Modelling of Groundwater Level Using Artificial Neural Network

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Abstract

Groundwater is an important resource which is gotten to by means of wells for home agriculture and industrial uses. It is evolved from precipitation and recharge from surface water; it is an intrinsic piece of the hydrological cycle. The utilization of groundwater step by step expanding on account of its simple accessibility, minimal effort and similarly high quality. So as to address the issue of these water over-shoots from underground water, have caused noteworthy falls in groundwater level. With the goal that estimation of water level is significant for arranging a capable and maintainable groundwater the board. Here, the artificial intelligence approach is applied for assessing groundwater level change, in Ujjain area of province of Madhya Pradesh (India). The outcomes reveal that Artificial Neural Network (ANN) is a specific tool to read the exact behavior of input and output for assessing groundwater level fluctuation without utilizing any physical involvement. An ideal network is made for the two hidden layers with Levenberg Marquardt (LM) algorithm and Scaled Conjugate Gradient (SCG) algorithm. Rainfall, relative humidity, and temperature (most extreme and least), utilized as input layer while static groundwater level utilized as target layer. Result proved that LM algorithm is comparatively better than SCG algorithm.

Keywords — *Artificial Neural Network (ANN), LM Algorithm, SCG Algorithm, Ujjain*

I. INTRODUCTION

Groundwater is a significant wellspring of drinking, industrial and agricultural activities. Precipitation and excess surface water which consistently streams towards a release point, recharge the underground water and put away in underground geological formations called groundwater. Due to increasing water demand and depleting resource underground, it is important to deal with the groundwater level, for a viable and feasible administration of groundwater.

Groundwater system has complex features as nonlinearity, multi-scale and randomness which are administrated by normal and anthropogenic components, which make troubles in the dynamic predictions. In this manner numerous hydrological models have been developed to simulate the system. Models dependent on their association of physical attributes, characterized into three primary categories, which are black box models, conceptual models and physically based models. Model other than black box model i.e. theoretical models are the essential devices for foreseeing hydrological factors and compacting the material procedures which are occurring in this methodology but that are laborious and also have practical limitations due to interrelated variables. So that the black box models for example ANN models, Adoptive Neuro Fuzzy Inference System (ANFIS) etc. mostly utilized for analysis in numerous zones of science and technology. There are huge flood of records on use of ANN in water resource problems for example rainfall forecasting, rainfall-runoff model and stream flow prediction. In the space of groundwater, ANN has been utilized for underground water recovery, groundwater level prediction and defilement.

Therefore the objective of the present study is to evolve groundwater model, which requires lesser types of data using ANN techniques. Also to provide the mathematical relationship for the LM algorithm and SCG algorithm and compare the result of both the model. These technique can be efficient to perform and are not stochastic in nature.

II. DATA COLLECTION AND PREPARATION

Present study is based on open wells located in Ujjain district in the Malwa region of Madhya Pradesh (as shown in fig.1) in central India. The city is situated between 23° North and 75.78° East, with an average elevation of 491 m. The city situated on the eastern bank of the Shipra River, which is one of the holy blessed urban communities of India. It is also one of the spots in the nation where the Kumbh Mela is held.

Fig. 1. Location Map: Source of Figure Google

The data cover 10-year period, from 2004 to 2013, and are collected on an average monthly basis. Rainfall, temperature (min. and max.), and relative humidity were found to the model as input, collected from www.mpwrd.gov.in and www.globalweather.tamu.edu whereas static underground water levels of study wells were introduced as the target output of the ANN model collected from the Ground Water Department, Ujjain. Table 1 shows the location of observation wells in study area

Table 1. Location of Study Wells

No.	Location of well	Latitude	Longitude	MSL
1	Moulana(Barnagar)	23°04’31”	75°24’27”	500m.
2	Hamukhedi(Ujjain)	23°07’26”	75°50’11”	496m.
3	Rui(Ghatiya)	23°17’06”	75°39’05”	513m.
4	Ghonsla(Mahidpur)	23°26’24”	75°52’27”	499m.
5	Kaytha(Tarana)	23°12’50”	76°01’02”	499m.

III. MODEL TRAINING AND EVALUATION

Nnstart tool of ANN was used to build and train the model by choosing LM algorithm and SCG algorithm. The model has been trained utilizing 7 years data, validated utilizing 2 years data and tested utilizing 1 year data. 2 layers and 4 neurons utilized for training and after approximate 24 iterations the estimated value comes.

3.1 Levenberg Marquardt (LM) Algorithm

The LM algorithm is a repetitive procedure which finds the base of a multivariate capacity which is imparted as the entirety of squares of non-direct genuine esteemed capacities. It is a basic technique for non-direct least squares problems. It is a mix of Steepest Descent and the Gauss-Newton techniques, when the present solution is long way from the right one the algorithm behave like a steepest descent technique which is moderate however ensure converge, when the present solution is close to the right solution, it turns into a Gauss-Newton technique. To refresh weights and biases, the calculation utilizes a ballpark of the Hessain Matrix, which is

$$w_{k+1} = w_k - [J^T J + \mu I]^{-1} J^T e \qquad (1)$$

Here w means weight and J means Jacobian framework which holds first subordinates of the system error blunder concerning the weights and biases, the e is a vector of system mistakes, and μ is a scalar that governs the learning.

3.2 Scaled Conjugate Gradient (SCG) algorithm

SCG is a supervised learning algorithm for feed forward neural networks and is member of the class of Conjugate Gradient Methods. In the Conjugate Gradient algorithm the weights adjust in the direction in which the performance function is decreasing most rapidly and step size (weight update) is adjusted at each iteration. A search is made along the conjugate gradient direction to determine the step size, which minimizes the performance function along that line. Thus with superliner convergence rate SCG is a variation of a conjugate gradient method which avoids the line search per learning iteration, by using LM approach in order to scale the step size.

3.3 Performance Evaluation

Five statistical evaluation criteria were utilized to assess and look at the presentation of models are as follows:

1) The coefficient of efficiency (CE):

$$CE=1-\frac{\sum_{j=1}^{n}(Y_j-X_j)^2}{\sum_{j=1}^{n}(Y_j-\bar{Y})^2} \tag{2}$$

When,
CE > 0.90 Perfectly Acceptable.
CE bet^{n} 0.6 and 0.9 Acceptable Simulation.
CE < 0.6 Unacceptable.

2) Mean square error (MSE):

$$\text{MSE} = \frac{1}{n}\sum_{j=1}^{n}(Y_j - X_j)^2 \tag{3}$$

It must be positive, nearer to zero

3) Coefficient of Determination. (R^2):

$$R^2 = \left[\frac{n \,.\, \sum(XY) - \sum(X) \,.\, \sum(Y)}{\sqrt{[n \,.\, \sum X^2 - \left(\sum X\right)^2] - [n \,.\, \sum Y^2 - \left(\sum Y\right)^2]}}\right]^2 \tag{4}$$

The range is 0-1.
A higher coefficient means a better goodness of fit.

4) Mean absolute error (MAE):

$$\text{MAE} = \frac{\sum_{j=1}^{n}\text{abs}(Y_j - X_j)}{n} \tag{5}$$

5) Coefficient of Correlation (R):

$$R = \frac{n.\sum(XY) - \sum(X).\sum(Y)}{\sqrt{[n.\sum X^2 - (\sum X)^2] - [n.\sum Y^2 - (\sum Y)^2]}} \tag{6}$$

The range is -1.00 to +1.00.
+1.00 demonstrates valid positive association
-1.00 demonstrates valid negative association
0.00 demonstrates no relation at all.
Where Y_j and X_j observed and modelled water table values separately, while n means number of tests.

3.4 Scatter Plots for Different Study Wells

Scatter plots between observed levels and estimated levels for different study wells for LM algorithm and SCG algorithm are shown in Fig. 2, 3, 4, 5, 6, 7, 8, 9, and 10, 11 respectively for well no. 1,2,3,4 and 5 accordingly Table number 1.

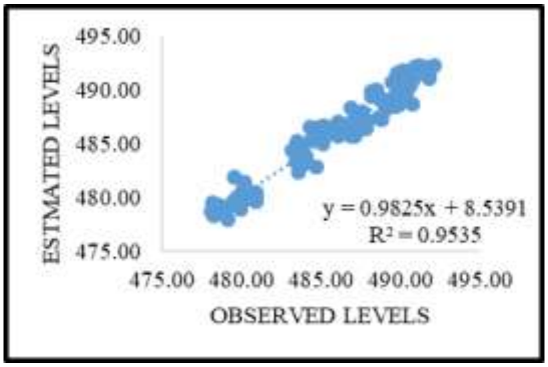

Fig. 2. Scatter plot for Well No.1 by LM algorithm

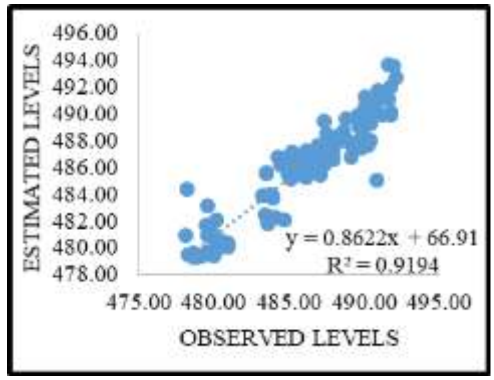

Fig. 3. scatter plot for Well No.1 by SCG algorithm

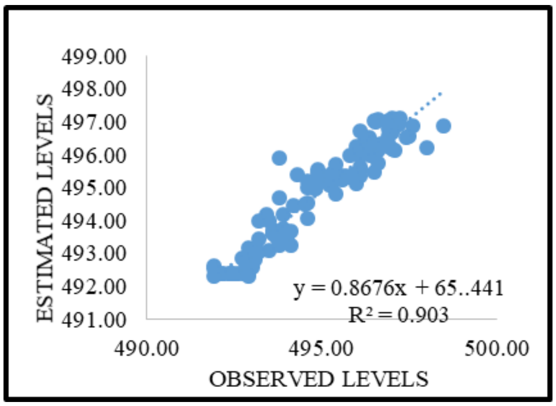

Fig. 4. Scatter plot for Well No.2 by LM algorithm

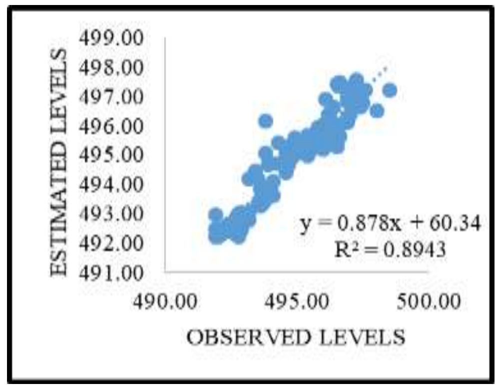

Fig. 5. Scatter plot for Well No.2 by SCG algorithm

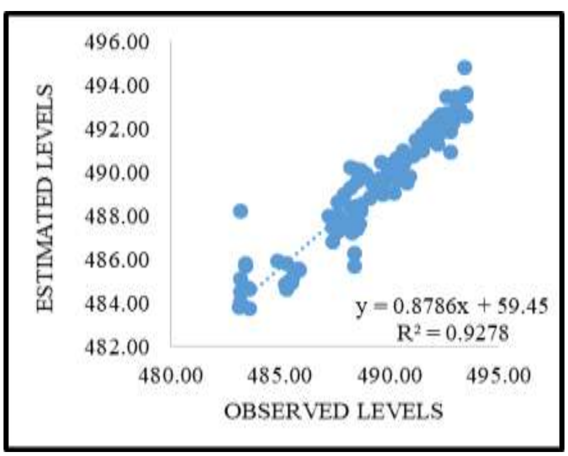

Fig. 6. Scatter plot for Well No.3 by LM algorithm

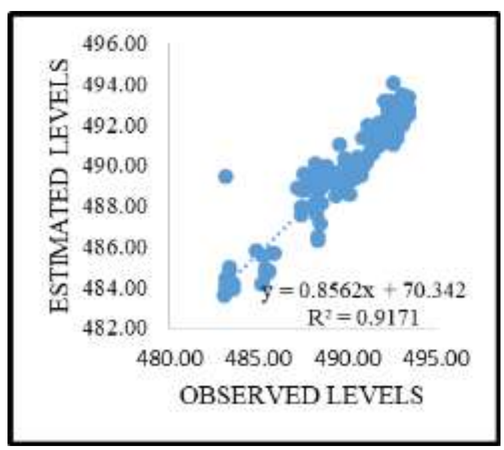

Fig. 7. Scatter plot for Well No.3 by SCG algorithm

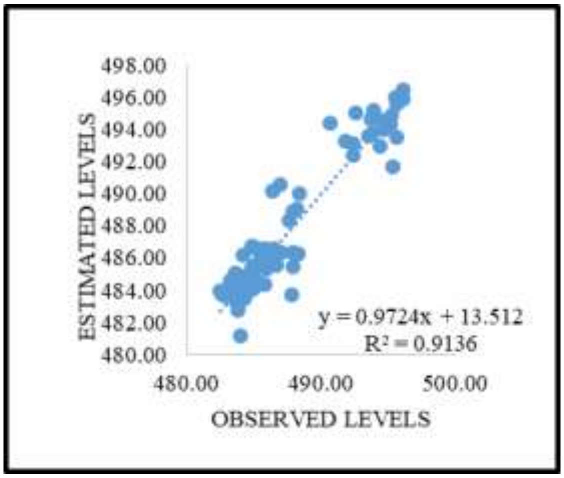

Fig. 8. Scatter plot for Well No.4 by LM algorithm

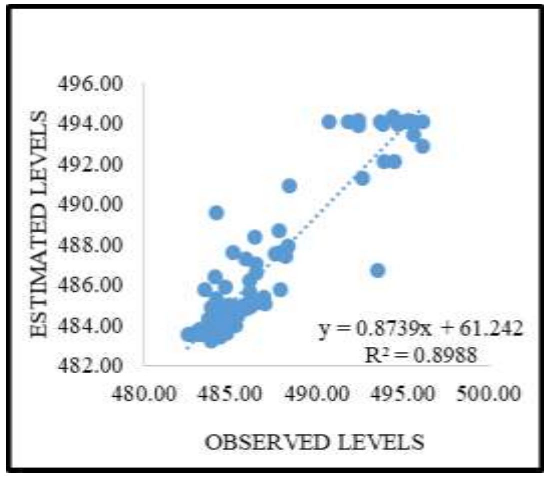

Fig. 9. Scatter plot for Well No.4 by SCG algorithm

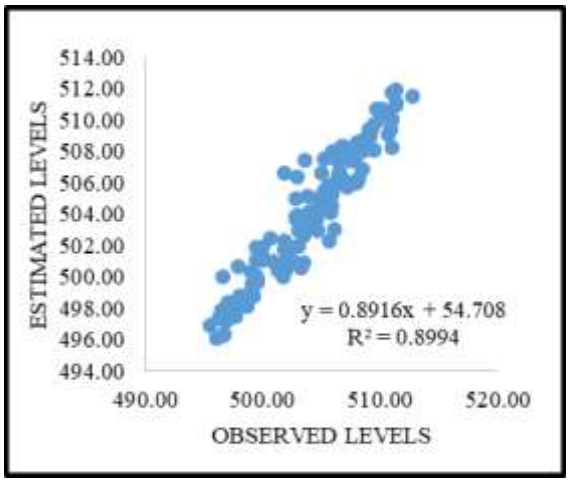

Fig. 10. Scatter plot for Well No.5 by LM algorithm

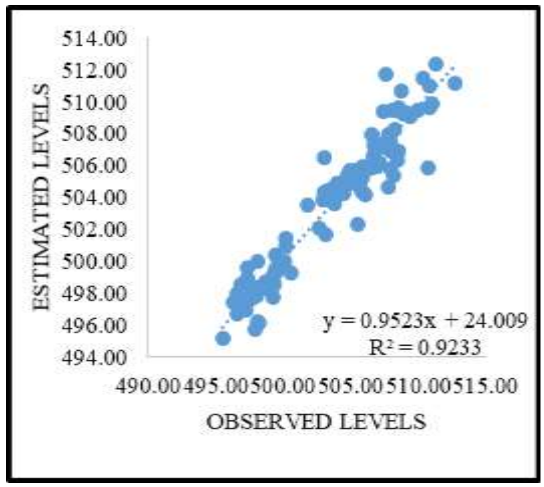

Fig. 11. Scatter plot for Well No.5 by SCG algorithm

3.5 Comparision of estimated levels and observed levels of different study wells

A comparative analysis of estimated levels and observed levels for different algorithm are shown in Fig. 12, 13, 14, 15, 16, 17, 18, 19, 20 and 21 respectively for well no. 1,2,3,4 and 5 accordingly table number 1.

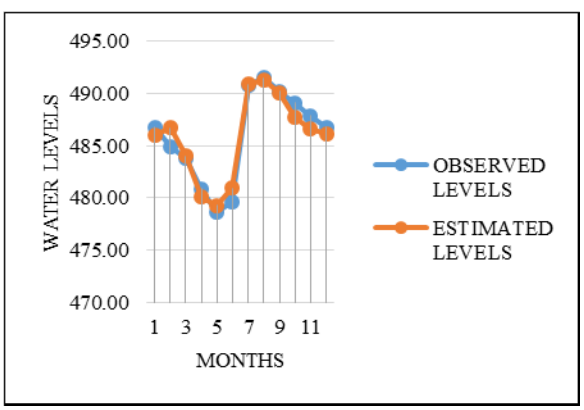

Fig. 12. Comparative analysis for Well No.1 by LM algorithm

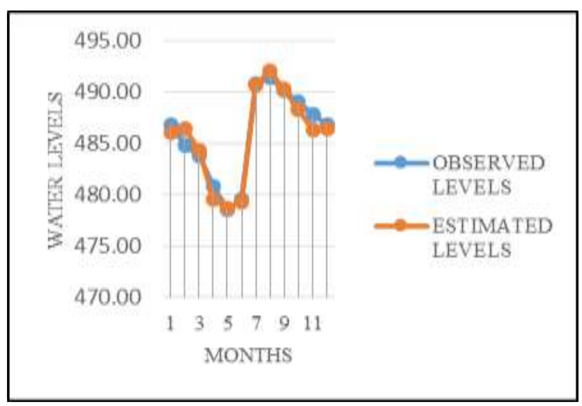

Fig. 13. Comparative analysis for Well No.1 by SCG algorithm

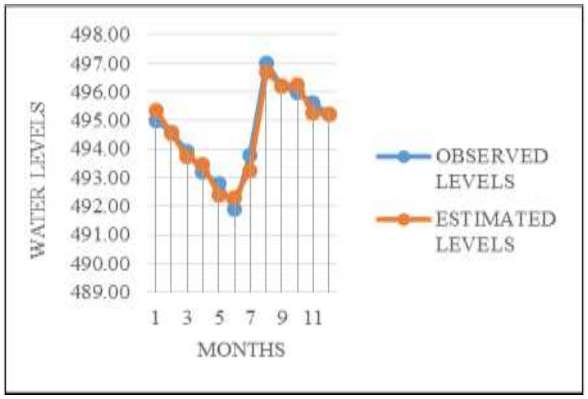

Fig. 14. Comparative analysis for Well No.2 by LM algorithm

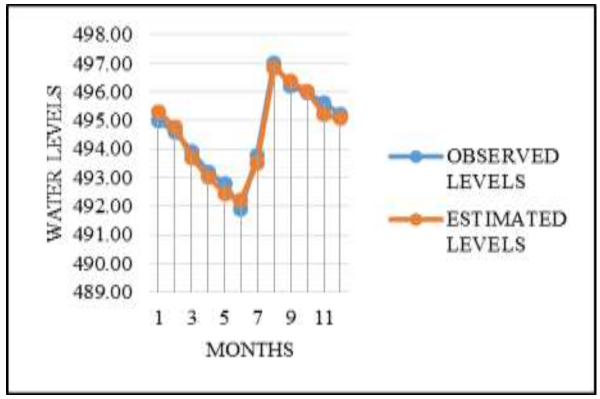

Fig. 15. Comparative analysis for Well No.2 by SCG algorithm

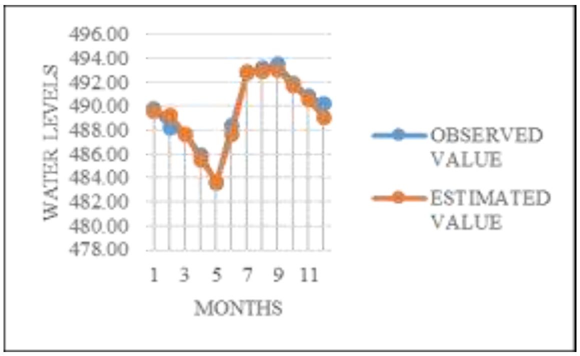

Fig. 16. Comparative analysis for Well No.3 by LM algorithm

Fig. 17. Comparative analysis for Well No.3 by SCG algorithm

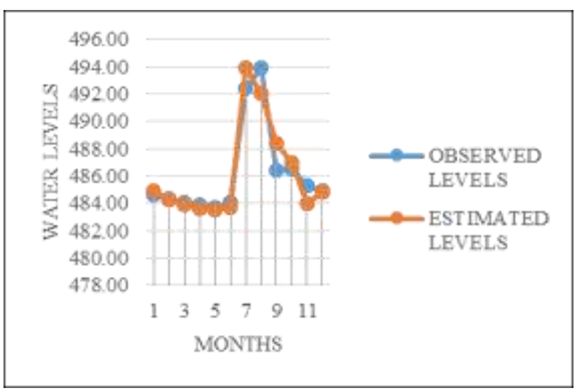

Fig. 18. Comparative analysis for Well No.4 by LM algorithm

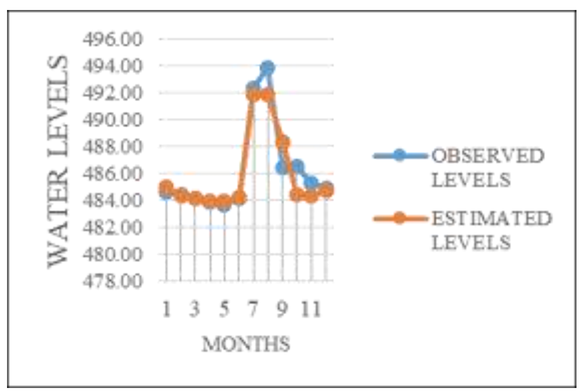

Fig. 19. Comparative analysis for Well No.4 by SCG algorithm

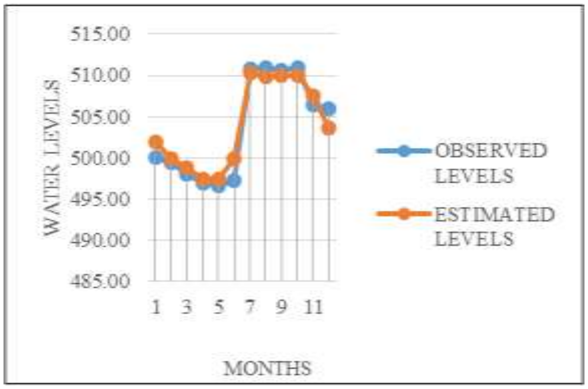

Fig. 20. Comparative analysis for Well No.5 by LM algorithm

Fig. 21. Comparative analysis for Well No.5 by SCG algorithm

IV. RESULTS & DISCUSSION

Five distinct criteria utilized to assess the viability of every system and its capacity to make accurate and exact forecasts, which are coefficient of efficiency, mean square error, coefficient of determination, mean absolute error and coefficient of correlation, as shown in Table 2.

Results indicates that LM algorithm gave better estimations of water table depths in the investigations zone for five different study wells than SCG algorithm. Well No. 2 (Ghonsla) is giving minimum mean square error and well 5 (Rui) gave maximum mean square error. Similarly well no.3 (Kaytha), 2 (Ghonsla) and 1(Hamukhedi) are giving maximum value of correlation coefficient that means the relation between the actual value and estimated value is very high, and actual and estimated ground water level are in similar pattern.

Table 2. Testing Statistics of LM Algorithm and SCG Algorithm

Study well	Model Step	CE		MSE(M)		R^2		MAE (M)		CC	
		LM	SCG	LM	SCG	LM	SCG	LM	SCG	LM	SCG
W1	Training	0.95	0.83	0.89	0.92	0.95	0.92	0.75	1.26	0.92	0.91
	Validation	0.96	0.83	0.62	1.23	0.97	0.94	0.68	1.29	0.96	0.92
	Testing	0.95	0.81	0.77	0.80	0.93	0.90	0.63	1.16	0.91	0.89
W2	Training	0.91	0.90	0.25	0.35	0.94	0.92	0.38	0.40	0.94	0.90
	Validation	0.87	0.85	0.45	0.53	0.97	0.93	0.54	0.57	0.96	0.89
	Testing	0.91	0.92	0.11	0.18	0.90	0.92	0.36	0.41	0.98	0.90
W3	Training	0.88	0.85	0.88	1.21	0.96	0.94	0.66	0.82	0.95	0.91
	Validation	0.93	0.93	0.82	0.75	0.89	0.94	0.49	0.61	0.93	0.90
	Testing	0.91	0.90	0.98	0.71	0.93	0.93	0.67	0.76	0.96	0.96
W4	Training	0.86	0.79	1.60	1.50	0.92	0.91	0.85	1.01	0.90	0.89
	Validation	0.92	0.72	0.73	1.80	0.89	0.87	0.73	1.10	0.91	0.91
	Testing	0.89	0.88	0.20	0.70	0.93	0.95	1.28	1.30	0.92	0.93
W5	Training	0.77	0.66	1.58	1.30	0.90	0.92	1.55	1.78	0.90	0.88
	Validation	0.85	0.77	2.70	2.92	0.86	0.89	1.56	2.09	0.89	0.93
	Testing	0.90	0.72	1.54	0.87	0.92	0.94	1.51	2.50	0.90	0.89

V. CONCLUSION

The results indicate that Artificial Neural Network is an effective tool to get the exact behavior of input and output for estimating groundwater level fluctuation, without using any physical involvement. The LM is a fast training algorithm and less memory consuming. Its utilization is very simple also gives better results in groundwater estimation. It allows farmers and water resource planners to detect static groundwater level variations in a timely manner and to manage groundwater related issues more efficiently. It is helpful to industrialists also to know availability of water in each month

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