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Groundwater Level Assessment in an Alluvial Aquifer Using Neural Networks

Shiwanshu Shekhar[1], Medha Jha[2], Manvendra Singh Chauhan[3,*], Pranav Kumar[1], Santosh Kumar[1]

[1]Muzaffarpur Institute of Technology, Muzaffarpur-842003, India
[2]Indian Institute of Technology (BHU), Varanasi-221005, India
[3]Holy Mary Institute of Technology and Science, Hyderabad-501301, India

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Abstract Groundwater is an important source of water worldwide due to its wide availability and generally good quality. Earlier groundwater was easily accessible to meet various domestic demands, but recently, it is vulnerable depletion in many areas due to over exploitation and mismanagement of groundwater resources. This study used the Artificial Neural Network (ANN) model to forecast groundwater (GW) level near Varanasi. ANN is a way to develop a prediction model based on the human brain's functions. This research provides a flawless prediction using the LM (Levenberg-Marquardt) and GDX training algorithms (Adaptive Learning rate with back Propagation). Data from eight wells, annual precipitation, the maximum and minimum temperatures, and relative humidity are all accepted as inputs, while the output is expected groundwater levels. The R (regression coefficient) and RMSE (root mean square error) values were used to measure model competency and precision. The observed R and RMSE values for the majority of the wells were heading towards unity using the LM technique. This LM technique is effective when we have a limited amount of data, and it is believed that this strategy will produce a precise result for a large amount of data. When there is a data constraint, the LM approach is found to be appropriate for determining any forecast of water fluctuations. This technique produces accurate results when the river location is used as an input in the artificial neural network (ANN).

Keywords Varanasi, ANN, LM, GDX, Ganga River, Groundwater Level Prediction

1. Introduction

Varanasi is a perfect illustration of a typical Indian metropolis in terms of demography and water use. Furthermore, the presence of the country's most crucial water body, the sacred Ganges, as a substantial source of water makes it a considerably stronger case to examine. Rapid urbanization in and around the city has taken a toll on its groundwater reserves, making it an important topic for investigation. The groundwater level is one of the most significant parameters to consider while forecasting in terms of availability. It depends on various parameters such as rainfall, humidity, solar radiation, evaporation etc., along with groundwater flow. The groundwater table is influenced by a variety of factors. Metrological, geomorphological, and hydrological factors can all be grouped together. Groundwater demand is becoming more uncontrolled and unaccounted as the population growing, stressing the importance of groundwater forecasting and management. Due to urbanization and rapid construction of buildings, fast development has negatively affected the nation's overburdened water sources and exhausted its groundwater reserves. Drought and depletion of groundwater reserves may result from excessive water use. Many communities are currently experiencing changes in the pattern of land [16,17,18], changes in the way of river Ganga [20,21,22,23,26,27] and rapid depletion in the level of GW due to high increase in population, which was 1.21 billion in 2011 as compared to 1991 (Census of India). Prior to overexploitation and poor groundwater management, groundwater was efficiently available to meet various daily demands; however, the groundwater table has been lowered in many regions [16, 17, 23, 25]. Several factors influence the groundwater table and river sediment load [6, 20, 21, 22, 26, and 27]. Water scarcity is a problem in India, which is one of the world's fastest expanding nations. A few theoretical and practical model studies were carried out to determine the groundwater level. Because of the randomness of data availability, they were not only extremely complex and time-consuming, but also erroneous. Various models developed previously, such as Physical [26, 32], Statistical regression [33, 34, 35], and Water balance [13, 14], all require a large dataset of groundwater. Additionally, it has been revealed, [28] output result was not appropriate due to high error in the observation head. In addition, [1, 9] provided an overview of the usage of ANN in GW studies. Maiti [12] developed a perfect model for predicting GW fluctuation in an alluvial aquifer using an artificial neural network (ANN). For the simulation of GW variations in the past, ANN models were used. ANN demonstrating has previously been used to mimic water table variations in several places [2,3,7,10,11,16,18,19,31,32]. These studies show that ANN models can be helpful in forecasting water table fluctuations, especially in areas where water cycle parameter records are scarce or non-existent. The current study continues these efforts by comparing two methods (Back Propagation), primarily LM and GDX, to anticipate groundwater levels in Varanasi, India.

Study Area

Varanasi is a sacred city located 76 meters above sea level. Climate conditions vary from hot in April to June to cold in December to February mid-season and rainy in July to September. The sunshine varies from 12 hours in January to 368 hours in May. The typical temperature is between 25°C and 26°C, with 1030 mm of precipitation on an average [5]. Throughout the year, humidity ranges from 2% to 98 %. This region contains an area of 152 km^2, and its geographical condition is 25°25'0" N to 25°5'0" N latitude and its longitude is 82°5'0"E to 82°55'0" E. Figure 1(a) shows the actual location of Varanasi in Uttar Pradesh, India, while figure 1(b) displays the location of the study area as determined by ARC-GIS, along with wells location. Ganga, a river known for its religious origin, is the mother of all water bodies in India and is located across a 6.5 km stretch, cutting across the city and quenching needs of its citizens on an everyday basis [4]. Table 1 shows the sites of 8 wells along with their distance from the river Ganga. Reduced levels of all eight wells with their geographical locations have been given in Table 1. Varanasi City contains a significant part of the alluvial plain.

Figure 1 (a). Location of Study area in India

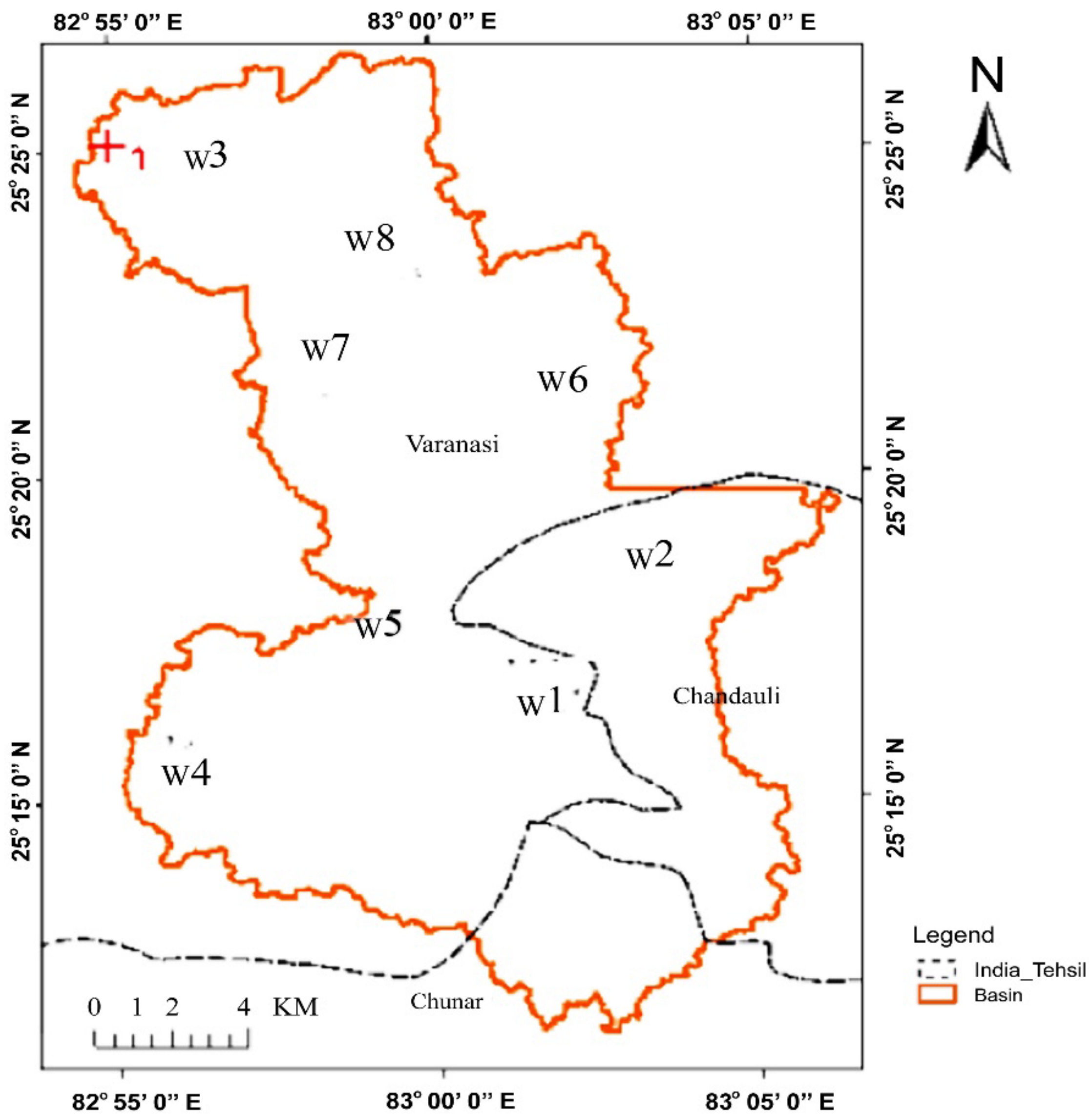

Figure 1 (b). Study area with well location

Table 1. Locations of wells with Reduced Level, distance from River Ganga and their Geographical Position

Sr. No	Well location	Latitude	Longitude	Length (km) from river Ganga	R.L of GW
1	Trauma Centre	25.274286	83.003579	1.2	73.9
2	CSC Centre	25.294212	83.035663	4.07	72.74
3	Babatpur	25.43778	82.84778	22.46	70.36
4	Khandwa Road	25.2643	82.958419	8.36	74.1
5	Chowka Ghat Bridge	25.335239	82.9961	4.88	67.5
6	Bela Road	25.369147	83.006056	4.32	75.4
7	Varuna Bridge	25.340091	82.980931	8.36	56
8	Shivpur	25.309485	82.9788	6.21	68.1

Varanasi experiences a humid sub-tropical climate with significant variations between summer and winter temperatures. The dry summer starts in April and lasts in June, followed by the monsoon season from July to October. The temperature ranges between 22 °C to 46 °C in the summers. In winter Varanasi see considerable diurnal variations, with warm days and downright cold nights.

2. Methodology

The use of ANN to construct prediction models is getting increasingly common. ANN is beneficial for solving difficult real-world situations. The job that cannot be completed by linear issues can be completed by the neural organization. The ANN method is based on how neurons in the human brain work. Three layers are used in the ANN process: input layer, output layer, and hidden layer. An ANN network is made up of many neurons that are all coupled to one other. Finding good weight values associated with independent variables and appropriate activation functions can be used to build the prediction model. The following sections go through the specificities of the various processes required.

Neural Architecture

The feed forward neural networks approach is used in this study to create the ANN network. The most common way of preparing neural architecture is; this one. There are three layers to it: input, output, and hidden. One or more hidden layers are typically employed. Different researchers have used this technology to prepare neural architecture for development of various purposes, such as [8, 9, 13, 14, 25, 29 and 30] and others. This approach compares two algorithms, LM and GDX, using a training function, i.e., feed forward back propagation. TRAINLM is the learning function in both functions. LM and GDX are based on a function named LEARNGDM which is used to complete tasks.

Data Utilized in the Creation of the Neural Model

The groundwater level is used as an output in the prediction model, which is then used in the output layer. Input variables were rainfall, the maximum and minimum temperatures, Ganga River water level, and humidity. All input data were given by the Indian Meteorological Department (IMD). The Central Ground Water Board provided the groundwater level (CGWB). The prediction model was built using data from the previous 20 years. All of the data were split into two groups. In the first set, 70% of the data were used, while the remaining data were kept in the second set. The first set of data was used for training purposes, while the second set of data were used for testing. The interpretation diagram of the study is presented in Fig. 2. Table 2 shows the range of the data used as input and output.

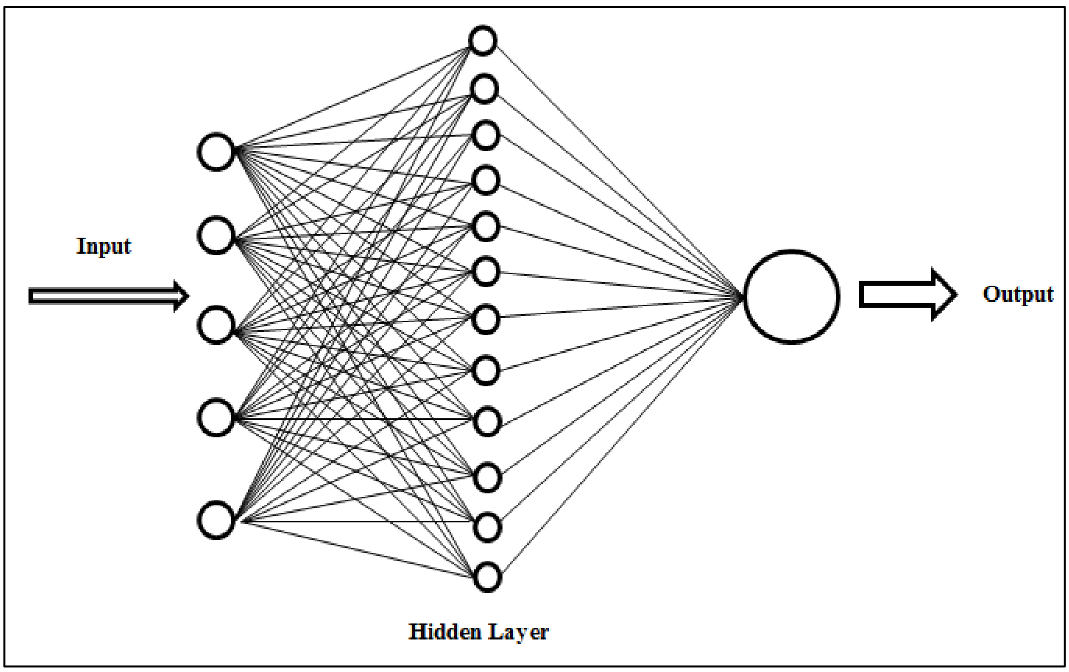

Figure 2. ANN structure of a 5-12-1 for neural network

Training Algorithm

Training is done on the selected set of input and output data. Through the training process weight associated with the input variable is evaluated for minimum error. More than 23 different algorithms are available for training of neural networks. In this study two different algorithms Levenberg-Marquardt (LM) and Variable Rate Learning. (GDX) used for training purposes and the performance of these two methods were compared. The details of these two processes are presented in following sections.

Levenberg-Marquardt

Nowadays, FFNN with LM algorithm is a popular approach when it comes to form a neural architecture. In the FFNN technique, the learning rate is settled with weights that provide a map to fit appropriately in training. The given LM set can be assumed as following equation 1.

$$F(x,w) = y \tag{1}$$

Wherein x represents input-vector, w represents the weight of desired network, and y represents the output vector calculated by a preferred network [15, 24]. LM back propagation is a method, which finds minimum value of an approach function, which is termed as square of a function which is non-linear. This algorithm can be represented as this equation 2 [14, 15].

$$x_{k+1}=x_k-[J^TJ+\alpha I]^{-1}\nabla f \tag{2}$$

Where, J is a Jacobian matrix, which is known as first derivative so far network that consist of errors can be calculated with the help of a BP method. ∇f represents transpose of Jacobian. A is a scalar quantity and when α tends to zero, this method becomes equivalent to Gauss Newton technique. Scalar α plays a very important role in this method.

GDX algorithm

While using a back propagation method in ANN, the rate of learning is steady throughout the training of a model (GDM). It is required to set the speed of learning correctly as it affects the algorithm and its performance. The algorithm starts oscillating and also becomes not stable if the rate of learning is kept too high. Hence, GDM is combined with an adaptive back propagation rate of the learning algorithm (GDX). A versatile rate of learning endeavours to keep the learning step as extensive as possible to give stable learning. This preparation of the algorithm is one of the least complex and the most typical approaches for network training.

3. Results and Discussion

Results obtained from the ANN analysis which shows the performance of different algorithms is presented in Fig. 3-6. Scatter plot of predicted and observed groundwater level obtained from the training with GDX and LM process is presented in Fig. 3 and Fig. 4 respectively. The comparison of LM and GDX, Based on training data GDX algorithm shows R^2 value equal to 0.8415, while LM algorithm shows R^2value equal to 0.8935. In the case of testing data GDX algorithm shows R^2 value equal to 0.7994 and LM algorithm shows R^2 value equal to 0.8231 respectively. It can also be observed that scattering in the case of the LM algorithm is lesser than the GDX algorithm. This indicates that the LM algorithm performs better than the GDX algorithm for prediction of groundwater level. The results obtained from the GDX analysis and LM analyses are presented in Table 2. Total eight wells were selected for the analysis. Data presented here are in terms of R^2 and Root mean square error (RMSE). With the GDX algorithm R^2 varies from 0.8124 to 0.8427 for well data considered during training. RMSE varies from 1.8448 to 1.9465 for training data and from 1.9054 to 1.9954 for testing data. In case of testing data with GDX algorithm R^2 varies from 0.7511 to 0.7994. Results of ANN done with LM algorithm are presented in Table 3. It can be observed that R^2 values for training data varies from 0.8432 to 0.8935 and for testing data varies from 0.7632 to 0.8221. RMSE varies from 0.6531 to 0.8123 for training data and from 0.7633 to 0.8953 for testing data. All the data of R^2 and RMSE for different well also show that LM method is more suitable than GDX method in prediction of the groundwater level. It can also be observed that groundwater level for well number 7 is predicted best among others.

It can be further observed from table 2 and table 3 that the best results of ANN depend upon the network architecture. For well number 7 the best result was obtained when ANN architecture was 5-12-1. Here '5' indicates number of input variables and '12' indicates number of neurons in hidden layer and '1' indicates number of outputs.

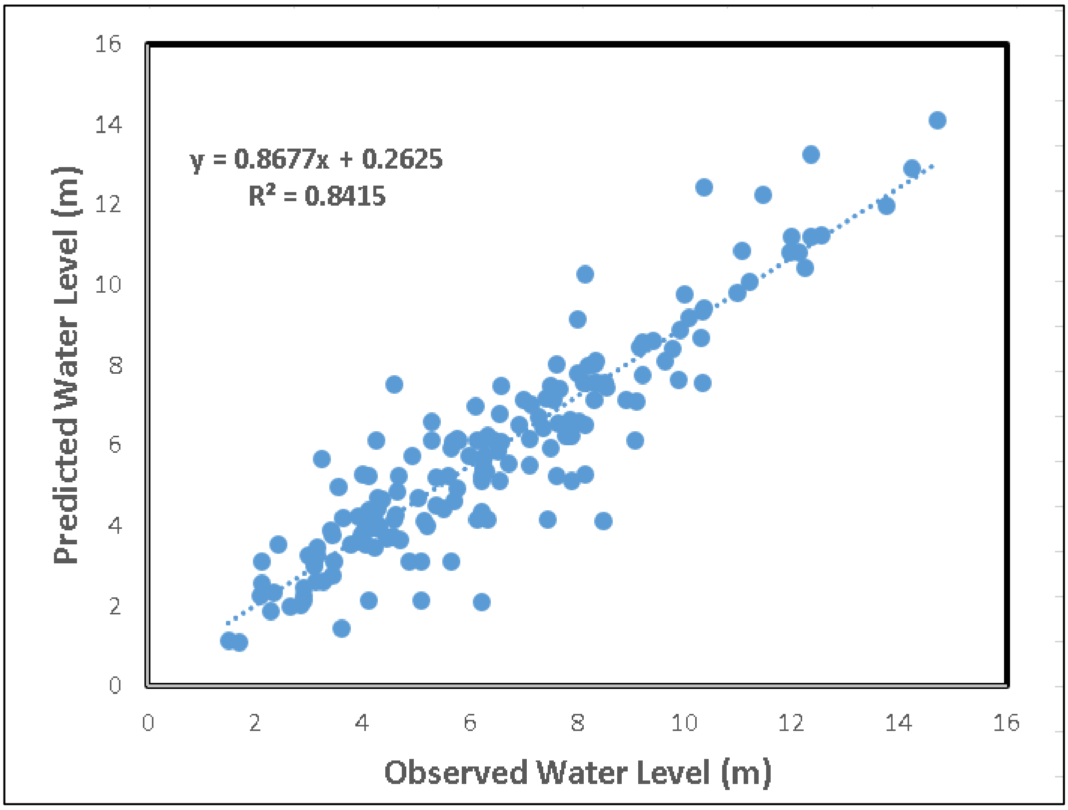

Figure 3. Performance of ANN model during Training with GDX algorithm

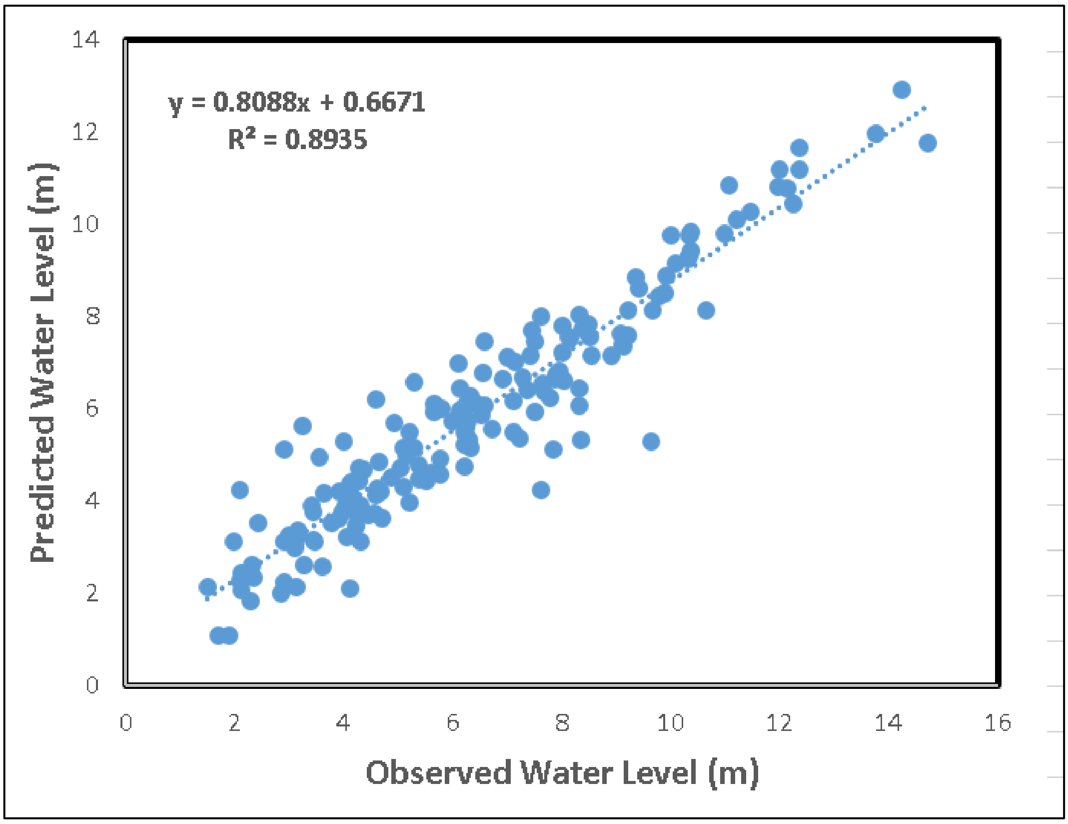

Figure 4. Performance of ANN model during Training with LM algorithm

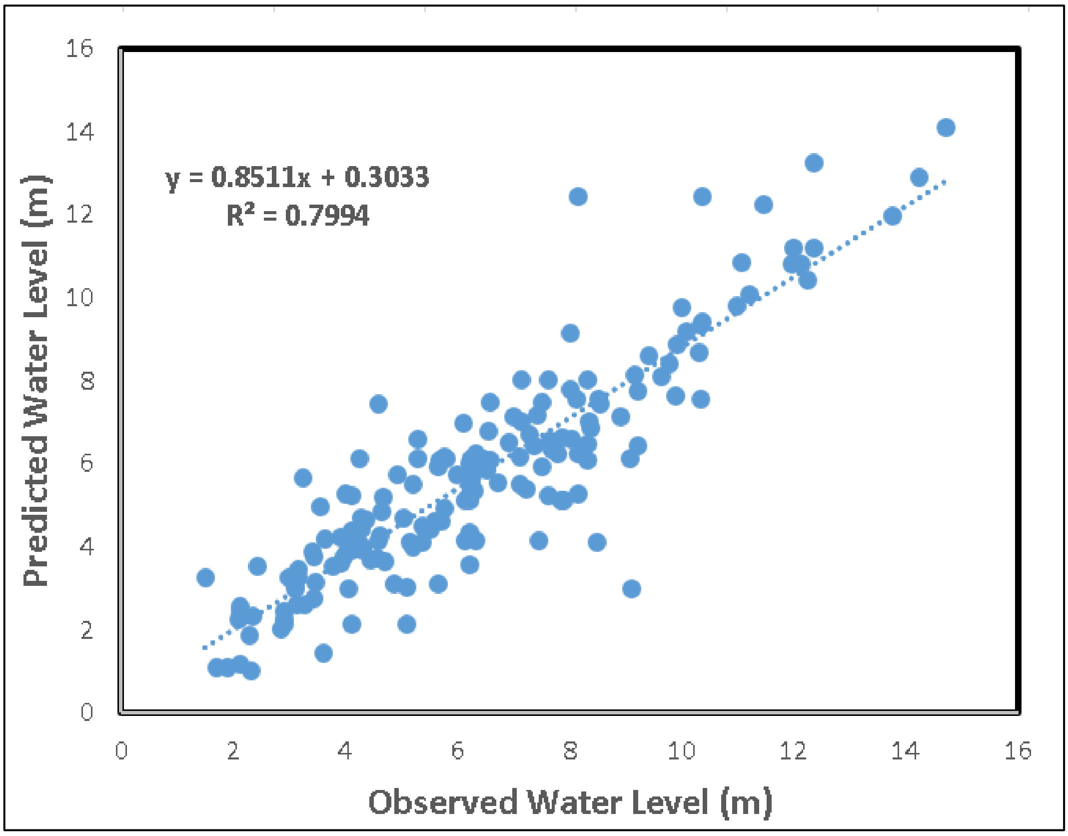

Figure 5. Performance of ANN model during Testing with GDX algorithm

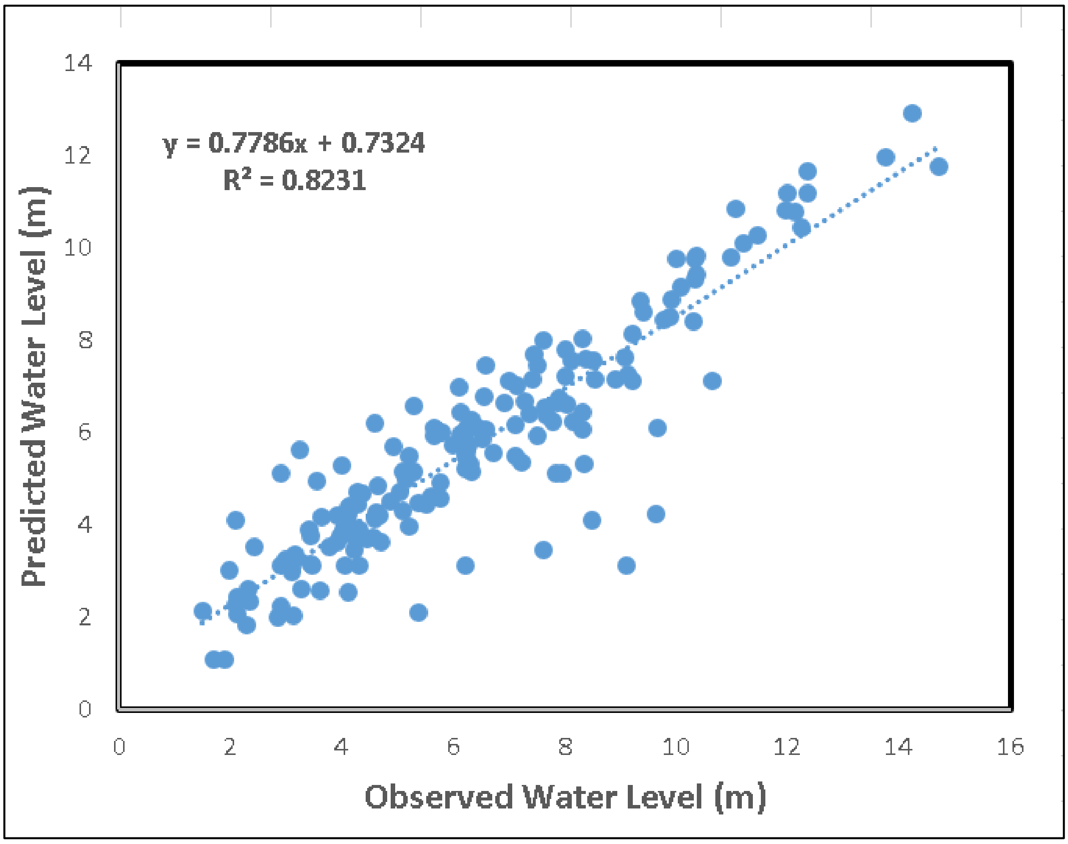

Figure 6. Performance of ANN model during Testing with LM algorithm

Table 2. ANN Network, Training and Testing Performance of GDX algorithm

Well No	Network	R^2		RMSE	
		Training	Testing	Training	Testing
w1	5-12-1	0.8221	0.7594	1.8892	1.9084
w2	5-11-1	0.8316	0.7792	1.9054	1.9268
w3	5-13-1	0.8398	0.7815	1.9452	1.9655
w4	5-14-1	0.8415	0.7994	1.8448	1.9846
w5	5-12-1	0.8269	0.7791	1.8652	1.9954
w6	5-14-1	0.8375	0.7644	1.9233	1.9452
W7	5-13-1	0.8414	0.7687	1.9326	1.9438
w8	5-11-1	0.8286	0.7568	1.9465	1.9576

Table 3. ANN Network, Training and Testing Performance of LM algorithm

Well No	Network	R^2		RMSE	
		Training	Testing	Training	Testing
w1	5-12-1	0.8561	0.7746	0.7611	0.8542
w2	5-11-1	0.8775	0.7632	0.8154	0.8491
w3	5-13-1	0.8643	0.7913	0.7516	0.7936
w4	5-14-1	0.8935	0.8231	0.6531	0.7633
w5	5-12-1	0.8426	0.7842	0.8218	0.8857
w6	5-14-1	0.8868	0.7651	0.8365	0.8953
W7	5-13-1	0.8797	0.7759	0.8417	0.8612
w8	5-11-1	0.8654	0.7681	0.8045	0.8354

The predicted groundwater level and observed groundwater level of different well is presented in Fig. 7 to Fig. 14. The predicted value presented here was obtained when LM algorithm was used. It can be observed that in all the cases, ANN has predicted the groundwater level satisfactory. The best result of prediction was observed in case of well number 4. During the monsoon period from June to September peak groundwater level was observed. Such finding was also indicated by output obtained from the ANN. All these findings indicate that the ANN can be satisfactorily used in prediction of groundwater level.

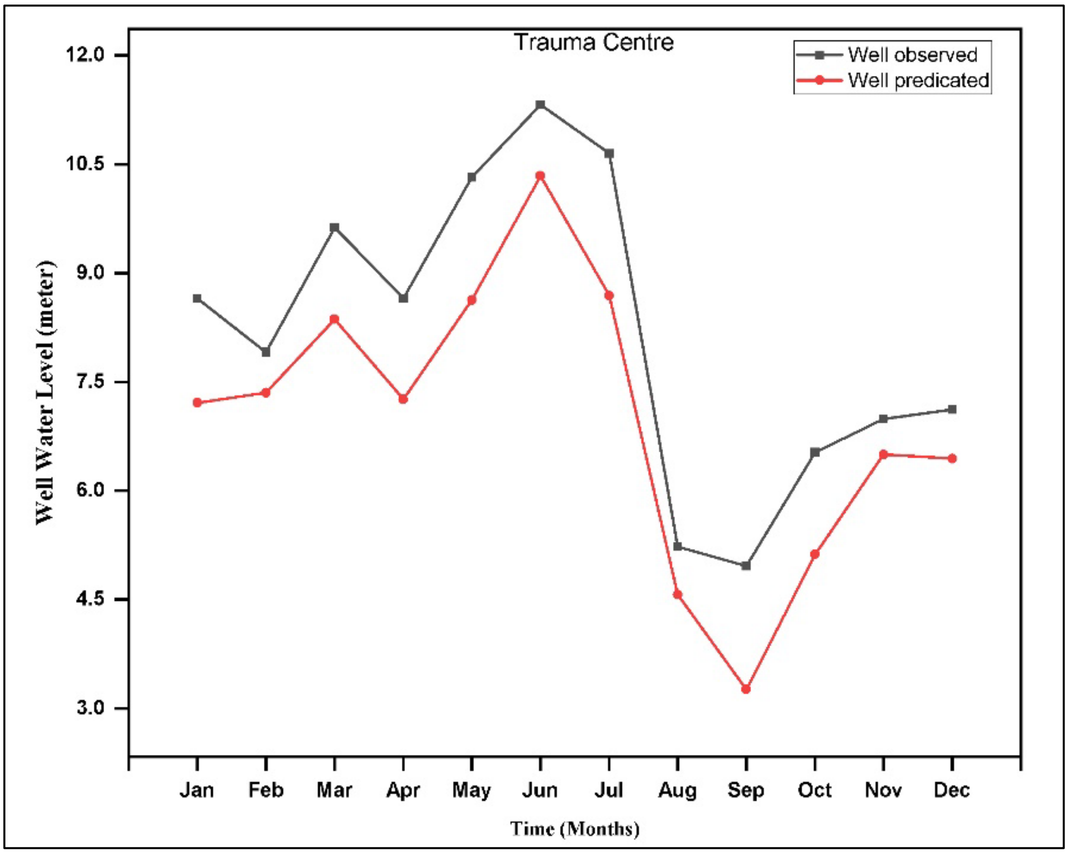

Figure 7. Estimated observed and predicted W1GW levels from LM method

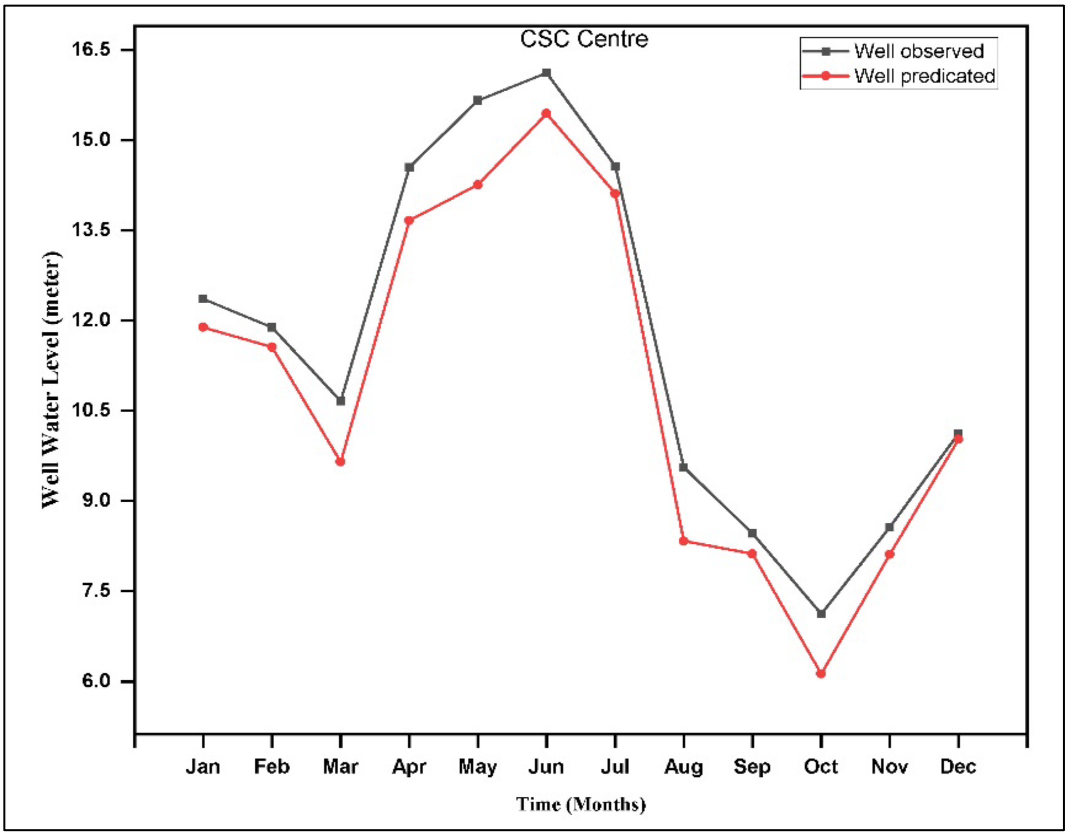

Figure 8. Estimated observed and predicted W2GW levels from LM method

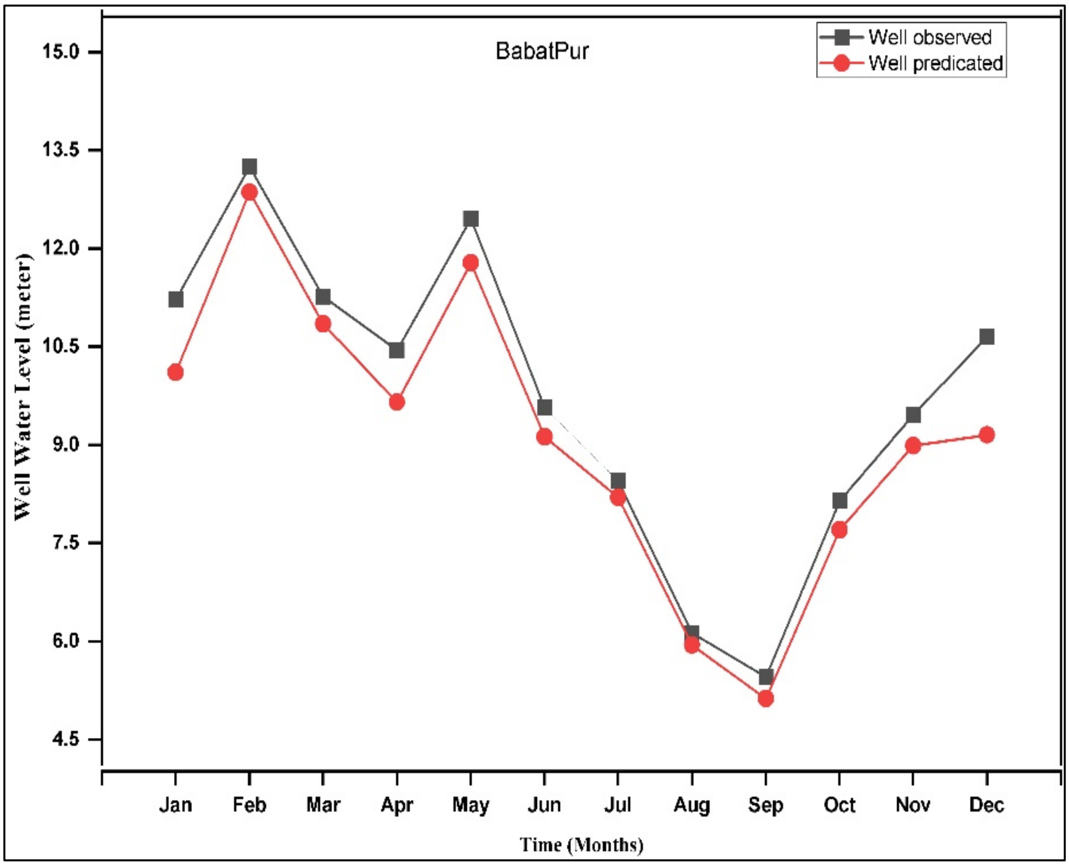

Figure 9. Estimated observed and predicted W3 GW levels from LM method

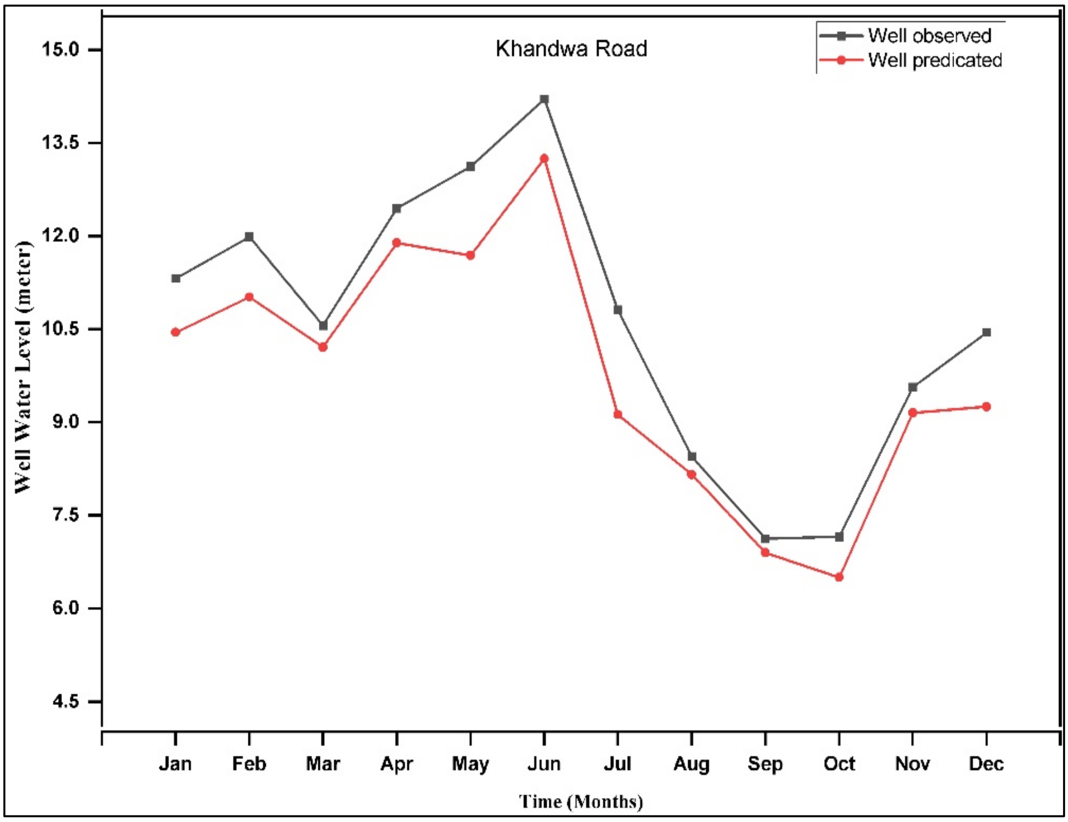

Figure 10. Estimated observed and predicted W4 GW levels from LM method

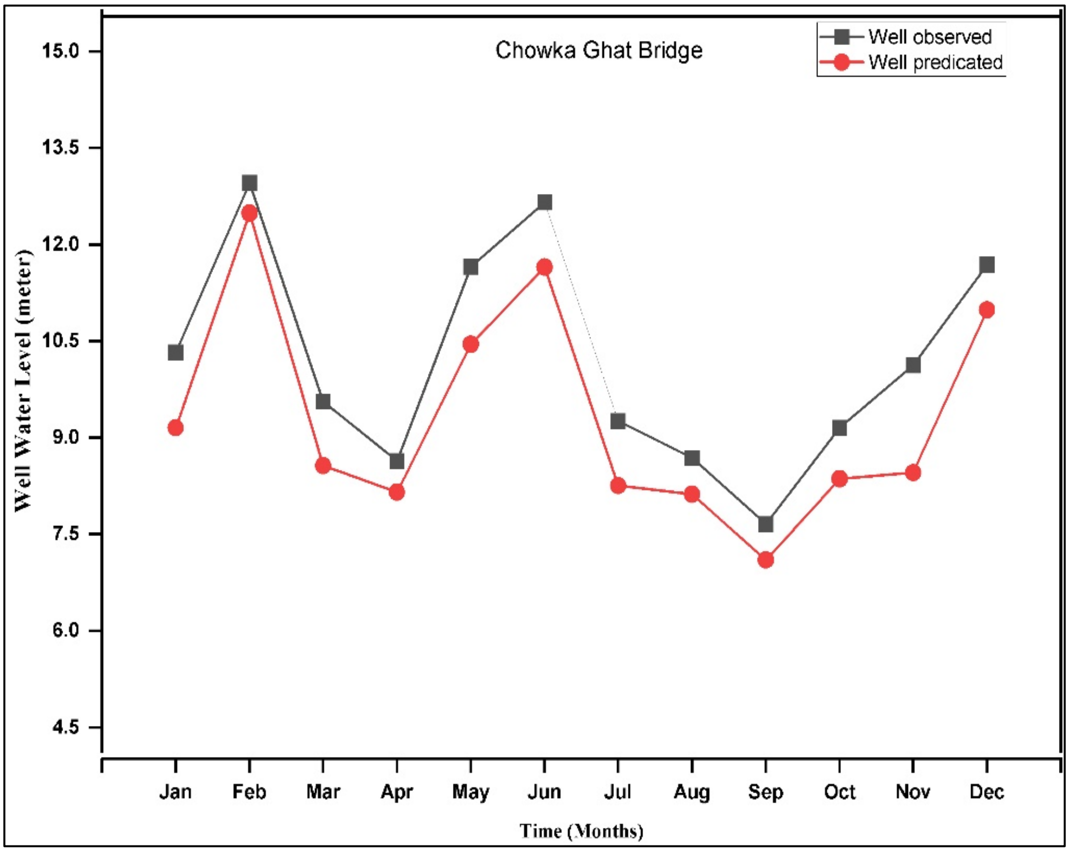

Figure 11. Estimated observed and predicted W5 GW levels from LM method

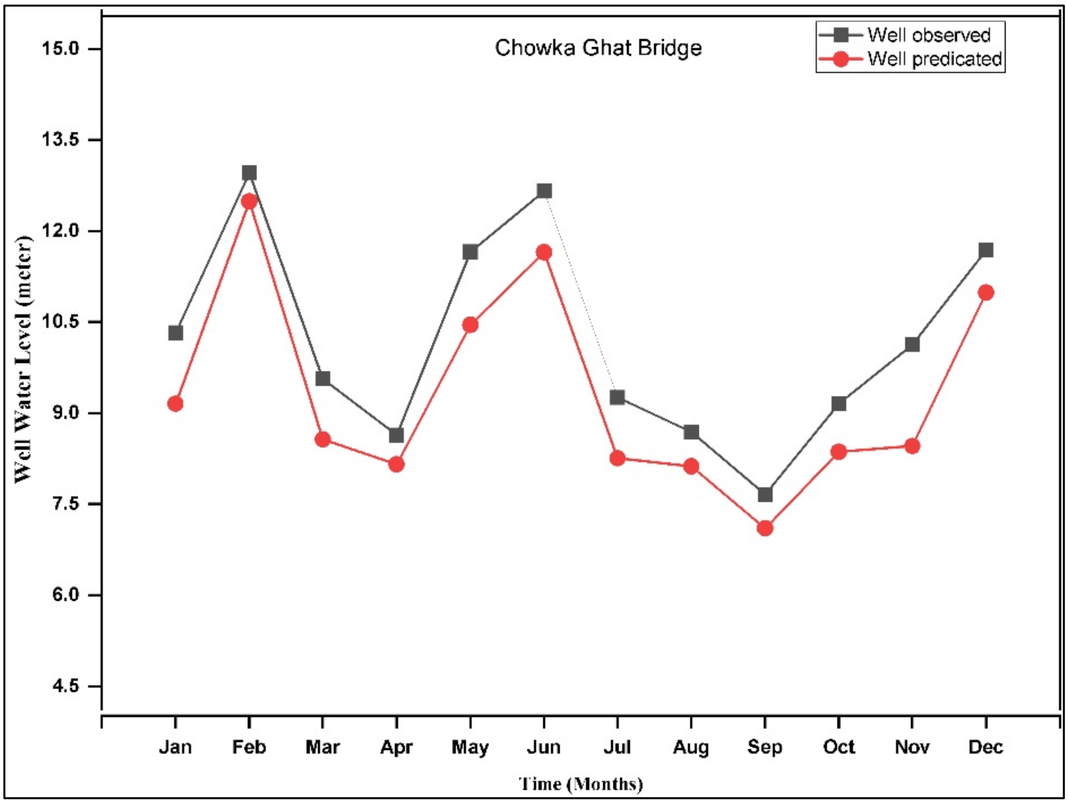

Figure 12. Estimated observed and predicted W6GW levels from LM method

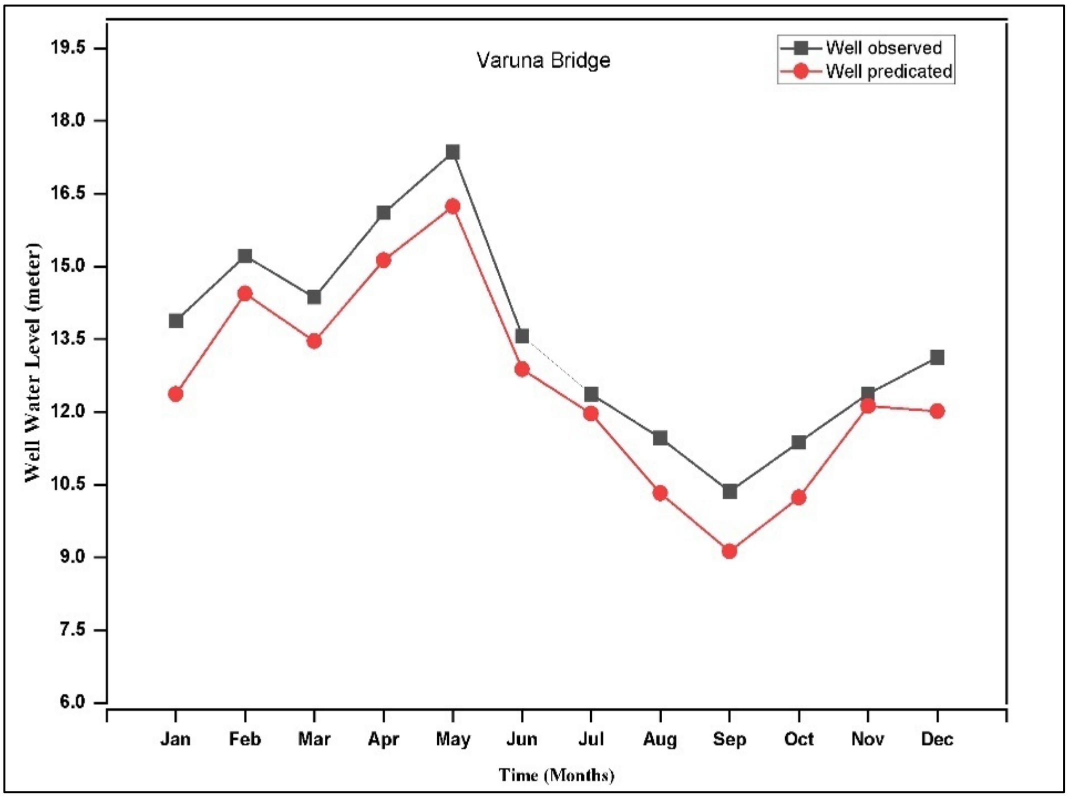

Figure 13. Estimated observed and predicted W7 GW levels form LM method

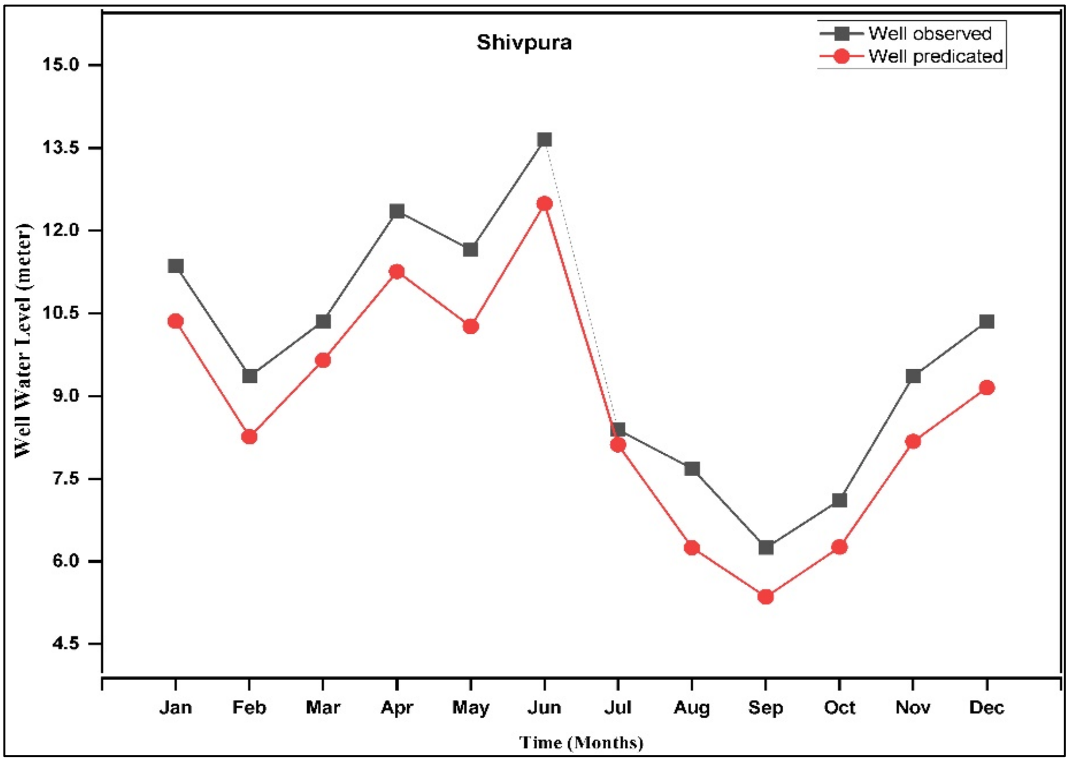

Figure 14. Estimated observed and predicted W8GW levels from LM method

4. Conclusions

To predict the groundwater level ANN architecture was prepared by the help of feed forward network. For training two different algorithms LM and GDX were used. Results have shown that ANN with both of the algorithm can predict well. The accuracy of prediction is better with LM algorithm. The R^2 value obtained from LM algorithm varies from 0.798 to 0.871 and RMSE varies from 0.733 to 0.798. It indicates that range of error is less which is satisfactory in prediction of the well level. It was also found that for well number 7 prediction model was found most satisfactorily. All these predictions are done based on rainfall, temperature, humidity, ground water well data from last 20 years and have run significantly. It is varying for all 8 wells because of its fluctuations. In LM prediction, testing results are giving a satisfactory value which is good for prediction and GDX is varying because of some constraints and hence it's R^2 value is below 0.84 percent. Groundwater is changing not because of uneven rainfall, but also due to urbanization. No of buildings in 2011 was 500 in one of the Well (W6) surrounding area which is now 1500 (2021). Population has increased and hence the consumption as well. Rainfall water is not reaching to the wells properly and there is need to conserve and look into this matter. These ANN algorithms are helpful in prediction of Groundwater with a very limited data set.

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Compliance with Ethical Standards

Disclosure of Potential Conflict of Interest:

The authors declare that they have no potential conflict of interest.

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Not Applicable.

Statement of Human and Animal Rights

Ethical Approval

All applicable institutional and/or national guidelines for the care and use of animals were followed.

Informed Consent

For this type of study formal consent is not required.

Author Contribution

The authors confirm contribution to the paper as follows; study conception and design: Shiwanshu Shekhar and Medha Jha; Data collection and literature survey, interpretation: Shiwanshu Shekhar and Medha Jha. Results and drafting, documentation: Shiwanshu Shekhar, Medha Jha and Manvendra Singh Chauhan. All authors reviewed the results and approved the final version of manuscript.

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