International Journal of Research in Engineering, Science and Management
Volume-3, Issue-8, August-2020
journals.resaim.com/ijresm | ISSN (Online): 2581-5792 | RESAIM Publishing

Implication of Artificial Intelligence Approach On Groundwater Level

Pratyush Saini[1], Rajani Srivastava[2*]
[1]*Research Scholar, Department of Environment & Sustainable Development, Banaras Hindu University, Varanasi, India*
[2]*Assistant Professor, Department of Environment & Sustainable Development, Banaras Hindu University, Varanasi, India*
*Corresponding author: srivastava_252003@yahoo.com

***Abstract*: Groundwater is considered as one of the most important water resources for humans and environment, but now this is declining at faster rate. Various models have been developed to analyze the hydrological aspects of water resources. Due to complexity in data acquisition and extensive data requirement for physical models, they are very hard to model the water resources problems. Now-a-days with the development of advanced computational techniques artificial intelligence or machine learning has emerged as a new field in data science or data mining. Artificial neural network is one such part of artificial intelligence. This is very simple approach in machine learning/artificial intelligence which requires preliminary knowledge of problem and solution and then predicts the upcoming solutions arising due to different future problems. The research aims to simulate and model groundwater level and finding how much impact climate change is imposing in groundwater scenario using Artificial Intelligence as an alternative approach over physical based models. The climate change parameters (rainfall, solar radiation, maximum temperature, minimum temperature) were obtained through regional climate model (REMO) RCP 4.5 scenario. Water table data for historical scenario was obtained from India-WRIS a web-based GIS for water information developed by National Remote Sensing Center (NRSC). The findings of study show that climate change has significant impact on groundwater level depletion. Not only humans are responsible but also climate change plays a significant role in groundwater table fall.**

***Keywords*: Artificial intelligence, Artificial neural network, Climate change, Groundwater level forecasting.**

1. Introduction

Water is an integral part of biosphere. It is distributed across whole of the earth. Nearly 70% of the area is covered with water. Due to increasing population pressure, urbanization, industrialization, race to unsustainable development overexploitation of water resources is inevitable. Since, groundwater is reliable source for water so it is highly exploited. In addition to overexploitation, there are many other sources that degrade its quality like pollutants from agricultural fields, industries, sewage effluents etc. The degraded groundwater is now unsuitable for human activities. These pollutants are mixed down with water and consumed by human cause's serious health effects. Therefore, groundwater management is need of hour. Various modelling techniques have been evolved to simulate the groundwater level. Artificial Neural Network (ANN) is an advantageous approach since it is best suited for non-linear system modelling (Daliakopoulos et al. 2005). The advantages of ANN over physical models have been discussed in detail by French et al. (1992). Aziz and Wong (1992) were the first one to determine aquifer parameters using artificial neural network. ANN modelling in hydrological aspects like rainfall-runoff modelling, precipitation forecasting and water quality modelling have been reviewed by Govindaraju and Rao (2000). More applications of ANN have been discussed in detail by ASCE Task committee on Application of Neural Networks in Hydrology (ASCE Task committee 2000). ANN has been successfully applied in predicting groundwater level (Coulibaley et al. 2001). The main purpose of this article is to assess the suitability of ANN approach-based model and finding the impact of climate change scenario in groundwater level.

2. Study Area

The study area is Varuna river basin covering most part of Allahabad, Sant Ravidas Nagar (Bhadohi), Jaunpur and Varanasi. Varuna river is an important tributary of river Ganga. It originates near Mau-Aima in Allahabad and drains into river Ganga near Mughalsarai in Varanasi (Fig. 1). We selected 18 stations in this basin which are located in above mentioned four districts. The river basin is an integral part of Indo-Gangetic plain. The basin area is intermixed with various settlement patterns i.e. it varies from sparse rural settlement of remote villages of Jaunpur and Bhadohi to highly congested city of Varanasi and also from fertile agricultural fields to big commercial centers reflecting contrasting groundwater problem.

3. Methodology

A. Data collection

The climate data (rainfall, maximum temperature, minimum temperature, solar radiation) from 1996 to 2040 was taken from output of Regional climate model (REMO) RCP 4.5 scenario. Groundwater level data of dug wells from 1996 to 2015 for pre-monsoon season was taken from India-WRIS (Water resource information system) - a web-based GIS interface for water resources information developed by National Remote Sensing center (NRSC).

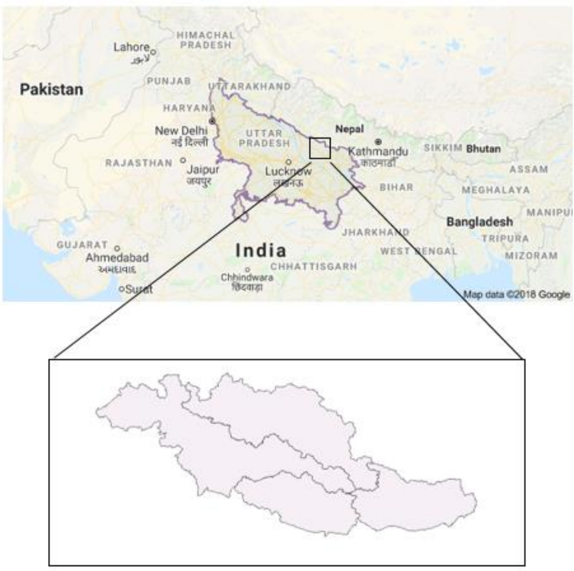

Fig. 1. Map of study sites, showing locations of Varuna river basin covering most part of Allahabad, Sant Ravidas Nagar (Bhadohi), Jaunpur and Varanasi in Uttar Pradesh, India

Table 1
Performance evaluation based on error analysis in at four different locations

Station	RMSE		Prediction error
	Training	Testing	
Allahabad	0.323	1.506	0.596
Bhadohi	0.0134	2.45	0.122
Jaunpur	0.0046	1.317	0.058
Varanasi	0.0048	3.78	-0.128

B. Data preprocessing

In REMO RCP 4.5 scenario climate data was on daily basis, so from that data the daily wise data was converted to year wise by averaging the maximum temperature, minimum temperature, solar radiation. Daily rainfall data was summed up to get yearly rainfall in mm/yr. Potential evapotranspiration (PET) was calculated on the basis of Heagreave's equation,

$$PET = 0.0023 * (T_{mean} + 17.8) * (T_{max} - T_{min})^{0.5}$$

PET was further multiplied by 0.8 to get actual evapotranspiration (AET). The entire dataset was then divided into three subsets: training instance from 1996 to 2007, testing instances from 2008 to 2015 and 2016 to 2040 data was used for forecasting.

C. Development of ANN model

We used Neural Designer software to perform entire artificial neural network experiment. It has been developed from open source library open NN and entire programming is written in C++. It contains graphical user interface which simplifies data entry and interpretation of results. Although neural designer provides various methods for analytics but here in our study, we used approximation method. Approximation method is used to approximate the output data based on characteristics of input data. The model was individually developed for four different districts with identical input parameters and conditions. In model development processes following processes are involved:

1) Selection of input variables

Generally, input variable identification and selection are based on prior knowledge. As in this paper, there is only emphasis on climate change impact on groundwater fluctuation, so we are selecting only climate parameters. Rainfall is an important factor for groundwater recharging. Actual evapotranspiration is another factor for release out of groundwater naturally. Rest parameters like maximum temperature, minimum temperature and solar radiation are less important in respect of groundwater fluctuation, but they are important for study of long-term water table forecasting. Therefore, we selected 5 variables as input node (rainfall, evapotranspiration, maximum temperature, minimum temperature and solar radiation). Water table is selected as output node.

2) Number of layers and hidden neuron

Till now, no such formula has been derived for finding the number of layer or hidden neuron.

Trial and error method are only suited approach to determine number of neurons and hidden layer (Maier and Dandy 1996). In our study approach, number of layers and hidden neuron was based on performance criteria i.e. for each trial or iteration Root mean square error (RMSE) and loss index was measured and the structure was then selected on the basis of minimum RMSE and loss index**.** So, after rigorous trial and error method we found number of hidden layers to be 5 and number of neurons to be 30, 25, 20 15, 10 in each consecutive hidden layer.

D. Neural Network Training

After model selection training is performed to train the given datasets. Main stress is given to reduce error as far as possible. In model training, synaptic weights are then adjusted through forward and backward propagation until minimum error or predefined limit has been achieved (Durrant 2001). We implemented multilayer feedforward network architecture with two algorithms: Quasi-newton method and Levenberg-Marquardt algorithm (LM). In our study LM is found to be best suited training algorithm as it showed minimum error and it has also been proposed by Daliakopoulos et al. (2005) and Chitsazan et al. (2015). The hyperbolic tangent (tanh) function was used as an activation function for hidden layers and linear function was chosen as an activation function for output layer. The tanh function range is [-1,1] whereas for that of sigmoid function has range of [0,1]. Therefore, tanh provides stronger gradient and good results. Stopping criteria is used to avoid the tendency of the network to overfit the training data. Normalized squared error was selected as main criteria to measure performance of model (Murells, 2008).

E. Evaluation criteria

After the model has been trained the best performance model was selected or evaluated on the basis of various methods. The entire evaluation criteria were majorly based on testing instances. They are root mean squared error, linear regression, prediction error (Mohanty et al. 2010; Nayak et al. 2006).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(O_i - P_i)^2}{N}}$$

where Oi = observed value for ith data
Pi = predicted value for ith data

The best fit between observed and predicted value under ideal condition would yield RMSE=0. Neural designer also computes linear regression between predicted scaled output with observed scaled output using maximum-minimum scaling criteria (maximum value is assigned 1 and minimum value is assigned -1 and all other values in between these two are adjusted between 1 and -1). Therefore, linear correlation analysis is also an evaluation criterion in this study. The next evaluation criteria were prediction error. The prediction error was calculated by difference of observed datasets and predicted datasets for testing years.

F. Forecasting using ANN model

After the model development process, a rigorous training is applied among datasets until minimum RMSE is reached. Firstly, the prediction was tested on historical datasets and error was calculated and after minimum error the model was then applied to predict future water table scenario. For this REMO data was used from 2016 to 2040.

4. Result and Discussion

A. Performance evaluation of model

The performance of these models is based in terms of RMSE, linear correlation analysis and prediction error. The final values of these errors have been obtained by taking the average of values for 18 observation stations located in four districts. The prediction error evaluates how much accurate our model is to predict the future scenario. Note that in figure 2, the positive values represent overestimation and negative values represent underestimation (Mohanty 2010). In our case prediction error ranges from -1 to +1 signifying best results.

The linear correlation analysis by neural designer software for historical testing data sets between predicted scaled output and observed scaled output is shown in figure 3. From the RMSE, regression analysis and prediction error we can say that the developed model is good to some extent and can be applied to predict our future scenario. Üneş et al. (2017) compared performance evaluation by creating Multi Linear Regression (MLR) and Artificial Neural Networks (ANN) models and concluded that ANN model gave better results than the MLR model.

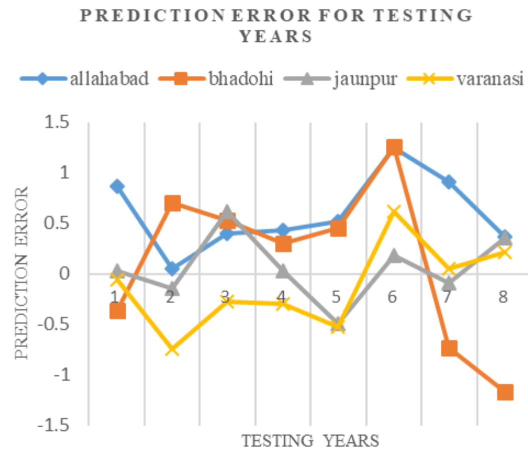

Fig. 2. Prediction error for four different districts (Allahabad, Sant Ravidas Nagar (Bhadohi), Jaunpur and Varanasi) of Uttar Pradesh, India

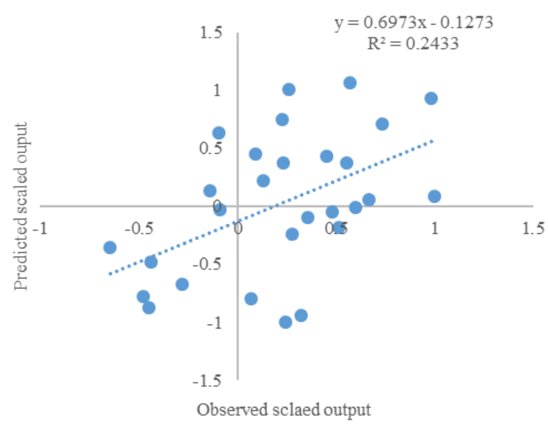

Fig. 3. Linear correlation analysis between predicted scaled output and observed scaled output in present study

B. Predicting the groundwater table using REMO and ANN

After model development and performance evaluation, only input parameters were taken from 2016 to 2040 using REMO. These input data were then fed into respective models and output water table was generated which was then plotted in MS-Excel. The water table elevation in meters from mean sea level has been plotted against the years for historical and predicted scenario. The figure 4 graph shows a glimpse of water level for historical and projected scenario. It is showing very slight decline in water level for Allahabad and Jaunpur. It remains stationary to very slight increase in Bhadohi. A steeper decline is observed in Varanasi region. This method proved to be much better over physical models since it does not require extensive field's surveys and resources. Though it is better than other modelling techniques but, in our study, it has some limitations regarding data acquisition: since historical water table is available from 1996 therefore, we got only 12 instances to be trained and 8 instances to be tested which increases the chance of error. Had we got more variables to be trained the error scenario would be more and more minimized.

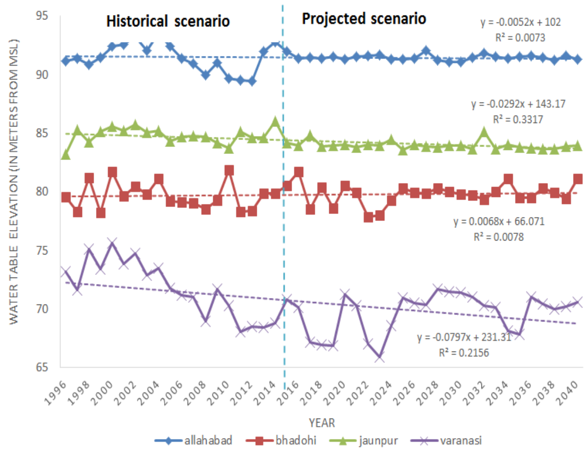

Fig. 4. The water table elevation (meters) from mean sea level against the years (1996-2040) for historical and predicted scenario

5. Conclusion

In this paper impact of climate change on groundwater level is studied using artificial neural network approach. In relation to the earlier data, the trend from the coming years is established using the ANN modelling approach. The results from ANN model was effective showing good trend in projected scenario as that was in historical scenario. The results obtained for projected scenario in the study area is an alarming situation. The study proves that there is sharp fall in groundwater table due to climate change. Though the current study considers the climate variables regarding water level impacts, anthropogenic effects should not be neglected. If the anthropogenic effects were to be considered the scenario would be different. It may lead to much steeper fall in groundwater.

Acknowledgement

We thank the Head and Course Co-ordinator of Environmental Science (Environmental Technology), RGSC, Institute of Environment and Sustainable Development, Banaras Hindu University for providing laboratory and field facilities. We are also thankful to Professor R. K. Mall, for assigning this topic and extending their heartfelt cooperation and support during experimentation.

Conflict of Interest

The authors confirm that there are no conflicts of interest involving any networks, organizations, or data centers referred to in this paper.

References

[1] Daliakopoulos IN, Coulibaly P, Tsanis IK (2005) Groundwater level forecasting using artificial neural network. J. Hydrol 309: 229-240.
[2] French MN, Krajeweski WF, Cuykendall RR (1992) Rainfall forecasting in space and time using neural network. J Hydrol 137: 1-31.
[3] Aziz ARA, Wong KFV (1992) Neural network approach the determination of aquifer parameters. Groundwater 30(2): 164-166.
[4] Govindaraju RS, Rao RA (2000) Artificial Neural Networks in Hydrology, Kluwer Academic Publishers, The Netherlands.
[5] ASCE Task committee (2000). Artificial neural network in hydrology-I: preliminary concepts. J. Hydol. Eng. ASCE, 5(2), 115-123.
[6] Coulibaly P, Anctil F, Aravena R, Bobe EB (2001) ANN modelling of water table depth fluctuations. Water res. 37(4): 885-896.
[7] Maier HR, Dandy GC (2000) Neural networks for the prediction and forecasting of water resources variables: a review of modelling issues and applications. Enviro. Modell. Software, 15: 101-124.
[8] Durrant PJ (2001) Win Gamma TM: a non-linear data analysis and modelling tool for the investigation of non-linear and chaotic systems with applied techniques for a flood prediction system. PhD thesis. Department of Computer Science, Cardiff University.
[9] Chitsazan M, Rahmani G, Ahmad N (2015) Forecasting Groundwater Level by Artificial Neural Networks as an Alternative Approach to Groundwater Modeling. J Geolog Soc India 85: 98-106.
[10] Murrells CM (2008) Twist Liveliness of Spun Yarns and the Effects on Knitted Fabric Spirality. PhD thesis of Stuart David Paris. The Hong Kong Polytechnic University.
[11] Mohanty S, Jha M, Kumar A, Sudheer KP (2010) Artificial Neural Network Modelling for Groundwater Level forecasting in a river island of eastern India. Water Res Manag 24: 1845-1865.
[12] Nayak PC, Rao Satyajit YR, Sudheer KP (2006) Groundwater Level Forecasting in a Shallow Aquifer Using Artificial Neural Network Approach. Water Res Manag 20: 77-90.
[13] Üneş F, Demirci M, Ispir E, Kaya YZ, Mamak M, Tasar B (2017) Estimation of Groundwater Level Using Artificial Neural Networks: a Case Study of Hatay-Turkey. “Environmental Engineering” 10th International Conference Published by VGTU Press.