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Artificial neural network simulation of ground water levels in uplands of a coastal tropical riparian

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Wetlands play an important role in the ecological balance of the coastal region. Understanding groundwater level behaviour in uplands is important for the management and the development of coastal tropical riparian wetland. Artificial Neural Networks has proved to be robust techniques in modeling and prediction of hydrological processes. This paper presents the application of ANNs to model groundwater levels in uplands around a wetland environment. Weekly hydro meteorological observations have been used as an input to model groundwater fluctuation observed in sevel open wells in the region. A comparison of different training algorithms has also been carried out. The results obtained show that the use of Artificial Neural Networks in modeling the groundwater levels was successful. With Root Mean Square Error values in the range of 0.09 to 0.16, the study also reasserts that the same training algorithm need not provide the best results for different conditions.

Key words: Artificial neural networks, wetlands, stepwise linear regression.

INTRODUCTION

The Ramsar convention (Ramsar, 1971) defines wetlands as areas of soil covered by a shallow layer of seasonal of permanent, flowing or static, salt or freshwater. Wetlands can be natural or artificial and include areas of marine water. Riparian wetlands are the wetlands along lakes, rivers and streams. Riparian wetlands are very productive ecosystems providing vital habitat and hence their conservation is very important. Wetlands form a major ecological part of a watershed. It helps regulate the water levels within the watershed, helps in eutrophication of lakes, reduces flood and storm damages, and provides an important habitat for flora and fauna. Wetland management is an integral part of watershed management. These wetlands were not given their due importance till recently. These wetlands have been drained and converted to farmlands, filled up for housing and infrastructure thus reducing their area and their purpose. Anthropogenic activities continue to affect the working of the wetland hydrology. The ‘uplands’ of a wetland is that region which is adjoining to the wetlands which are at a slightly higher altitude. Groundwater discharge to the wetlands usually occurs near the edge where the plains meet regional uplands. The wetland’s surface water is dependent upon the groundwater levels of uplands. Drilling wells in upland to supply water for development or agriculture will reduce the ground water level and decrease the depth of water and the hydroperiod (the length of time the surface is inundated) in the nearby wetland. This decrease can cause changes in the structure and composition of the wetland community. The usual result following drainage of a wetland is a replacement of the plant and animal life adapted for deeper water and a longer hydroperiod with those species adapted for shallower water and/or shorter hydroperiods. Small wetlands are the most vulnerable to changes in water levels and small wetlands with short

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hydroperiods can easily be completely eliminated.

Although conceptual and physically based models are main tools for depicting hydrological variables and understanding the physical processes involved in the dynamics of groundwater levels, they do have practical limitations. When data is not sufficient and getting accurate responses is more important than conceiving the actual physics, empirical models remain a good alternative method, and can provide useful results without a costly calibration time. Artificial Neural Network (ANN) models are such ‘black box’ models with particular properties which are greatly suited to dynamic nonlinear system modeling (Coulibaly et al., 2001a).

The ANN technology is an alternate computational approach based on theories of the massive interconnection and parallel processing architecture of biological systems. The main theme of ANN research focuses on modeling of the brain as a parallel computational device for various computational tasks that were performed poorly by traditional serial computers. ANNs have a number of interconnected processing elements (nodes) that usually operate in parallel and are configured in regular architectures. The collective behavior of ANN, like a human brain, demonstrates the ability to learn, recall, and generalize from training patterns or data (Balkhair, 2002). Artificial neural networks (ANNs) have proved to be a robust tool that can be applied to simulation and prediction of non linear hydrological processes. Literature reviews reveal that the ANNs have been successfully used in modeling hydrological processes (ASCE, 2000a, b; Maier and Dandy, 1998, 2000; Aytek et al., 2008; Dawson and Wilby, 1998; Ahmed and Simonovic, 2005; Peters et al., 2006). In the groundwater modeling, ANNs have been used in prediction of water levels (Coulibaly et al., 2000; Daliakopoulos et al., 2005; Nayak et al., 2006) and aquifer parameter estimations (Lin and Chen, 2006).

The present study aims at modeling the water table fluctuations in the uplands of a coastal riparian wetland which are the main source of water to the wetlands, on a weekly basis, determining the ability of Artificial Neural Networks in simulating the water level fluctuations using only hydro-meteorological inputs and to evaluate the performance of different network types and training algorithms in modeling the hydrological process. A feed forward neural network is designed to observe water level fluctuations in eight wells in the study area and its performance evaluated. It is observed that the neural networks have successfully modeled the fluctuations with low RMSE values.

Study area and data description

Coastal Karnataka forms a part of the Malabar Coast in the south-west of India with a long coastline running 290 km, indented with promontories, headlands, picturesque estuaries, encompassing tidal wetlands essaying complex mangroves and long linear beaches. The study area is the humid tropical ‘Padre Wetland’ ($13^o00'0''$N to 13°01′4″N and 74°47′35″E to 74°48′35″E), near to National Institute of Technology Karnataka (NITK) Surathkal, Mangalore city in Karnataka State of India (Figure 1). It is a coastal flood plain wetland of 1.5 km^2 has **a**ltitude range of +0.0 m to +4 m with respect to MSL in the lowlands of the Nandini sub-watershed, which is about 17 km^2 in area and at an elevation ranging from +0.0 to +68 m above mean sea level in the coastal region, around 21 km north of Mangalore. It is just upstream of a vented dam, which was constructed in the year 1965 to control salt-water intrusion.

There are mainly two types of soils in the study area: coastal alluvium and laterite soils. The coastal alluvium exists along with silt and clay, which is evident from laboratory tests. The clay deposits differ from each other that depend upon geological processes such as sea level changes, erosion of superimposed load and desiccation.

The hydraulic conductivity in the uplands ranges from 2×10^{-2} to 5×10^{-3} cm/s in lateratic formations and in the order of 10^{-4} cm/s in clayey formations. Since then, the humid tropical wetland complex has been degrading rapidly by conversion of Padre Wetland into agricultural, horticultural, residential and for other purposes by anthropogenic activities (Nyamathi, 2008).

Daily data of rainfall, evaporation, maximum temperature and average temperature were obtained for the study from the meteorological station at NITK, Surathkal. The daily data was transformed to weekly data to be given as input. This was done as the remaining input parameters namely: stream levels and well observations were taken on a weekly basis. Data of two years (May 2004 to May 2006) were used for the study. Antecedent data of two weeks were considered as inputs also.

ARTIFICIAL NEURAL NETWORKS

An ANN is a massively parallel distributed information processing system that has certain performance characteristics resembling biological neural networks of the human brain (Haykin, 1994). ANNs are arranged into three basic layers—*input, hidden* and *output.* The input nodes in this representation perform no computation but are used to distribute inputs into the network. This kind of network is called a feed forward network as information passes one way through the network from the input layer, through the hidden layer and finally to the output layer. Recurrent networks, such as Hopfield nets allow feedback between layers. Figure 2 provides an overview of ANN topology.

The following equation sums up the calculations that undergo in each neuron represented by Figure 3.

$$Sj = \sum_{i=1}^{n} w_{ij} x_j + b_{oj} \tag{1}$$

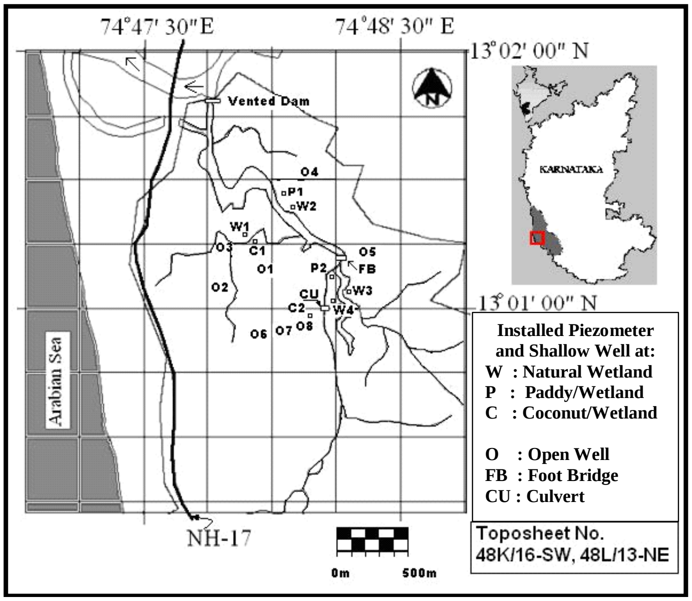

Figure 1. Location map of Padre Wetland.

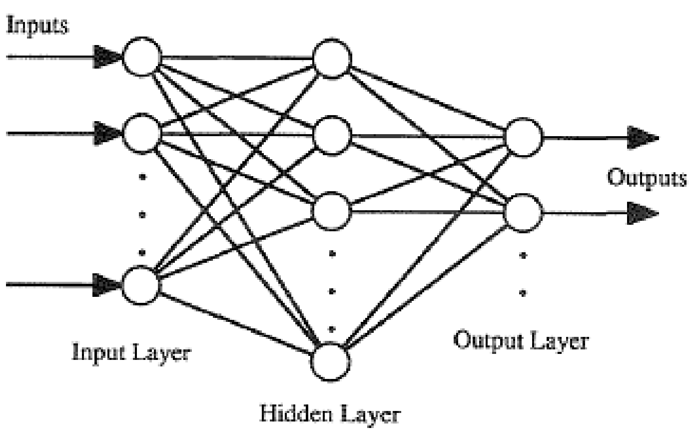

Figure 2. A basic overview of artificial neural network topology.

Where, w_{ij} is the weight which represents the strength or amplitude of a connection between two nodes. The final relationship between the input and the output of a network depends is detrermined by the weights assigned to each neuron. The weights are initialized randomly and are updated by iterations using optimization techniques. , x_j the input at node *j*, and b_{oj} is called the bias term which is a constant. For the present study, the back – propogation algorithm was applied. An activation function is applied to the value S_j, to provide the final output from the neuron. This activation function can be linear, nonlinear, discrete, or some other continuous distribution functions. However, in order to use the back-propagation algorithm to train a network, this function must have the

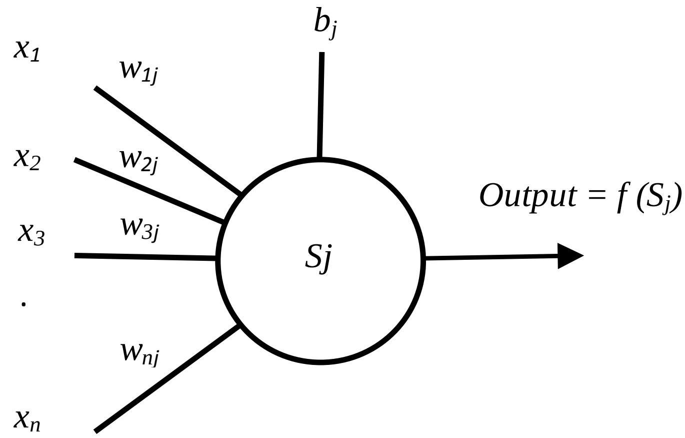

Figure 3. A single neuron.

property of being everywhere differentiable. The sigmoid function which is a smooth nonlinear activation function satisfies this criterion of having a positive derivative everywhere. It is the function generally used in most feed forward neural network applications and is represented by Equation 2. The readers are encouraged to refer to ASCE (2000a) for a detailed description of the backpropogation algorithm and the mathematics of weight updating and error backpropogation.

$$f(S_j) = \frac{1}{1 + e^{-S_j}} \tag{2}$$

METHODOLOGY

ANN model development

An optimal architecture may be considered the one that yields the best performance in terms of error minimization while retaining a simple and compact structure. No unified theory exists for determination of such an optimal ANN. A feed forward network with a single hidden layer can approximate any continuous function (ASCE, 2000a). For the present study, a static three layer feed forward back propagation neural network was used. The tan-sigmoidal transfer function was used for both the hidden layer and the output layer. The selection of network architecture and network inputs is discussed below.

Selection of input parameters

Not all of the potential input variables will be equally informative since some may be correlated, noisy or have no significant relationship with the output variable being modeled (Maier and Dandy, 2000). Any dependent variables (output parameters) may be a function of one or more independent variables (input parameters). The weekly rainfall, stream levels, average temperature, maximum temperature and evaporation along with their antecedent values of two weeks have been taken as input. To determine the optimum number of input parameters, Stepwise Linear Regression (SLR) was carried out between all the inputs and the output (Figure 4). The partial regression coefficient was

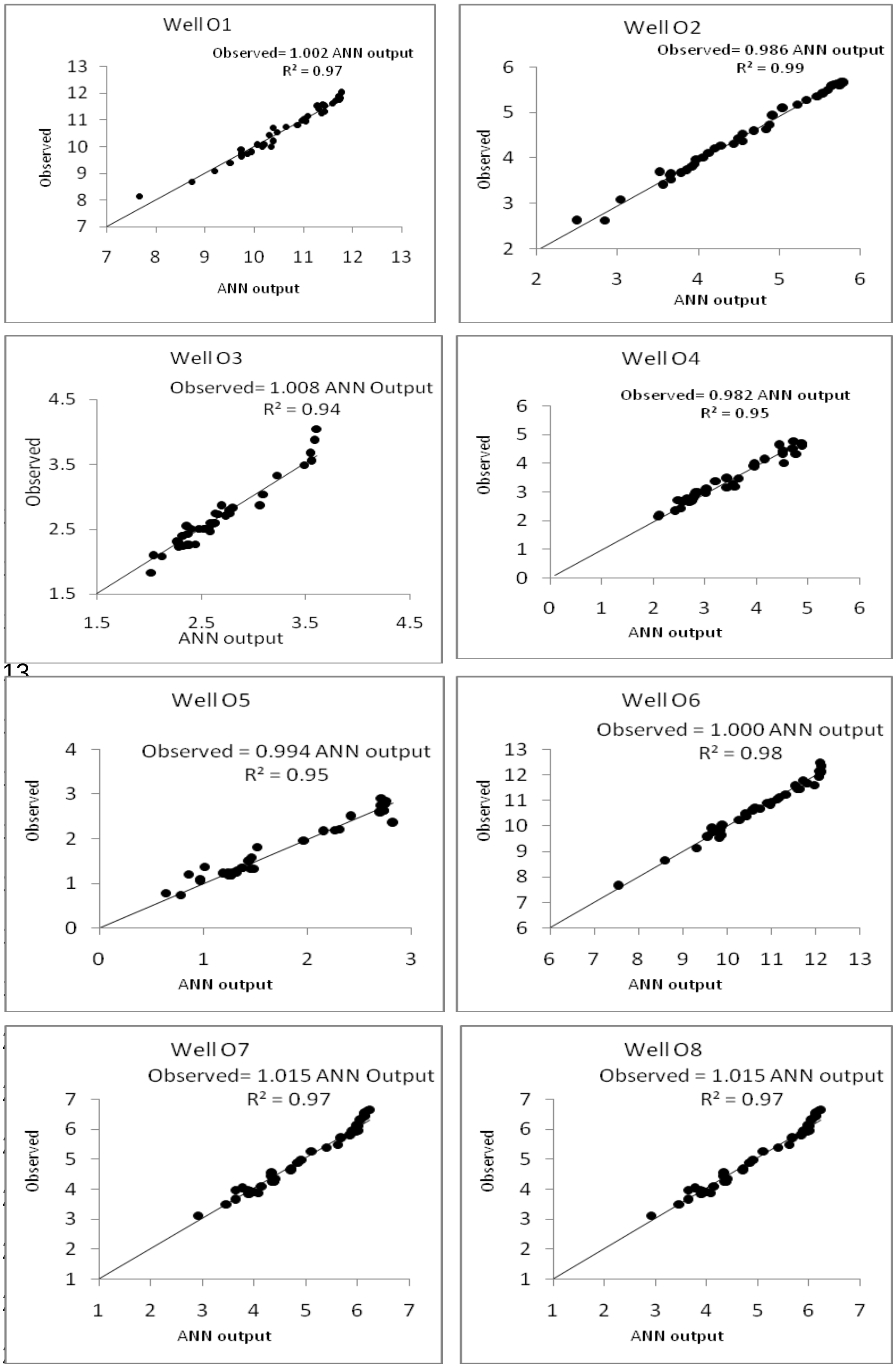

Figure 4. Regression plots between observed and obtained water levels for wells O1 to O7. An R^2 value close to 1 is considered a good fit between model output and observed data.

Table 1. Input variables considered for simulation studies. The variables considered are Rainfall (P), stream level (Str. Lvl.), Evaporation (E), Mean temperature (T_{mean}), Max. Temperature (T_{max}), water level at influencing wells (Lvl@Ox).

S/no.	Variable	Time steps at well O1	Time steps at well O2	Time steps at well O3	Time steps at well O4	Time steps at well O5	Time steps at well O6	Time steps at well O7	Time steps at well O8
1.	P	t, t - 1	T, t – 1, t – 2	t, t – 1, t - 2	t, t – 1, t - 2	t, t – 1, t - 2	t, t - 1	t	t, t - 1
2.	Str. lvl	t - 1, t - 2	-	t, t – 1, t - 2	-	t, t – 1, t - 2	-	t, t - 2	t
3.	E	t, t - 1	t, t - 1	t, t – 1, t - 2	t, t – 1, t - 2	t, t – 1, t - 2	t – 1, t - 2	t, t – 1, t - 2	t
4.	Tmean	t, t – 1, t – 2	t, t – 1, t - 2	t, t – 1, t - 2	t, t – 1, t - 2	t, t – 1, t - 2	t, t – 1, t - 2	t, t – 1, t - 2	t - 2
5.	Tmax	t – 1, t - 2	t, t – 1, t - 2	t, t – 1, t - 2	t, t - 1	t, t – 1, t - 2	t – 1, t - 2	t – 1, t - 2	t – 1, t - 2
6.	Lvl@Ox	O2: t – 1, t – 2; O1: t – 1	O2: t – 1, t - 2	O3: t – 1, t - 2	O4: t – 1, t - 2	O5: t – 1, t - 2	O7: t – 1, t – 2; O6: t - 1	O7: t-1, t-2	O7: t, t-1; O8: t – 1, t - 2

determined and the parameters which did not show any effect on the output were omitted. This procedure was carried out for each of the wells and the input neurons were determined. The major disadvantage with such an analytical method of input selection is that the nonlinear influence of the input parameters with the output cannot be determined and hence is should be used when there is no clear understanding of the physical relationships of the hydrological process. However in the present study, even with the input parameters that have only linear dependence the networks have generalized very well. SLR was carried out for each of the wells and input nodes determined. Table 1 provides information on the input parameters after identification of most influencing parameters using SLR.

Standardization of input parameters

Due to the nature of the sigmoidal function used in the backpropagation algorithm, it is prudent to standardize all input values before passing into the neural network. Without this standardization, large values input into an ANN would require extremely small weighting values which can cause a lot of problems (Dawson and Wilby, 1998). For the present study, the built-in function of the neural network toolbox of MATLAB 7.5 "*mapminmax"* was used to limit the inputs to the range of (-1,1).

Network training

The network was trained using four training algorithms namely, the Levenberg-Marquardt algorithm (LM), the resilient backpropagation (RP), the scaled conjugate gradient (SCG) algorithm and the Broyden Fletcher Goldfarb Shanno (BFGS) quasi Newton algorithm. Each training algorithm uses the gradient of the performance function to determine how to adjust the weights to minimize the performance function. A detailed description of these training algorithms can be found in Demuth et al (2007). All the selected training algorithms have a speed faster than the conventional gradient descent algorithm.

Providing the complete data for training will result in redundant information as there will not be any new data to be provided as input to test the performance of the network. Hence the data was divided into two sets, one for training and the other for testing. The training set comprised of the first 15 months that had great variations as the data contained two monsoon seasons in it and the testing set comprised of 9 months which had relatively less variations.

Determination of hidden neurons

The size of the hidden layer influences the output significantly. Though many empirical relationships to determine the number of hidden neurons have been suggested (Maier and Dandy, 2000), since network architecture is always problem dependent, it is widely accepted that the neurons are best decided by trial and error. For the present study, the network was trained with only 2 hidden neurons and increased by a step size of one neuron until there was a reduction in the performance of the network or no increase in efficiency with neuron increase was observed in the network output.

Criteria for evaluation

The R^2 statistic and the root mean square error were the criteria used to evaluate the goodness of fit of the network. While the R^2 statistic gives the overall performance of the network, the RMSE provides the global goodness of fit.

RESULTS AND DISCUSSION

All network programming was carried out using the neural network toolbox available in Matlab 7.5. The number of input nodes varied from well to well based on the variable selection using SLR. Time lags up to 2 weeks were considered for the inputs. The number of hidden neurons was determined by trial and error. Three error measures namely, Root mean square error (RMSE) and the coefficient of determination (R^2) were used to determine the best fitting training algorithm. A low value of RMSE and high values of R^2 were considered to finalize a combination as the best fitting combination of architecture-training algorithm. The best fit combination of each of the network–algorithm combination has been shown in Table 1.

It is observed from Table 1 that the selected training algorithm is not consistent and varies from well to well. This also reconfirms the general notion that

Table 2. Optimum network architecture considered for each training algorithm.

Algorithm	LM		RP		SCG		BFGS	
Well no.	Architecture							
	R^2				RMSE (m)			
01	**14 - 5 - 1**		**14 - 6 - 1**		**14 - 3 - 1**		**14 - 6 - 1**	
	0.96	0.19	0.97	0.19	0.96	0.19	**0.97**	**0.16**
02	**13 - 3 – 1**		**13 – 4 – 1**		**13 – 5 - 1**		**13 - 8 - 1**	
	0.99	0.10	0.98	0.11	**0.99**	**0.09**	0.99	0.11
03	**17 – 3 - 1**		**17 – 4 - 1**		**17 - 3 - 1**		**17 – 5 - 1**	
	0.89	0.14	0.87	0.15	**0.94**	**0.12**	0.91	0.13
04	**13 – 4 - 1**		**13 – 7 - 1**		**13 – 6 - 1**		**13 – 5 - 1**	
	0.94	0.20	0.92	0.21	0.92	0.23	**0.95**	**0.18**
05	**17 – 4 - 1**		**17 - 4 - 1**		**14 – 7 - 1**		**14 - 3 - 1**	
	0.95	**0.15**	0.89	0.23	0.95	0.15	0.94	0.17
06	**12 – 5 - 1**		**12 – 7 - 1**		**12 – 4 - 1**		**12 – 3 - 1**	
	0.97	0.18	0.97	0.19	**0.98**	**0.18**	0.98	0.19
07	**13 - 4 - 1**		**13 – 4 - 1**		**13 - 3 - 1**		**13 – 6 - 1**	
	0.97	0.18	0.96	0.20	**0.97**	**0.17**	0.97	0.18
08	**11 – 4 - 1**		**11 - 6 - 1**		**11 - 5 - 1**		**11 – 6 - 1**	
	0.97	0.16	0.97	0.20	0.97	0.18	**0.97**	**0.17**

the ANN methodology is problem specific and its generalization is not advisable. The values obtained in Table 1 shows that the network has simulated the water level fluctuations satisfactorily with RMSE values ranging from 0.09 to 0.19 m for different wells. The algorithm that has provided fair results for more wells is the scaled conjugate gradient algorithm, followed by the BFGS quasi Newton algorithm (Table 2). Figure represents the regression plots between observed water levels and model outputs. An R^2 value greater than 90% is observed consistently thus showing the accuracy of ANN in simulating the water levels.

Conclusions

This study was carried out to determine the performance of ANNs in modeling water level fluctuations on a weekly basis. Results obtained have shown that the network has been able to model the process with low RSME values. The different network algorithms that have simulated the water levels indicate that that the same algorithm need not provide the same result for different conditions. It is also observed that a clear understanding of the field conditions is also required for the decision of input parameters. Also it can be concluded that the network performs well even with antecedent conditions of only two weeks considered for input along with the input parameters at current values. However this study provides an insight into the application of ANN in wetland management and further understanding of the physical processes will increase the performance of the network.

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