Modeling of Groundwater Level Fluctuations in a Coastal Aquifer, using Data Driven Approaches

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Abstract
Estimating the groundwater level (GWL) fluctuations is a vital requirement in hydrology and hydraulic engineering which is commonly settled through Artificial Intelligence (AI) models. This study investigated the performances of two different soft computing methods, Multilayer Perceptron Neural Network (MLPNN) and M5 model tree (M5-MT). The models are used in estimation of monthly GWL, observed in a shallow unconfined coastal aquifer. Data from observation wells located near the Ganjimatta, in India were used to estimate the GWL fluctuations. To do this, two scenarios were provided to achieve optimal input variables for modeling GWL at present time. The input parameters applied for developing the proposed models, were monthly time series of total rainfall, average temperature within their lag times, and historical groundwater level observations during the period of 1996 to 2006. The efficiency of each proposed model in Ganjimatt, was investigates in the training and testing stages. Performance evaluation indicated that the M5-MT outperforms the MLPNN model in estimating GWL in the aquifer case study. Based on the M5-MT approach, the development of this model, gives acceptable results for the Indian coastal aquifers.

Keywords:
Groundwater level estimation; multilayer perceptron neural network; M5 model tree; Indian coastal aquifers; Time series modeling

1. Introduction

Analysis of groundwater level within the hydrology and hydraulic studies, and particularly in developing countries with overexploitation problem is crucial. This will, also lead to effective and integrated management and planning for groundwater resources in the future. Accurate assessments of groundwater levels allow water managers, engineers, and stakeholders to develop better strategies to avoid or reduce detrimental effects such as, land surface subsidence, and aquifer compaction (Prinos et al. 2002). Furthermore, water level evaluation, forecasting and modeling are beneficial in developing better understanding of the dynamics and underlying factors that affect groundwater levels and also to balance the needs of urban, agricultural, industrial and trade off benefits and costs of water conservation (Adamowski and Fung Chan 2011; Moosavi et al., 2013). Although conceptual and physically-based models are the most important tools to describe hydrological variables and physical processes, taking place in a system, they have practical limitations (Nourani et al. 2008; Nourani et al., 2011). However, the calibrations of these models are very difficult because a lot of parameters need to be determined especially in the chalky media. Furthermore, these models require a large quantity of good quality data and a comprehensive understanding of the underlying physical processes in the system (Chen et al., 2009). Sometimes data are not sufficient and obtaining accurate predictions is more important than conceiving the actual physics. In this case, empirical models can be good alternative methods, where some data are available for analyzing long period.

In recent decades, soft computing techniques including artificial neural network (ANN), adaptive neuro fuzzy interference systems (ANFIS), gene expression programming (GEP), group method of data handling (GMDH) and support vector machine (SVM) have been utilized as suitable approaches to estimate complex nonlinear time series in hydrological processes and hydraulic engineering (Shiri and Kisi, 2011; Etemad-Shahidi and Taghipour, 2012; Kisi et al. 2013; Buyukyildiz et al. 2014; Hamidi et al. 2015; Najafzadeh and Zahiri, 2015; Zeroual et al. 2016; Rahimikhoob, 2016; Hosseini and Mahjouri 2016; Najafzadeh et al., 2016; Kisi and Parmar, 2016; Rezaie-Balf et al., 2017).

ANNs provide an appealing way to simulate water resources systems (Maier and Dandy, 2000). Multilayer percepetron (MLP) feed-forward network types have been widely applied to simulate hydrological processes (Isik et al., 2013). Additionally, soft computing techniques have been used for estimation of GWL fluctuations. For example, Shiri and Kisi (2011) evaluated the performance of genetic programming (GP) and adaptive neuro-fuzzy inference system (ANFIS) to predict groundwater level fluctuations using several benchmarks. According to their findings, the performance of GP was relatively better than ANFIS model. Shiri et al. (2013) investigated the performance of adaptive ANFIS, support vector regression (SVM), GEP and also ANN models to estimate the depth of GW. They concluded that GEP provided the precision prediction compared with other models. Mohanty et al. (2015) have made use of artificial neural network (ANN) to predict the levels of GW

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in multiple wells within a river basin. Their results showed that ANN model was useful method for GW level prediction and the model performance during shorter lead times, was outperformed than ones at the longer time periods. Many AI approaches based data driven models, such as Multilayer Perceptron Neural Network (MLPNN) and M5 model tree (M5-MT) can obtain a robust correlation (between predicted and observed value) to estimate monthly GWL fluctuations.

Successful applications of black-box models in water resources considerations have inspired the exploration of their ability to estimate GWL fluctuations. Extending previous studies reviewed in the introduction, the focus of this paper is to investigate the ability of MLPNN and M5-MT to estimate monthly GWL fluctuations. This paper presents some of the important points regarding MLPNN and M5-MT, development of proposed models in GWL estimation will be described further using a case study area and datasets. This will be, terminated by estimating the results and research conclusions .

2. Methodology

Forecasting hydrological processes is one of the important elements in providing reliable and accurate applications for water resources activities. Therefore, M5 MT has rarely been used for hydrological issues (e.g., rainfall–runoff modeling, flood forecasting, Groundwater modeling, etc.). It should be noted that one of the key aspects in using M5 MT is the capability of this method in giving mathematical expression between the input–output variables, which is not the case in MLPNN model. Furthermore, development of two different soft computing techniques including traditional MLPNN and M5 MT approaches which are applied to estimate monthly GWL fluctuations is briefly described in this.

2.1 Multilayer Perceptron Neural Network (MLPNN)

ANNs computational method is inspired from biological nervous system, which is based on the human brain. The most noteworthy benefit of this method over conventional hydrological models can be its ability in successfully identifying both the linear and the nonlinear hydrologic relationship between the inputs and outputs. Furthermore, ANN model can adapt itself to changing circumstances which leads to improve model performance, reduces calculation times and accelerates model enhancement (Birikundavyi et al. 2002). Even though, there are different ANN types, Multilayer Perceptron Neural Network (MLPNN) is the common type of neural system which is most widely used in resolving hydrologic problems (McGarry et al., 1999). The network of MLPNN can comprise one to many neurons and layers. Generally, the structure of the network consists of three layers: i. the input layer, through data entering the network; ii. the hidden layer or layers, where data are processed; and the iii. output layer, which is responsible for producing an appropriate response to the given inputs.

To establish the structure of a neural network, the number of its layers and neurons in each layer, and excitation function of each neuron should be determined to minimize the error. Different schemes and methods are available for the above mentioned process. Some methods proposed to minimize errors in training processes are the Levenberg-Marquardt algorithm, steepest descent, conjugate gradient algorithm, Bayesian approach, and Momentum that are in ascending order of calculation speed, all of which follow back propagation approach. Firstly, some random values are assigned to the weight and bias of each neuron. Subsequently, the initial training sample vector is fed into the network and the output is calculated and compared to the available observed data. The process is followed by modifying weights or parameters using an iterative algorithm (methods are mentioned above) in order to make the error become smaller than its present value (Abbasi farfani et al., 2015). Fig. 1 shows a schematic of a typical MLPNN.

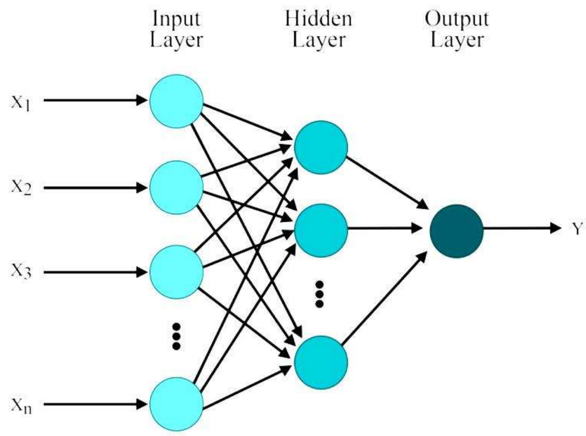

Figure 1. The MLPNN architecture (shown with a single output variable)

For more information on ANN structures Haykin (1998).

2.2 M5 Model Tree (M5-MT)

M5 model tree is a supervised learning method which have been widely used to numeric attributes. This technique was first introduced by Quinlan (1992), and Wang and Witten (1997) who enhanced his method in an algorithm called M5′. Model tree is a tree that contains a root node and leaves with linear regression functions at the top and bottom of the tree. The main purpose of this model is to determine the relevancy of independent and dependent variables (Witten and Frank, 2005). One of the advantages of model tree is to Distribution space of input variables into some disparate regions to create a linear regression in each of these regions. This advantage raises the accuracy of a model. It divides problems to some sub-problems and combines the results of these sub-problems to resolve those (Najafzadeh et al., 2016).

This algorithm is mainly formed by two distinct steps: 1.the growth of tree step and 2.the tree pruning step. Initially, M5 algorithm builds a regression tree by recursively splitting the instance space. The splitting condition is applied to minimize the intra-subset variability in the values down from the root, through the branch to the node. The variability is assessed by the standard deviation of the values that reach the node from root through the branch, calculating the expected reduction in error as a result of testing each attribute at the node. Afterwards, the attribute which maximizes the expected error reduction is chosen. If the values of all output instances that reach a node vary slightly or only a few data records remain, then the splitting process ceases (Witten and Frank, 2005). Fig. 2a schematically illustrates the splitting phase of input space and the general structure along with the dependent leaves is presented in Fig. 2b.

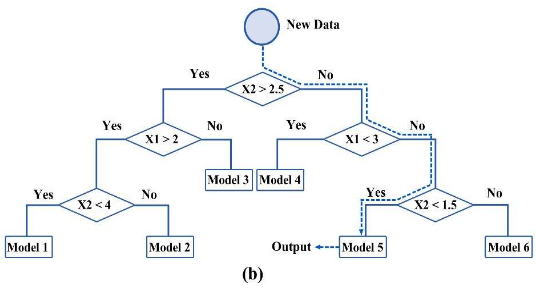

Figure 2. Splitting the input space and prediction by the model tree for a new data record (Najafzadeh et al., 2016)

To organizing the basic tree, Standard Deviation Reduction (SDR) is applied as splitting criterion in M5 model tree. This criterion can be calculated as:

$$SDR = sd(K) - \sum_i \left|\frac{K_i}{K}\right| \times sd(K_i) \qquad (1)$$

where K indicate a set of data that reach the node; K_i denotes the subsets of data that have the i_{th} outcome of the potential set; and sd is abbreviation of the standard deviation (Witten and Frank, 2005). This splitting process forces child node to have smaller value of standard deviation as compared to parent node thus making them more pure (Quinlan, 1992). The design of M5 model tree chooses the split that maximizes the expected error reduction after examining all the possible splits. This data division created during M5 algorithm process, produces a large tree which may be the cause of over fitting with testing data. To solve the problem of over-fitting, Quinlan (1992) offered using some pruning method to prune back the over grown tree. In general, this pruning is achieved by replacing a sub tree with a linear regression function. More details in this respect can be found in Quinlan (1992) and Witten and Frank (1997).

3. Case Study Area Description and Data Analysis

In present study, the selected observation for development of proposed models is located in an adjacent micro-watershed that comes under the Gurpura river catchments. The observation well located at Ganjimatta is located at 12°59′02″ north latitude and 74°57′15″ east longitude as shown in Fig.3. The study area is dominated by the southwest monsoon (June–September) and non-monsoon period (October–May). The average annual rainfall over the watershed is around 3,500 mm.

In this investigation, Lateritic soil is the predominant with highly porous and permeable nature. Due to this lateritic soil property, the infiltration rate is high and the shallow wells give very quick response to rainfall with water table rising immediately, but subsequent drastic draw down is also observed during a short period of time.

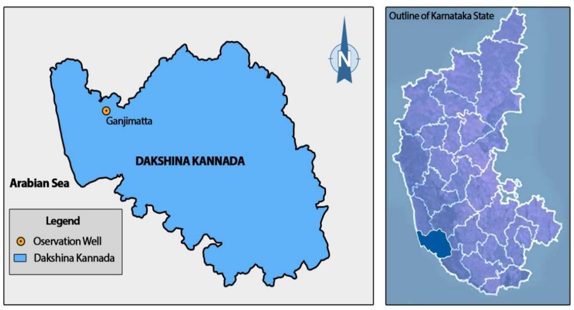

Figure 3. Case study location and observational well

The main data input to the groundwater level in the micro-watershed is from the monsoon rainfalls. The point rainfall observed at the rain gauge stations established at National Institute of Technology Karnataka (NITK) campus, Bajpe is being utilized in this. The rainfall data of this station between years 1996 to2006 have been used in this study. The average temperature and monthly rainfall data points within their lag times and past groundwater level observations are used to correlate the measurement of groundwater levels in the observation wells on a monthly basis. The data were divided into two phases: approximately 70% (84 data points) of the datasets were used for the training phase while the remained datasets (30% of the whole data set, 41 data points) were kept for testing purposes.

The water-table data of the observation well at Ganjimatta used in the study for the years 1996–2006, which were obtained from Department of Mines and Geology, Dakshina Kannada Dist. From the data analysis, the maximum, minimum, mean, and standard deviation values of all the variables influencing GWL fluctuation for each training and testing phases are given in Table 1.

Table 1. Descriptive Statistics for estimation of GWL in Ganjimatt location

Dataset	Variable	Statistical Parameters			
		X_{mean}	X_{max}	X_{min}	S_d
Training	GWT	4.41	9.45	0.95	2.25
	Rainfall	305.32	1466.30	0.00	424.95
	Temperature	27.53	31.21	23.81	1.51
Testing	GWT	4.41	9.55	1.32	1.96
	Rainfall	269.71	992.80	0.00	349.54
	Temperature	27.41	30.10	25.90	1.12

Figure 4. Display the time series of observed rainfall and GWL data points

4. Performance Evaluation Criteria

To compare the rainfall-runoff simulation performance of the developed models, different statistical indices (Eqs. 2-4) were used. The indices include correlation coefficient (R), root mean squared error (RMSE) and relative absolute error (RAE):

$$R = \frac{\sum_{i=1}^{M}\left(O_i - \overline{O}\right)\left(P_i - \overline{P}\right)}{\sqrt{\sum_{i=1}^{M}\left(O_i - \overline{O}\right)^2 \sum_{i=1}^{M}\left(P_i - \overline{P}\right)^2}} \tag{2}$$

$$RMSE = \frac{\sum_{i=1}^{M}\left(P_i - O_i\right)^2}{M} \tag{3}$$

$$RAE = \frac{\sum_{i=1}^{M}\left|P_i - O_i\right|}{\sum_{i=1}^{M}\left|O_i - \overline{O}\right|} \tag{4}$$

Where O and P signifies the observed runoff and predicted runoff by the model, respectively. $\overline{O}$is the mean of the observed values and $\overline{P}$ represents the mean of the predicted values. M shows the total number of dataset samples. The R measures how well considered independent variables account for the measured dependent variable. The RMSE is used to measure estimating accuracy, which produces a positive value by squaring the errors. RMSE would increase from zero for perfect estimates to large positive values as the differences between simulations and observations grow. Small value of RMSE and high value of R (up to one) show high efficiency of the model. RAE is the ratio of the absolute error of the measurement to the accepted measurement. Lower value of the RAE illustrates high performance of proposed model (Kisi and Parmar 2016; Rezaie-Balf and Kisi, 2017).

5. Results and Discussion

5.1 Development of GWL simulation approaches

In this study, the MLPNN and M5-MT approaches are investigated for present monthly GWL forecasting located at Ganjimatta. As there is not any defined procedure in selecting the relevant inputs to forecast monthly GWL, two scenarios were applied using MLPNN in the case study. These two scenarios (i.e., S1 and S2) are given bellow:

S1 $GWL(t) = f(T(t), R(t))$ (5)

S2) $GWL(t) = f(GWL(t-1), T(t), T(t-1), R(t), R(t-1))$ (6)

Where $GWL_{(t-1)}$, $T_{(t-1)}$ and $R_{(t-1)}$ represent previously recorded monthly groundwater levels, temperature and rainfall values, respectively, whereas the output corresponds to the GWL value at the current time (t).

Thereafter, with calculating the statistical measures that presented in Table 2, the optimal input combination were selected for forecasting the monthly GWL fluctuations in Ganjimatta. The performance evaluation of MLPNN technique through the R, RMSE and RAE statistical indexes is made in Table 2. As seen from the table, two different MLPNN models with different configurations were applied for this location. 5-3-1-1 in 2nd column of the table indicates and ANN model having 5 input, 3 nonlinear hidden, 1 linear hidden and 1 output nodes, respectively.

Table 2. Test performance measures of the MLPNN model in ground water level forecasting

Scenario	Best structure of the ANN model	RMSE	R	RAE
S1	2-2-1-1	1.514	0.763	0.882
S2	5-3-1-1	1.151	0.856	0.511

It is noteworthy that the optimal number of neurons in the hidden layers was determined by trial and error method starting with two neurons. Then number of neurons in each layer was increased up to 10 with a step size of 1.

Based on the performance evaluation results (Table 2), it is clear that S2 (Scenario 2) for Ganjimatta has the higher correlation (R=0.856) and the lower errors in term of RMSE (1.151) and RAE (0.511) compared to the S1 (R=0.763, RMSE=1.514 and RAE= 0.882).

The M5-MT procedure for estimation of GWL was applied using open source machine learning, Weka 3.6 software. Capability of M5p-MT is evaluated in order to find the mathematical formulation in form of linear relationships for GWL fluctuations forecasting. The default parameters of M5-MT technique were formed to their default values; pruning factor 4.0 and smoothing option. After classifying, model tree including five inputs and one output parameter was implemented for forecasting monthly GWL using several linear rules. These rules are based on conditional sentences presented as follow:

If $R_{(t-1)} \leq 156.15$ **then** $GWL_{(t)} = 0.7362GWL_{(t-1)} + 0.383T_{(t)} - 0.0041R_{(t)} + 0.0004R_{(t-1)}$ (7)

If $R_{(t-1)} > 156.15$ **then** $GWL_{(t)} = 0.3061GWL_{(t-1)} + 0.105T_{(t)} - 0.0025R_{(t)} + 0.004R_{(t-1)}$ (8)

From these rules, it is clear that all input parameters except $T_{(t-1)}$ were taken into account in the estimation of GWL and also are considerably significant in development of the proposed linear models.

5.2 Compression of the proposed models

Two different artificial intelligence techniques were developed for forecasting the monthly GWL fluctuations in Ganjimatta's observation well which comes under the Gurpura river catchment. The performance of tested approaches was analyzed by computing the statistical error functions for monthly GWL using the MLPNN and M5-MT, is presented in Tables 3 and 4.

Table 3. Results of performances for the MLPNN model

	MLPNN model		
	RMSE	R	RAE
Training phase	0.933	0.92	0.298
Testing phase	1.151	0.85	0.511

From the training stages, it can be seen that M5-MT estimated the GWL with a higher correlation (R=0.96) and lower error statistics of RMSE (0.636) and RAE (0.173) compared to the MLPNN (R=92, RMSE=0.933 and

RAE=0.298). It should be noted that one of the key aspects in using M5-MT is the capability of this method in giving mathematical expression between the input–output variables, which is not the case in MLPNN model.

	M5-MT model		
	RMSE	R	RAE
Training phase	0.636	0.96	0.173
Testing phase	0.693	0.94	0.252

As a result of Tables 3 and 4 for testing phases, it can be noted that proposed equations given by M5-MT estimated the monthly GWL with a higher accuracy than results by using MLPNN technique similar to the training stage. Figs 5 and 6 show the proposed models' predictions and observed GWL values for the training and testing phases, respectively.

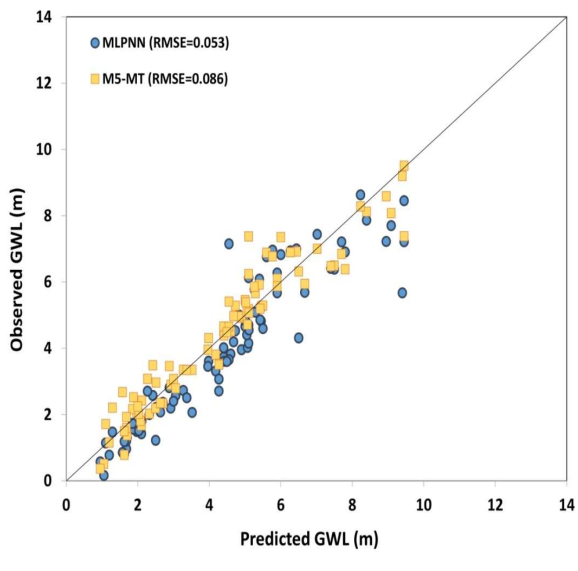

Figure 5. Scatter plot of the observed and estimated values for training performance

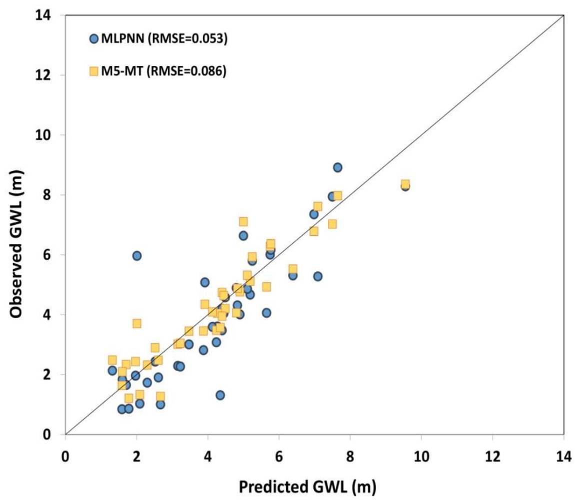

Figure 6. Scatter plot of the observed and estimated values for testing performance

Fig. 7 also shows the time series graphs of the observed versus estimated monthly GWL fluctuations using MLPNN technique in the training and testing stages. This figure shows that the accuracy of the model for extreme values is smaller than of the middle values. Fig. 8 illustrates the time series graphs of the predicted and observed monthly GWL forecasts in the training and testing stages at Ganjimatta case study for M5-MT. In contrast to MLPNN, the M5-MT has a better performance in forecasting extreme values of GWL fluctuations.

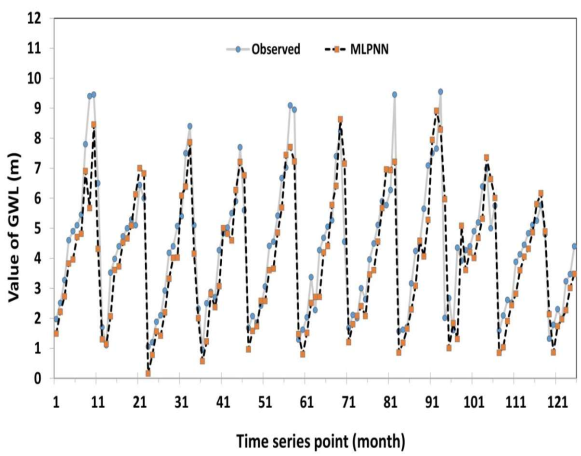

Figure 7. Time series graphs for the observed vs. estimated GWL fluctuations using MLPNN

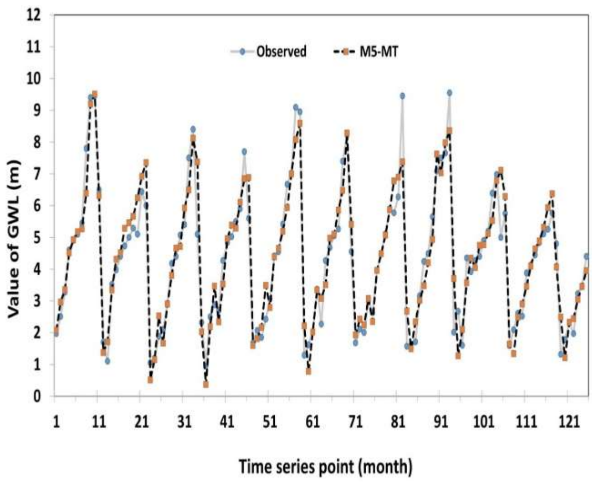

Figure 8. Time series graphs for the observed vs. estimated GWL fluctuations using M5-MT

6. Conclusion

In this study, MLPNN and M5-MT models were employed for modeling the monthly groundwater level fluctuations using inputs from present and previous GWL, temperature and rainfall of observation well, located at Ganjimatta, Dankshina Kannada Region of India. The MLPNN model was tested by applying into different input combinations of monthly groundwater level, temperature and rainfall data points. After selecting optimal input combination by MLPNN, the performances of the two proposed methods was evaluated based on three different criteria, R, RMSE and RAE. The obtained results indicated that the M5-MT model was superior to the MLPNN model in forecasting monthly GWL for the studied well. MLPNN model could not simulate the monthly GWL values for observation well and the accuracy of this predictive model was generally found to be low. On the other hand, the M5-MT approach provided a better forecast of the extreme value than the MLPNN technique. The main advantage of the M5-MT model is its explicit mathematical formulations. It can be simply used in practical applications. Instead, the MLPNN is black-box model that their formulations. The proposed techniques may also be compared within other hydrological applications (e.g., short-term wind speed predictions, sea water level forecasting, and prediction of daily evapotranspiration). As an extension of the current work, different data-derived techniques such as GMDH and GEP can also be used and compared for GWL modeling.

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