 2001; Altunkaynak and Nigussie 2017)

1. It is sensitive to input-signal shifts because they produce unpredictable variations in coefficients of DWT;
2. DWT has weak directionality as a result of the representability of DWT coefficients by only three spatial orientations; and
3. DWT cannot define nonstationary signal behavior due to the absence of phase information.

To overcome mentioned drawbacks and enhance the prediction accuracy of water levels for extended lead times, a preprocessing method, preferably with a simple procedure, should be developed. The season algorithm (SA) is a preprocessing method with a simple procedure which decomposes the observed time series data into three components, including a trend cycle, a seasonal component, and an irregular component (error term). To the best of the author's knowledge, this procedure has not been used for predicting lake level fluctuations. Altunkaynak and Nigussie (2015, 2016, 2017) combined a season algorithm tool and ANNs to predict hydrological variables, namely daily streamflow, daily precipitation, and monthly water consumption. The SA outperformed the DWT technique with accurate predictions for extended lead times. Furthermore, SA has yielded high performance as a preprocessing method, and it has been suggested that this method must be studied for different hydrological variables. For this reason, this study researched the performance of the additive season algorithm (ASA) as an effective preprocessing technique and compared it with DWT using observed monthly water levels.

The objectives of this study were to (1) develop predictive models to improve the prediction accuracy and extend the lead time of predictions of water levels in Lake Van using a hybrid additive seasonal algorithm–multilayer perceptron (ASA-MP) model; (2) develop a new alternative preprocessing method utilizing the season algorithm which has a simple implementation procedure and does not involve drawbacks and complicated mathematical processes as does discrete wavelet transform; (3) avoid the limitations of the DWT technique and develop a more accurate preprocessing method which can be employed for decomposing the original data only depending on simple arithmetical processes; and (4) investigate a preprocessing technique that may remove the trend and seasonality components sufficiently from original data. In addition, the performance of the standalone multilayer perceptron (MP), combined DWT–multilayer perceptron (DWT-MP), and ASA-MP models were quantitatively evaluated based on RMS error (RMSE) and coefficient of efficiency as performance indicators.

Material and Methods

Data Collection and Analysis

Lake Van is the world's largest soda lake and is located at 38.5° N and 43° E (Fig. 1). The salt-soda water of the lake limits biological diversity. There are 103 species of phytoplankton, 36 kinds of zooplankton, and only one kind of fish, the pearl kefal (*Chalcalburnustarichi*) (Kempe et al. 1978), known to be living in the lake. In the winter months it is very cold and wet; precipitation is usually snow showers. Severe winters occur, frequently with temperatures below 0°C. In the spring, rainfall intensity decreases, and as snow melts, a high flow rate provides more than 80% of the annual discharge from the watershed into the lake in this period. In the summer period, from July to September, the climate is warm and dry, with an average temperature of 20°C. The drainage watershed of Lake Van is 12,500 km^2. The average elevation of the surface water level above mean sea level is approximately 1,649 m. The average and maximum depths of the lakes are 171 and 451 m, respectively (Kempe et al. 1978). There are four islands, namely Akdamar, Çarpanak, Adır, and Kuş, in the eastern part of the lake. The islands have historical and touristic characteristics and were declared an archaeological site in 1990. The Lake Van watershed is surrounded by mountains with elevations up to 4,500 m above mean sea level. One of the mountains around the Lake Van watershed is Suphan Mountain, rising to 4,434 m. There is no natural exit (outlet) from Lake Van; that is, Lake Van has a closed watershed. Annual average evaporation loss from the surface of Lake Van is 4.2 km^3. This is balanced by the average annual precipitation and mean annual runoff amounts

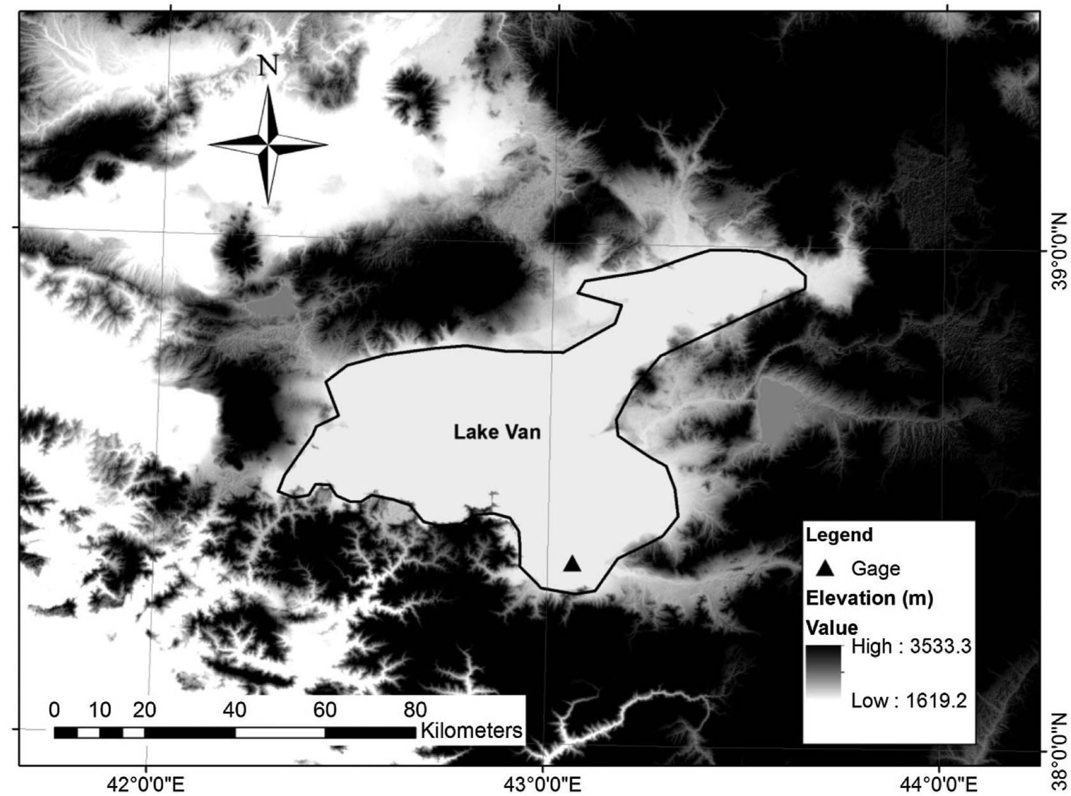

Fig. 1. Geographic map of the study area.

of 2.5 and 1.7 km^3 (Altunkaynak and Şen 2007), respectively. Kadioglu et al. (1997) indicated that the water level fluctuations of Lake Van are strongly related to the natural variability. The population of the basin is about 1 million. Major financial activities and industries in the basin include manufacturing, tourism, and agriculture (Altunkaynak et al. 2003).

This study used 57 years of monthly water level data of Lake Van consisting of 684 data points. The water level in Lake Van has been accurately monitored since the middle of the twentieth century. The monthly historical water level data of Lake Van were obtained from State Water Issue (DSI) for the period from 1960 to 2017. The total monthly water level data from October 1960 to September 2016 were divided into two groups: the first 31 years (55%) of observed monthly water level data (from October 1960 to September 1990) was used for training (calibrating) the models, and the remaining 26 years (45%) of observed monthly water level data (from October 1991 to September 2016) was used for testing (validating) the performance of the three models. The time variation of monthly water level data in Lake Van is depicted in Fig. 2. The water level data had a nonstationary trend pattern. According to Fig. 2, the water level time series data exhibited an increasing trend for some time intervals and a decreasing trend for some other time intervals, which is based on seasonality forming nonstationary behavior (Altunkaynak 2007). The mean, standard deviation, and skewness coefficient of the observed monthly water level data were calculated as 202.74 cm, 69.55 cm, and −0.1204, respectively. In this study, the observed monthly water level (original) data were decomposed to eliminate trend and seasonal components by using the preprocessing techniques of DWT and ASA. The observed monthly water level data were divided into three wavelets (spectral bands) using the DWT technique [Figs. 3(a–c), respectively]. In addition, the monthly water level data were separated into trend-cycle, seasonal index, and irregular (error term) components using ASA [Figs. 4(a–c), respectively]. The subseries water level data that were decomposed using DWT and ASA tools were used as inputs into the MP model to develop combined DWT-MP and hybrid ASA-MP models. Three models, namely standalone MP, DWT-MP, and ASA-MP models, were implemented to predict monthly water levels of Lake Van for lead times of 1, 2, 3, 6, 9, and 12 months. The performance of the MP, DWT-MP, and ASA-MP models was evaluated with observed data using RMSE and CE (Nash and Sutcliffe 1970). The results of this study are crucial in terms of effective water resources management, flood inundation, coastal maintenance, ecosystem sustainability, human recreational activities, and economic development.

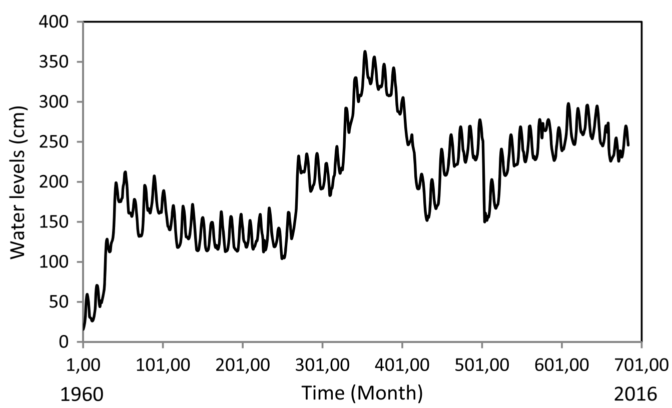

Fig. 2. Monthly water level time series data of Lake Van (centimeters).

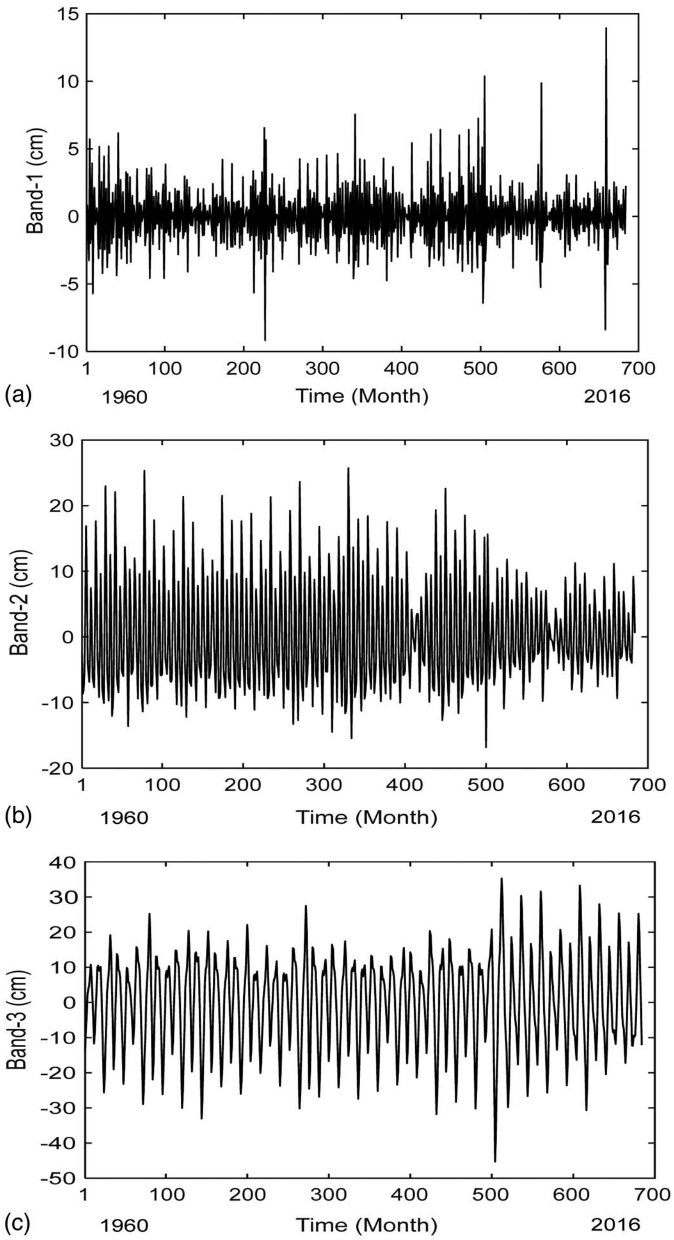

Fig. 3. Plots of the three bands of the observed monthly water level data of Lake Van decomposed by DWT tool: (a) Band-1 (D_1); (b) Band-2 (D_2); and (c) Band-3 (D_3).

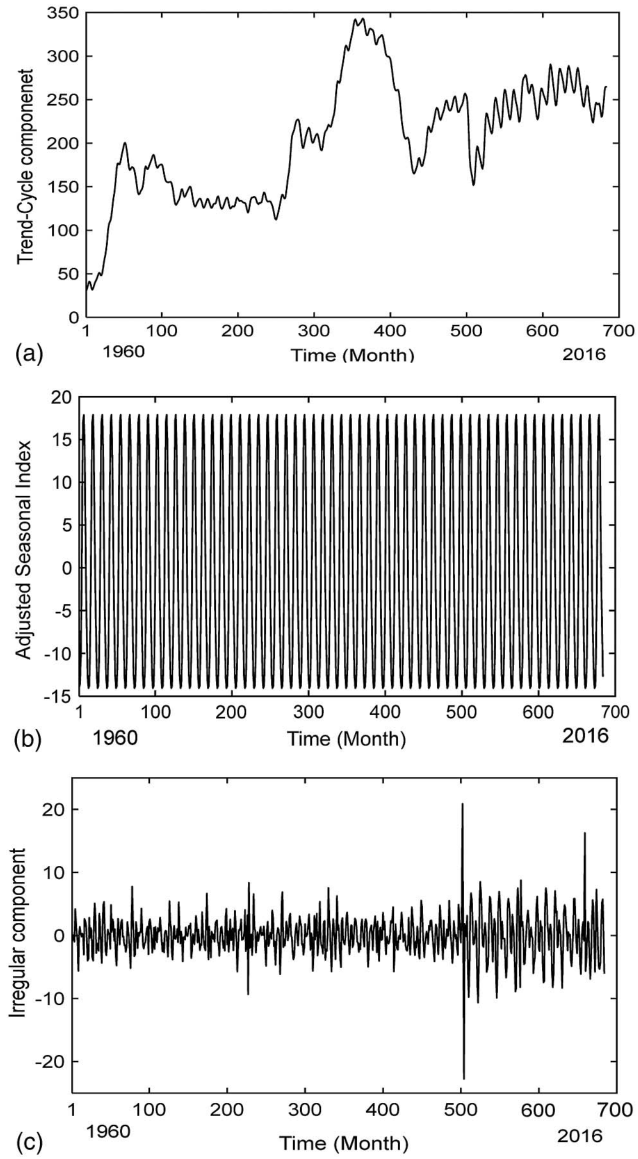

Fig. 4. Plots of components of monthly water levels of Lake Van decomposed by ASA tool for (a) trend cycle; (b) adjusted seasonal index; and (c) irregular component.

Description of Preprocessing Methods

Wavelet Transform

A wavelet is an improved preprocessing technique that is able to analyze signals, particularly nonstationary data, to generate subseries (wavelets), including time and frequency parameters with higher resolution. Wavelet transformation (WT) involves high-resolution short-time data at higher analysis frequencies of mother wavelets. WT helps to capture both time and frequency information with high resolution. In contrast to Fourier series, wavelet analysis separates original time series into shifted and scaled components of the mother wavelets which can be used to eliminate trend and seasonality components from the original time series, enhance the prediction accuracy, and identify nonstationary trend patterns of original time series (Torrence and Compo 1998). According to Cobaner (2013), WT is able to determine each segment of the time-domain signal individually at different frequencies. WT converts the signal into a mutually orthogonal family of wavelets. In other words, it decomposes the original time series data into spectral bands (wavelets) using both time and frequency domains at different resolution levels (Tiwari and Chatterjee 2010). It can be performed for any time series data. The wavelet analysis is capable of detecting long time intervals for low-frequency signals and short time intervals for high-frequency signals. It also has the ability to remove data such as trends, jumps, shifts, and discontinuities that other signal analysis techniques may not capture (Ramana et al. 2013). The basic wavelet transform function, $\psi(t)$, is called a mother wavelet and is defined as follows:

$$\int_{-\infty}^{\infty} \psi(t)dt = 0 \tag{1}$$

The mother wavelet is determined before initiation of the application. The basic function is used to generate a new family of

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wavelets with scaled and shifted forms of the time-localized mother wavelet which can be used for wavelet decomposition and composition transforms (Ozger 2010; Ramana et al. 2013). An expansion (dilatation) and contraction of basic wavelet function $\psi(a,b)$ is defined to calculate position and scaled wavelets

$$\psi(a,b) = b^{-1/2}\psi\left(\frac{t-a}{b}\right) \tag{2}$$

where t = time; and a and b = position and scale (frequency) parameters, respectively, which stand for real numbers. If $a > 1$ it is defined as expansion, and if $a < 1$ it is defined as contraction; b is a translation parameter, which is defined as a shift of the wavelet function. The continuous wavelet transform (CWT) and discrete wavelet transform are widely used in the literature. According to Torrence and Compo (1998), the CWT of time series is defined as

$$W(a,b) = b^{-1/2}\int_{-\infty}^{+\infty} f(t)\psi^*\left(\frac{t-a}{b}\right)dt \tag{3}$$

where t = time; a and b = position and scale parameters, respectively; and * represents the complex conjugate. According to Altunkaynak (2014), CWT is used to decompose original time series data into a time-frequency domain to allow the determination of the dominant components of variability and to designate how those components change with respect to time. CWT is designed to run with real-valued functions for all real numbers and is used to decompose a continuous-time function into wavelets. However, CWT analysis requires a great deal of calculation time and a high-performance computer. Unlike CWT, DWT handles functions defined for an interval of integer transforms. DWT is an application of the wavelet transform by means of employing a discrete set of wavelet scales and translations which comply with some described wavelet rules. The modified DWT is defined as (Cannas et al. 2006; Sharma et al. 2014)

$$\psi_{i,j} = \frac{1}{\sqrt{|s^i|}}\psi\left(\frac{t-k\tau s^i}{S^i}\right) \tag{4}$$

where i and j = positive integers; and s = fixed dilation phase which is greater than 1 ($s > 1$). The signals are decomposed into exchange orthogonal set of wavelets by DWT, which requires less computation time and is more applicable than CWT (Adamowski and Sun 2010). For this reason, this study used DWT to decompose observed monthly water level fluctuations into three bands (subseries) (Fig. 3). The Morlet wavelet function is commonly employed as the mother wavelet function in various applications. It is described with a zero mean and changes with both frequency and time. It also constitutes a good balance between time and frequency localizations (Altunkaynak 2014; Altunkaynak and Ozger 2016). The Morlet function is

$$\psi(\beta) = \frac{1}{\pi^{1/4}}e^{-0.5\beta^2}(\cos\,\omega\beta + i\sin\,\omega\beta) \tag{5}$$

where ω = dimensionless frequency; s = scale parameter of the wavelet; and β = dimensionless time factor

$$\beta = \frac{S}{t} \tag{6}$$

DWT is able to extract both frequency and time information from the original time series data. Because of this advantage, DWT has a high capability to remove the undesired noise and keep the desired part of the data. Moreover, DWT involves inverse transforms. That is, inverse discrete wavelet transform (IDWT) can easily be calculated to reconstruct the time series data after the elimination of the noise term. The original time series data are decomposed into one approximation component (A) and one detail component (D) by DWT by making use of high-pass and low-pass filters which produce the detail and the approximation components, respectively. After implementing all high-pass filtering, detail (high-frequency) components are produced, and are referred to as the noise component. The approximation component obtained after the all low-pass filtering processes is named the smoothed signal; A is then further split into A_2 and D_2 parts such that $A_1 = A_2 + D_2$. That is, A_1 is split into two subbands. This process helps to provide better flexibility in terms of denoising. The further decomposition and reconstruction procedure is continued up to the desired levels of resolution (n).

In this study, among the wavelet functions listed earlier, Daubechies order five (db5) and symlet order two (sym2) were used to decompose the monthly water level data of Lake Van into three spectral bands—D_1 (Band-1), D_2 (Band-2), and D3 (Band-3)—and A3 (Fig. 3). Here, A_3 represents the low-frequency components of the signal, and D_1, D_2, and D_3 represent the high-frequency components of the signal.

Season Algorithm

A random function of time series that changes with time (t) can be denoted Y_t which may exhibit components such as trend and periodicity. These components of a time series should be decomposed before using observed time series (raw) data to predict the future of the hydrologic variables. The season procedure effectively eliminates the seasonal component from original time series data. There are two decomposition models, namely the additive season algorithm and the multiplicative season algorithm (MSA). Based on these models, the season algorithm decomposes observed time series data into trend-cycle, seasonal index, and irregular (error term) components. Trend (T) denotes a gradual shift or level change, season (S) denotes the seasonal effect that changes the function value (Y) based on the season, and the irregular component (I) is known as a random (error) term. The MSA and the ASA decomposition models were defined by Shiskin et al. (1967) as, respectively

$$Y_t = T_t \times S_t \times I_t \tag{7}$$

and

$$Y_t = T_t + S_t + I_t \tag{8}$$

where Y_t = observed (original) data; T_t = trend-cycle component; S_t = seasonal component; and I_t = irregular component or the error term (white noise). If there is a visible continuously increasing or decreasing trend in the observed data with respect to time, the multiplicative decomposition model is used; otherwise, the additive decomposition model should be used. In this study, based on Fig. 2, the additive decomposition model was used for time series of monthly water levels because there was no visible continuously increasing or decreasing trend. The steps for decomposing original time series data into three components based on the seasonal procedure are as follows (IBM 2011):

1. The observed time series data are smoothened by using the centered moving average method which determines the trend-cycle component;
2. A seasonal irregular index (SI) is detected by subtracting the observed data from the smoothened values when the model is additive and by dividing the observed data with the smoothened values when the model is multiplicative;

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3. For both models, the medial average (centered average, described as the mean value of a certain variable calculated for the central location) specific seasonal relatives are calculated for each unit period to separate the seasonal component from the seasonal-irregular term; and
4. The irregular components (error terms) are determined by subtracting the seasonal adjusted series (SAS) from the smoothened trend-cycle (STC).

The major advantages of the season algorithm technique over the wavelet transform method are

1. The season algorithm is simpler. This implies that, unlike DWT, it does not contain complicated mathematical processes. That is, the decomposition procedure is based on simple arithmetical processes. Furthermore, the season algorithm procedure does not require curve fitting and determination of optimal parameters.
2. A hybrid ASA-MP model can be developed by using MP with one best architecture model, whereas development of a combined DWT-MP model requires more than one MP model based on the decomposed number of wavelets (bands).
3. The season algorithm improves prediction accuracy better for longer lead times (Altunkaynak and Nigussie 2015, 2016, 2017).

Additive Season Algorithm

1. First, periodicity of the available data should be detected. Monthly, weekly, or daily time series data have a periodicity of 12 months, 7 days, or 1 h, respectively. This study used monthly observed water level time series data for the period from 1960 to 2016. Therefore, the periodicity of the time series data was selected as 12 months, which implies that the water level of a given month for any year was expected statistically to repeat its value after 12 months. As mentioned previously, the detailed steps of additive decomposition model are as follows: the periodicity time interval (P) of the original time series data is determined, and the centered (medial) moving average (MA) technique is used to generate a new smoothened time series, which is widely denoted Z_t.

   When the periodicity is odd

$$Z_t = \frac{1}{P}\sum_{j=t-[(P-1)/2]}^{t+[(P-1)/2]} Y_j, \quad \text{where } t = \frac{P+1}{2}, \frac{P+3}{2}, \frac{P+5}{2}, \ldots \tag{9}$$

   and for even periodicity

$$Z_{t+0.5} = \frac{1}{P}\sum_{j=t-[(P-1)/2]}^{t+[(P-1)/2]} Y_j, \quad \text{where } t = \frac{P}{2}, \frac{P}{2}+1, \frac{P}{2}+2, \frac{P}{2}+3, \ldots \tag{10}$$

   Afterward, Z_t is calculated as

$$Z_t = \frac{Z_{t+0.5} + Z_{t+1.5}}{2} \tag{11}$$

2. After computing Z_t, the seasonal irregular index (SI_t) is calculated by subtracting the generated smoothened time series values (Z_t) from the original time series. The seasonal irregular index is defined as

$$\mathrm{SI}_t = Y_t - Z_t \tag{12}$$

3. The unadjusted seasonal index (USI) is defined as the arithmetic mean of same period values to calculate the relative effect of each seasonal irregular value. For example, if SI_{13}, SI_{25}, SI_{37}, and SI_{49} are periodic values for January, the corresponding SI value for January is represented by the arithmetic mean of these values. USI can be expressed as

$$\mathrm{USI} = \frac{1}{N}\sum_{i=1}^{N} \mathrm{SI}_{(1+12i)} \qquad i = 1, 2, \ldots, N \tag{13}$$

   where N = number of years.
4. The adjusted seasonal index (ASI) is calculated by subtracting the mean unadjusted seasonal index (MUSI) from each unadjusted seasonal index value

$$\mathrm{ASI} = \mathrm{USI} - \mathrm{MUSI} \tag{14}$$

5. The seasonally adjusted series (SAS) is computed by subtracting the original time series from the ASI values. The seasonally adjusted series (SAS) is expressed as

$$\mathrm{SAS} = Y_t - \mathrm{ASI} \tag{15}$$

6. The smoothened trend-cycle (STC) component is calculated by using the following formula:

$$\begin{aligned}\mathrm{STC}_t = \frac{1}{9}[&(\mathrm{SAS})_{t-2} + 2(\mathrm{SAS})_{t-1} + 3(\mathrm{SAS})_t \\ &+ 2(\mathrm{SAS})_{t+1} + (\mathrm{SAS})_{t+2}], \\ t = 3,4,&\ldots,n-2\end{aligned} \tag{16}$$

   where n = number of samples. For the first and end points, respectively

$$\mathrm{STC}_1 = \left[(\mathrm{STC})_2 + \frac{1}{2}[(\mathrm{STC})_2 - (\mathrm{STC})_3]\right] \tag{17}$$

$$\mathrm{STC}_n = \left[(\mathrm{STC})_{n-1} + \frac{1}{2}[(\mathrm{STC})_{n-1} - (\mathrm{STC})_{n-2}]\right] \tag{18}$$

   and for the second and second-from-the-end points, respectively

$$STC_2 = \frac{1}{3}[(STC)_1 + (STC)_2 + (STC)_3] \tag{19}$$

$$STC_{n-1} = \frac{1}{3}[(STC)_{n-2} + (STC)_{n-1} + (STC)_n] \tag{20}$$

   can be used for calculation.
7. The irregular (white noise) component (I_t) can be obtained by subtracting the SAS values from STC values

$$I_t = (SAS)_t - (STC)_t \tag{21}$$

Following the steps of the ASA procedure, the original time series data can be decomposed into trend-cycle, seasonal index, and irregular (error term) components with simple arithmetical processes. The trend-cycle, seasonal index, and irregular (error term) components are used as inputs into the MP model, and the monthly water levels are reconstructed as the sum of the predicted trend-cycle, seasonal index, and irregular components.

Description of Models

Artificial Intelligence Technique

Artificial intelligence (AI) techniques include a set of approaches that imitate human intelligence with the objective of developing techniques using human-like skills such as training, reasoning, and decision making. AI technique includes artificial neural networks, support vector machines, fuzzy logic (FL), and genetic algorithms (GAs). (Goldberg 1989; Haykin 1994; Zadeh 1994; Khan and Coulibaly 2006; Ozger 2009; Cimen and Kisi 2009; Shiri et al. 2011; Altunkaynak 2014). Development of artificial intelligence reveals new approaches to overcome complex and nonlinear real-life phenomenon which could not be represented and solved by classical methods. Artificial intelligence methods have been widely used for simulating nonlinear time series systems in various applications.

Standalone Neuro Model

One of the important artificial intelligence methods is the artificial neural network, which was proposed by Rosenblatt (1958). ANNs were not widely used for solving complicated models for hydrological variables until Rumelhart et al. (1986) introduced the back-propagation algorithm as a training procedure of the model. Since then, ANNs have become very effective in many applications of hydrologic problems (Abrahart et al. 2004; Altunkaynak 2007; Alvisi et al. 2006; ASCE Committee 2000; Campolo et al. 1999; Dawson and Wilby 2001; Altunkaynak and Nigussie 2016). Furthermore, these techniques have been combined with preprocessing methods for time series modeling to improve the prediction accuracy for longer lead times (Nayak et al. 2004; Firat and Gungor 2008; Ozger 2009; Katambara and Ndiritu 2009; Shiri et al. 2011; Altunkaynak 2014; Altunkaynak and Nigussie 2016).

To meet the objective of this study, the characteristic features of a three-layer perceptron were particularly selected to obtain one of the simplest and most commonly used MP architecture models which is based on the number of neurons in the input, hidden, and output layers. The number of neurons in the hidden layer varies the ability of the model to represent the complex systems of the network. Nevertheless, excessive number of neurons in the hidden layer do not enhance the performance of the model. The presence of a relatively higher number of neurons can be time consuming and cause overlearning in many cases. It also leads to an increase in the number of unknown model parameters, which in turn reduces the model performance. For this reason, the number of neurons in the hidden layer should be between three and seven (Altunkaynak 2007).

According to Altunkaynak (2013), each neuron from the input layer is linked with a weight coefficient to each neuron in the hidden layer; in the same way, the neurons from the hidden layer are linked with a weight coefficient to each neuron in the output layer. The input and output signals of the model are denoted (X_1, $X_2, \ldots, X_m$) and ($Y_1, Y_2, \ldots, Y_t$), respectively. The output signals that generate the hidden neurons are termed ($H_1, H_2, \ldots, H_n$). The connection parameter from an input neuron i to a hidden neuron j is indicated by w_{ij}, whereas a_{jk} represents the connection parameter from a hidden neuron j to a neuron k in the output layer. The connection parameters in this model can be optimized in a training phase using observed data. Altunkaynak (2014) defined the following equations for the MP model with i, j, and k representing the neuron number in the input, hidden and output layers, respectively. The input for the jth neuron in the hidden layer is the weighted sum of the input variables (X_1, $X_2, \ldots, X_m$) and the bias. The output of this hidden neuron is defined as

$$H_j = f\left(\alpha_j + \sum_{i=1}^{p} w_{ijX_i}\right) \tag{22}$$

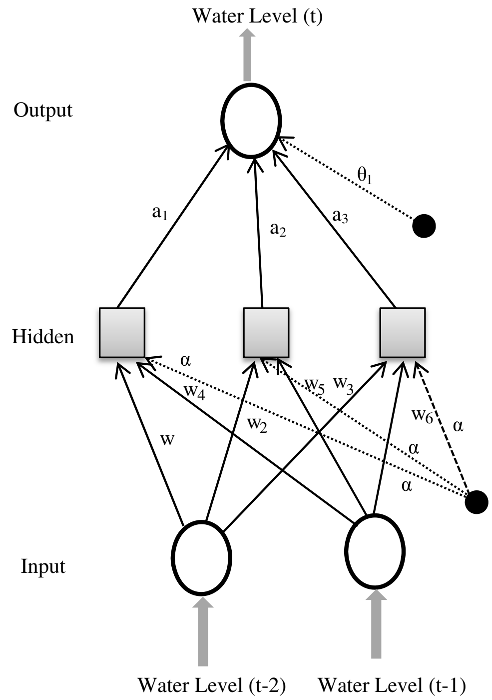

Fig. 5. Architecture of the best MP model.

where $f(.)$ is a transfer function for the hidden layer; and p = number of neurons in the hidden layer. Similarly, the result from the kth neuron in the output layer is defined as

$$Y_k = g\left(\theta_k + \sum_{j=1}^{q} a_{jk}H_j\right) \tag{23}$$

where $g(.)$ is a transfer function for the output layer; α_j and θ_k = bias for the jth hidden neuron and the kth neuron in the output layer, respectively; and q = number of neurons in the output layer.

To develop the MP model, appropriate transfer functions can be selected from among linear, step, sigmoid, or tangent sigmoid (tansig) functions for hidden and output layers based on minimum prediction error. There is no suggestion that one transfer function is superior to another. The mentioned transfer functions were tested by trial and error and the one with the lowest prediction error was selected as the most appropriate transfer function for hidden and output layers. In addition, the best architecture of the MP model was determined in terms of the number of neurons in the hidden layer and by taking the minimum prediction error into consideration. In this manner, the best architecture of the MP model was determined as one hidden layer with three neurons (Fig. 5). Furthermore, tansig and purelin transfer functions were selected for the hidden and output layers, respectively, based on the lowest prediction error.

Combined Discrete Wavelet Transform–Neuron Model

The observed monthly water levels were decomposed into three spectral bands (subseries) using DWT, which was combined with a multilayer perceptron to develop an improved method called the wavelet–multilayer perceptron (W-MP) model. The decomposed signals (three spectral bands) by DWT were individually used as inputs into the MP model to accurately predict water levels, especially for longer lead times. Each neuron in the input layer was fully linked with a weight coefficient to each neuron in the hidden layer;

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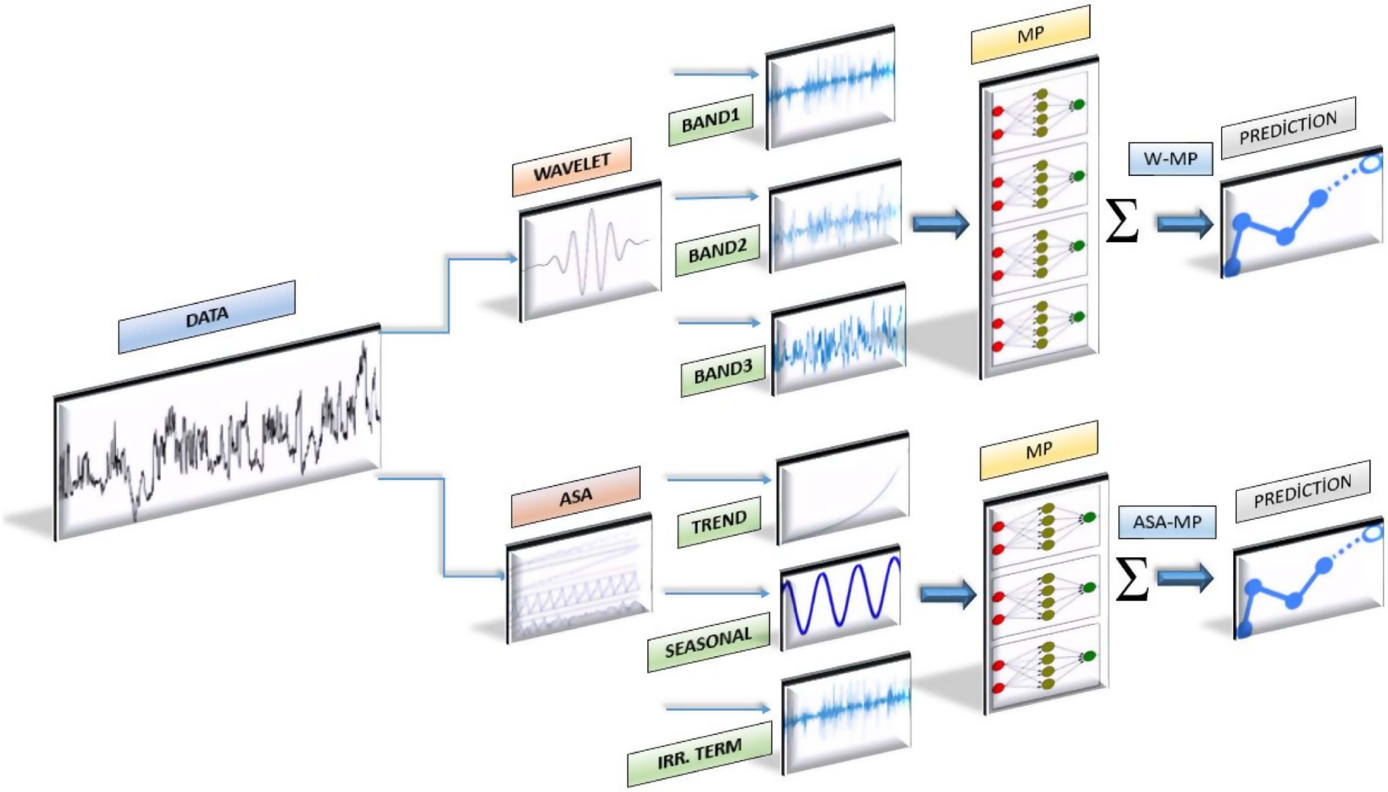

Fig. 6. Flowchart of W-MP and ASA-MP models.

in the same manner, each neuron in the hidden layer was also connected with a weight coefficient to each neuron in the output layer. Future monthly water level data for lead times of 1, 2, 3, 6, 9, and 12 months were predicted from two previous monthly water level values (time steps t-2 and t-1) which were used as inputs for the MP model. The same architecture of the MP model was used for each band (Band-1, Band-2, and Band-3) in predicting the monthly water level for various lead times. This was because the same modeling tool needed to be used, because the objective of the study was to compare the performance of the newly introduced ASA preprocessing technique with the widely used DWT preprocessing technique.

The implementation of the combined W-MP model for water level predictions can be addressed in five steps:

1. The noticeable bands (subseries) from average wavelet spectra were evaluated and taken into consideration;
2. The monthly water levels were decomposed into subseries data based on the intervals determined in Step 1;
3. To evaluate the decomposition accuracy, reconstructed subseries were validated with original time series;
4. Each spectral band was individually used as an input into the MP model; and
5. Final predicted monthly water level values were obtained by summing the predicted band values which were the outputs of the MP model.

A flowchart of the W-MP model is shown in Fig. 6.

Combined Additive Season Algorithm–Neuron Model

In this study, a new preprocessing technique, the additive season algorithm, was combined with the MP method to develop a predictive model to generate a good alternative to the W-MP model with high prediction accuracy and longer lead-time predictions; it is named the hybrid additive season algorithm–multilayer perceptron (ASA-MP) model. The objectives of this study were to (1) propose the season algorithm (SA), which is convenient and easy to implement, as a new alternative preprocessing method instead of wavelet transform; (2) propose usable and simpler arithmetical procedures for decomposition of original time series to avoid the drawbacks of the WT technique; and (3) improve the prediction accuracy and permit longer lead-time predictions. The observed water levels were decomposed into three components, namely trend-cycle, seasonally adjusted, and irregular (error) terms by using the additive season algorithm. Then these components were used as inputs into the MP model to predict the monthly water levels. Furthermore, the same architecture of the MP model was used for each component, namely the trend-cycle, seasonal index, and irregular (error) terms, in predicting the monthly water levels for various lead times. This was because the same modelling tool needed to be used, because the objective of the study was to compare the performance of the newly introduced ASA preprocessing technique with the widely used DWT preprocessing technique. Fig. 6 is a flowchart of ASA-MP model. A predictive model was developed using the ASA-MP model to predict water level fluctuations for lead times of 1, 2, 3, 6, 9, and 12 months.

Performance Evaluation Criteria

There are many statistical efficiency-evaluation criteria for a model described in the literature. The prediction performance of MP, W-MP, and ASA models was analyzed by taking the RMSE and the Nash-Sutcliffe coefficient of efficiency into consideration for calibration (training) and validation (prediction) phases. Solomatine and Shrestha (2009) stated that RMSE and CE are the most commonly used criteria as performance indicators in the literature.

This study used RMSE and CE indicator criteria to evaluate the performance of the developed models. According to Bowden et al. (2012), RMSE is a good criterion for performance evaluation of a model

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(WL_{pi} - WL_{oi})^2} \tag{24}$$

where n = total number of observations; and WL_{pi} and WL_{oi} = predicted water levels and observed values, respectively. The RMSE criterion measures the consistency between observed data and predicted values. A RMSE value close to zero indicates a perfect prediction, whereas an increasing positive value corresponds to growing mismatch between the observed data and prediction values. Another good indicator criterion between observed and predicted values is coefficient of efficiency, which is calculated as

$$\mathrm{CE} = \left[1 - \frac{\sum_{i=1}^{n}(WL_{pi} - WL_{oi})^2}{\sum_{i=1}^{n}(WL_{oi} - WL_{a})^2}\right] \tag{25}$$

where WL_a = average of the observed water levels; and the other variables are as defined for Eq. (24). According to Moriasi et al. (2007), the performance of a model can be considered acceptable if the CE value is greater than 0.5. Furthermore, Donigan and Love (2003) classified the model prediction performance in terms of CE value. When the CE value is between 0.65 and 0.75, the performance is said to be fair, performance is good if the CE value is between 0.75 and 0.85, and performance is very good when the CE value is greater than 0.85. As a result, in this study, the lowest RMSE and the highest CE values were considered for determination of the best model in terms of monthly water level predictions for lead times up to 12 months.

Results and Discussion

In this study, two preprocessing techniques were combined with the multilayer perceptron (MP) method to develop better predictive models. The season algorithm and wavelet transform techniques were used as preprocessing tools to remove trend, seasonality, and so forth from original data. A new predictive model was developed with a combination of the SA technique and the MP tool, termed the hybrid season–MP model. The SA was used as a preprocessing technique to decompose trend, periodicity and jump from original data. The WT tool was used to decompose the observed data (signal) into wavelets (subsignals) that expose valuable information such as trend, periodicity, and noise. For the first time, this study used the additive season algorithm (ASA) as an alternative preprocessing technique to predict water levels, and its performance was compared with that of the WT tool.

The monthly observed water levels of Lake Van from 1960 to 2016 are depicted in Fig. 2. Based on this figure, the water levels exhibited nonstationary trend patterns.

In this study, the standalone multilayer perceptron (MP), wavelet–multilayer perceptron (W-MP), and additive season algorithm–multilayer perceptron (ASA-MP) models were used to predict water levels in Lake Van. These models were developed to predict monthly water levels from two previous values of time steps (t-2 and t-1) for lead times of 1, 2, 3, 6, 9, and 12 months. For this purpose, monthly observed water level data from October 1960 to September 2016 were used (Fig. 2). For the calibration (training) of the model, monthly water level data of 31 years (from October 1960 to September 1990) including 372 data points were used, and with the remaining 26 years of data (from October 1991 to September 2016) consisting of 312 data points, the model was validated (tested). The WT tool was used as the preprocessing technique to decompose the observed monthly water level time series data into three wavelets (Fig. 3). The additive season algorithm was used to separate the observed time series data into trend-cycle, seasonal, and irregular (error) components [Figs. 4(a–c), respectively]. The decomposed data by the ASA and WT tools were used as inputs for the MP model in order to predict monthly water levels for all lead times.

Each neuron in the input layer was linked to each neuron in the hidden layer by weighting coefficients, and neurons in the hidden layer were linked with the neurons in the output layer by weighting coefficients. In order to develop MP based models, an appropriate number of neurons needed to be selected and calibrated by training data. The number of neurons in the hidden layer should be between three and seven in order to avoid overtraining and increasing the number of unknown weighting coefficients as well as time consumption (Altunkaynak 2007). In this study, for the best configuration of the model, two neurons in the input layer (two past values, t-1 and t-2) and three neurons in the hidden layer were used effectively (Fig. 5). The activation functions tansig and purelin were used for the hidden and output layers, respectively. However, the same architecture of the MP model was utilized for each band—namely Band-1, Band-2, and Band-3—and the trend-cycle, seasonal index, and irregular (error term) components in predicting the monthly water level for various lead times. This is because the same modeling tool needed to be used because the objective of the study was to compare the performance of the newly introduced ASA preprocessing technique with that of the widely used DWT preprocessing technique. A flowchart of W-MP and ASA-MP models is shown in Fig. 6.

The prediction performances of MP, W-MP, and ASA-MP models for all lead times up to 12 months were evaluated quantitatively in the validation phase based on RMSE and CE criteria which are calculated for each developed model from Eqs. (24) and (25), respectively, and presented in Table 1. The RMSE values of the water level predictions for the MP, W-MP, and ASA-MP models at a lead time of 1 month were 8.23, 5.98, and 3.63 m, respectively. The RMSE values of the standalone MP model were greater than those of the W-MP and ASA-MP models for all prediction lead times. In addition, the RMSE values of W-MP model were less than those of the standalone MP model and larger than those of the ASA-MP model for all prediction lead times. However, the ASA-MP model had smaller RMSE values than the MP and W-MP models for all prediction lead times. Without the combination of preprocessing techniques, the standalone MP model prediction results were worse than those of the combined W-MP and ASA-MP models for all lead times. The CE values of the standalone MP, W-MP, and ASA-MP models were 0.958, 0.977, and 0.992, respectively, for a lead time of 1 month, and 0.393, 0.501, and 0.992, respectively, for a lead time of 12 months. This means that according to the categorization

Table 1. Performance evaluation criteria of standalone-MP, DWT-MP, and ASA-MP models

Lead-time (months)	Standalone MP		DWT-MP		ASA-MP	
	RMSE	CE	RMSE	CE	RMSE	CE
1	8.23	0.958	5.98	0.977	3.63	0.992
2	14.98	0.857	9.92	0.937	3.82	0.991
3	21.46	0.706	13.34	0.887	3.95	0.990
6	33.45	0.286	20.30	0.738	4.16	0.989
9	32.16	0.340	26.37	0.557	3.93	0.990
12	32.33	0.393	27.98	0.501	3.55	0.992

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of Donigan and Love (2003), the performance of the standalone MP and combined W-MP and ASA-MP models was very good for prediction of a lead time of 1 month, but for a lead time of 12 months, the standalone MP and W-MP models performed poorly, whereas the ASA-MP model performed excellently in predicting the water level fluctuations. The newly developed ASA-MP model outperformed the standalone MP and combined W-MP models in terms of its lower RMSE and larger CE values for all lead times. The performance of the standalone MP and combined W-MP and ASA-MP models was good, with CE values 0.857, 0.937, and 0.991, respectively, for a prediction lead time of 2 months. The CE value of the standalone MP model was 0.706 for a lead time of 3 months. This means that the prediction performance of the model was fair according to the performance evaluation criteria described by Donigan and Love (2003). In other words, the standalone MP model may not be used to accurately predict monthly water levels of Lake Van beyond a lead time of 2 months. The CE values of the W-MP and ASA-MP models were 0.738 and 0.989, respectively, for a lead time of 6 months. This implies that the prediction performance of the ASA-MP model is very good, whereas the performance of the W-MP model is poor for a lead time of 6 months based on Donigan and Love (2003). The standalone MP and the combined W-MP models cannot be used for predicting water levels of Lake Van for lead times of 6–12 months. The combined ASA-MP model performed excellently for predicting the water levels, with the smallest RMSE and largest CE values for all lead times. Furthermore, the ASA-MP model was stable, with a CE value of approximately 0.99 for relatively longer lead times; even for lead times of 9 and 12 months, the CE values were 0.990 and 0.992, respectively. Accordingly, the prediction performance of the ASA-MP model is independent of the lead times used in this study. This shows that the ASA technique eliminates the trend and seasonality (periodicity) components remarkably from the original time series data. The WT tool may not be effective enough to remove trend and seasonality components from original time series data at the desired level due to the fair performance of W-MP model [based on Donigan and Love (2003)] in predicting water levels of Lake Van for longer lead times of 6, 9, and 12 months. It is concluded that the combined ASA-MP and W-MP models performed better than the standalone MP model for all lead times. Furthermore, the combined ASA-MP model prediction results outperformed the W-MP model results according to the evaluation criteria of RMSE and CE for all lead times. The water levels predicted by the standalone MP and the combined W-MP and the ASA-MP models versus the monthly observed water levels are plotted in Figs. 7–9. The 45° diagonal (1:1) line in these figures is called the perfect model line. There was a good agreement between the observed and predicted water level data by the standalone MP, the W-MP, and the ASA-MP models for a lead time of 1 month (Fig. 7). The ASA-MP model [Fig. 7(c)] performed better than the W-MP model [Fig. 7(b)] and the standalone MP model [Fig. 7(a)] for a lead time of 1 month. The results of the W-MP model were better than the standalone MP model values. Fig. 8 depicts the scatter diagrams of standalone MP, W-MP, and ASA-MP model results versus the observed water levels for a lead time of 6 months. Figs. 8(a and b) show that the standalone MP and W-MP models had poor performance in predicting water levels for a lead time of 6 months, whereas the ASA-MP model had very good performance [Fig. 8(c)]. The ASA-MP model also outperformed the standalone MP and W-MP models in predicting water levels for lead times longer than 6 months. This indicates that it is challenging to achieve quite accurate predictions for longer lead times using the standalone MP and W-MP models. Fig. 9(a) shows that for a 12-month lead time, there was disagreement between the standalone MP model results and the corresponding observed water level data. The standalone MP model overpredicted the observed water level values. Furthermore, the W-MP model had fair performance for a lead time of 12 months [Fig. 9(b)]. There was an excellent match between the observed water level data and the ASA-MP model results for a lead time of 12 months [Fig. 9(c)]. The combined W-MP model predictions were much better than the standalone MP model results but worse than ASA-MP model values for all lead times. As a conclusion, the prediction performance of the ASA-MP model is remarkable in terms of prediction accuracy and improving lead-time predictions. This implies that the trend and seasonality are eliminated sufficiently from the original time series data by the proposed preprocessing technique, ASA,

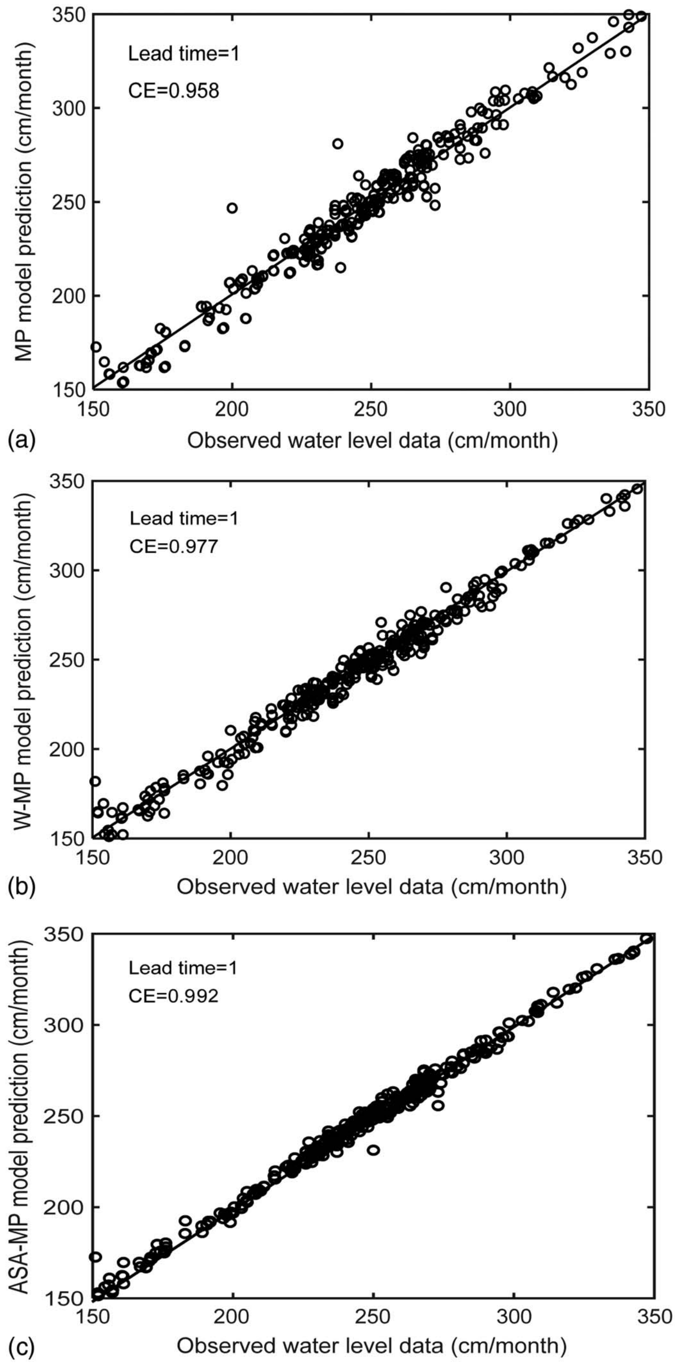

Fig. 7. Scatter plots of the observed data for prediction lead time of 1 month: (a) standalone MP model; (b) DWT-MP model; and (c) ASA-MP model.

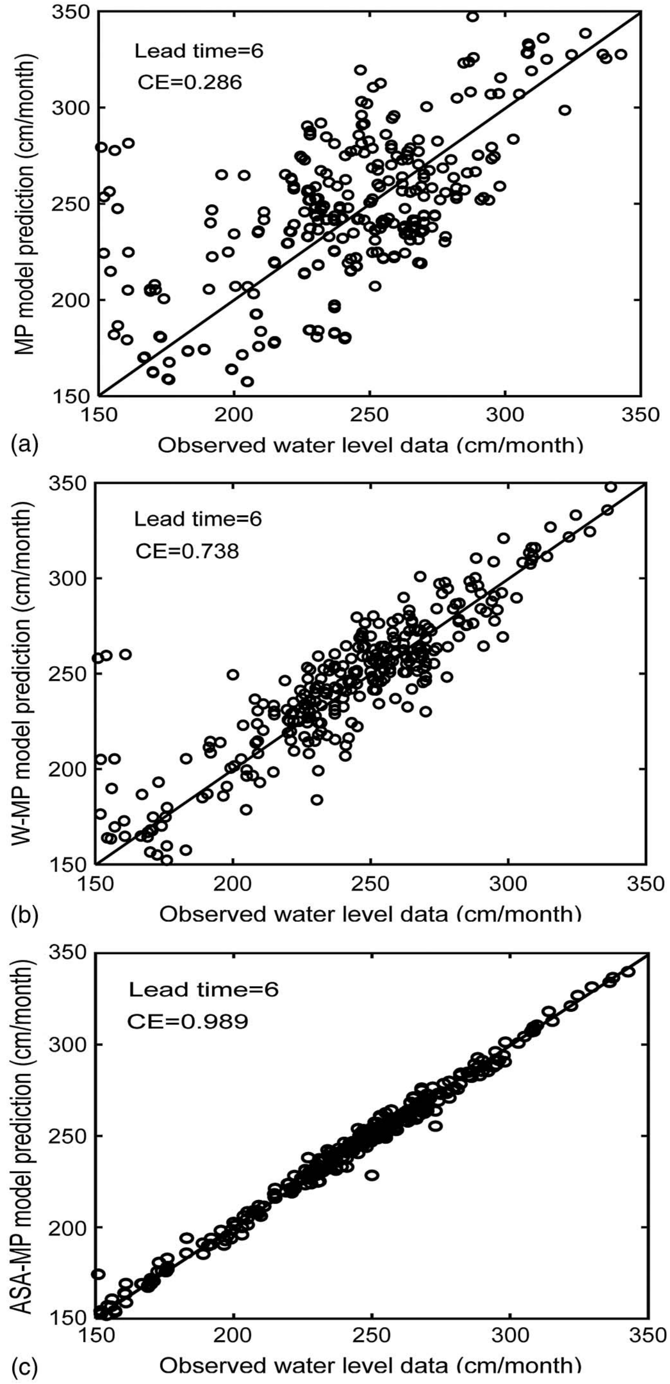

Fig. 8. Scatter plots of the observed data for prediction lead time of 6 months: (a) standalone MP model; (b) DWT-MP model; and (c) ASA-MP model.

which in this study performed better than the wavelet transform method. The results of the developed ASA-MP model in predicting water level data in this study confirmed the forecasted model values found by Altunkaynak and Nigussie (2015, 2016, 2017), who used different hydrological variables. The seasonal algorithm can be recommended as a good alternative decomposition technique to wavelet transform for development of a model in meteorological and hydrological variables.

In summary, the results of this study indicated that the standalone MP model performed very poorly in predicting water levels, particularly for lead times of 3–12 months. This study used a

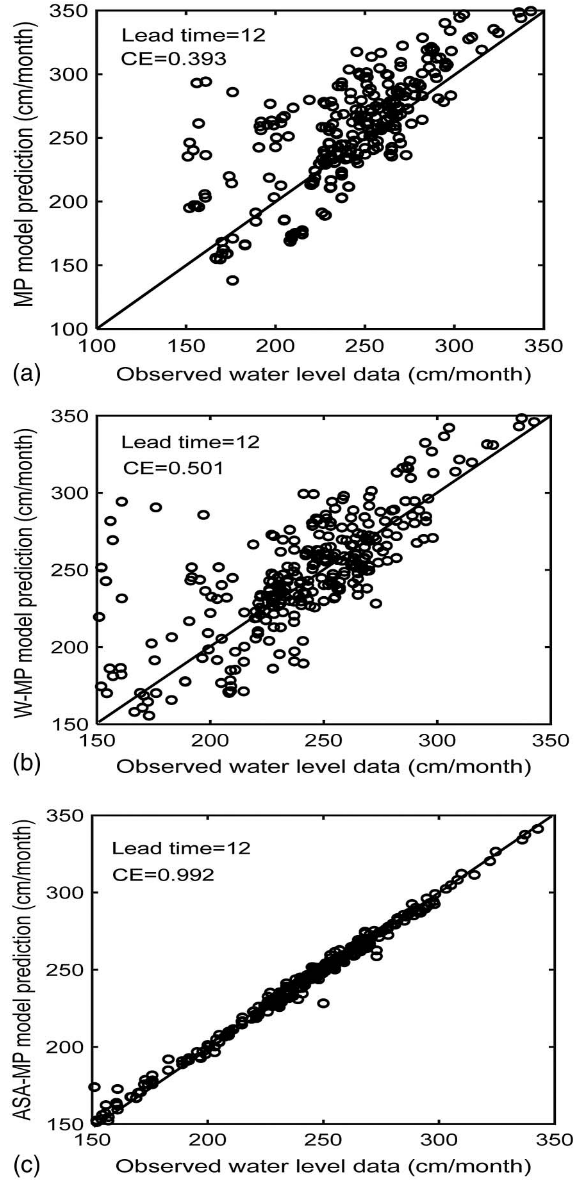

Fig. 9. Scatter plots of the observed data for prediction lead time of 12 months: (a) standalone MP model; (b) DWT-MP model; and (c) ASA-MP model.

seasonal algorithm preprocessing technique, the additive seasonal algorithm, in contrast to wavelet transform. Unlike the wavelet transform, the seasonal algorithm does not include complicated mathematical processes and other drawbacks. A three-layer feedforward multilayer perceptron model with one hidden layer having with neurons was optimized to predict the water levels accurately throughout all lead times. However, the combined W-MP model prediction performance was better than the standalone MP model performance. The developed hybrid ASA-MP model can predict the water levels very accurately and better than the combined W-MP model for all lead times.

Concluding Remarks

This study developed predictive models using the standalone MP, combined W-MP, and ASA-MP methods for accurate and improved lead-time predictions of monthly water levels of Lake Van.

The monthly observed water level data for the period 1960–2016 consisting of 684 data points were used. For development of the models, the observed monthly water level data were separated into two parts, 31 years of data with 372 data points for training (calibration), and 26 years of data with 312 data points for validation (testing). The MP model, which is one of the simplest artificial neural network models and has the best configuration, consisting of a three-layer perceptron, provided very accurate predictions for the monthly water level data. The performance of the developed models was quantitatively evaluated based on the RMSE and CE values. Both the ASA-MP and W-MP models performed better than the standalone MP model throughout all lead times.

The standalone MP model is not acceptable for monthly water level predictions beyond a lead time of 2 months. The combined W-MP model cannot be used in predicting water levels for more than a 6-month lead time. However, the hybrid ASA-MP model predicted the water levels quite accurately for all lead times. The results showed that the MP model should be combined with a preprocessing technique for more accurate predictions and to improve the accuracy of longer lead-time predictions. The combined ASA-MP model performed the best throughout all lead times. This implies that the ASA preprocessing technique is very effective in removing nonstationary data from original data, improving prediction accuracy and extending lead times, and is also user-friendly compared with the WT tool.

It is suggested that the ASA-MP model's capability should be further assessed in terms of more-accurate extended lead-time predictions as well as the overall accuracy of the model for meteorological and hydrological variables.

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