Journal of AgriSearch, 10 (2): 87-93
An Open Access International Peer Reviewed Quarterly

ISSN : 2348-8808 (Print), 2348-8867 (Online)
https://doi.org/10.21921/jas.v10i02.12720

Gamma Test-based MLP based ANN Model for Groundwater Fluctuation Forecasting in Kanpur District, Uttar Pradesh

SHASHINDRA KUMAR SACHAN[1*], ARPAN SHERRING[2] AND DERRICK M DENIS[3]

ABSTRACT

This study seeks to determine the accuracy of the groundwater level fluctuations forecasted at the Kanpur district of India using artificial neural networks (ANNs). An overview of how gamma tests can be useful together to decrease the huge amount of work involved in the process of trial-and-error in nonlinear modeling method is presented in this study. The results indicated that performance of multilayer perceptron (MLP) based neural network (M-16, architecture 4-18-1) is satisfactory in the groundwater level fluctuations forecasting. The performance assessment shows that the MLP model performs significantly better. In future studies, it might be useful to apply these approaches as a laborious approach for ensuring that the appropriate results are obtained very quickly even though they are time-consuming.

Keywords: Neural networks, Forecasting, Gamma test, Groundwater level fluctuations

ARTICLE INFO

Received on	:	10.06.2023
Accepted on	:	27.06.2023
Published online	:	30.06.2023

INTRODUCTION

The greatest significant feature in the management of water resources is a good attitude and a vision of what may happen in the future from a point of view of future events that will affect the natural resources (Vishwakarma *et al.* 2022). As an important basis for planning and designing the activities and activities of different sectors, such as domestic, industrial, and agricultural, an understanding of the status of water resources in a region is paramount. This is particularly true in arid and semiarid regions, where groundwater is scarce and essential. Since hydrologic parameters such as groundwater level are stochastic in nature, it is possible to predict the future status of this parameter by using statistical analysis and mathematical models, for example (Saroughi *et al.* 2023; Mirzania *et al.* 2023).

Due to an increase in withdrawal rates than recharge rates in recent years, many of the state's groundwater basins have experienced long-term overdraft. There are several negative effects of long-term overdraft, including the need to pump water from deeper wells which results in higher energy costs for pumping water, land subsidence, a reduction in river flow, as well as decreased water quality (Sahu *et al.* 2020). Consequently, decision makers are required to have access to accurate, reliable, and timely predictions of groundwater levels in order to make effective decisions.

The groundwater resources are mostly dependant on a wide variety of factors and have complex fluctuations, therefore it is necessary to present a mathematical method to decompose the complexity of the groundwater resources and their variations (Shukla *et al.* 2021; Vishwakarma *et al.* 2023). Hydro-climatological variables forecasting can be carried out by use of several robust tools, among which artificial neural networks (ANNs) is among the most common. Several methods of intelligence knowledge have been applied to the forecasting of groundwater levels, including neural networks and machine learning (Coulibaly *et al.* 2001; Nayak *et al.* 2006; Ch and Mathur 2012; Singh *et al.* 2016; Choubin and Malekian 2017; Solgi *et al.* 2021).

In contrast, in the previous studies, there was less emphasis placed on determining the optimal input variables for nonlinear models (such as ANNs) in the context of groundwater modeling. Rashidi *et al.* (2016) have suggested that the determination of optimal parameters is an important part of nonlinear modeling. Using gamma test, they selected the best input to simulate the suspended sediment from a wide variety of inputs. Additionally, Jajarmizadeh *et al.* (2015) applied the gamma test to identify what input variables are most appropriate for support vector machines (SVM) in order to predict the flow of water in a semiarid basin in Iran based on input variables.

A conventional approach to estimating groundwater depths, runoff or soil moisture is to use mechanistic, multi-scale and multi-physics simulation models, such as Hydrus, MODFLOW, PARFLOW, SWAT, HydroGeoSphere, and TOUGH, that are based on mechanistic multi-scale, multi-physics simulation models (Steefel *et al.*, 2015; Langevin *et al.*, 2017). Using partial differential equations, these models represent physical processes such as mass, momentum, and energy transfer. They also require extensive characterizations of hydro stratigraphic properties, precise boundary conditions, such as recharge sources, climate change, and changes in water use, in addition to extensive characterization of hydro stratigraphic properties (Sahoo *et al.*, 2017). The information of such parameters is often not available a priori,

[1] Associate Professor, Deptt. of Agricultural Engineering, Chandrashekhar Azad University of Agriculture and Technology, Kanpur, Uttar Pradesh, India.
[2] Professor, Deptt. of Irrigation and Drainage Engineering, Sam Higginbottom University of Agriculture, Technology and Sciences, Prayagraj, Uttar Pradesh, India.
*Corresponding Author E-mail: rameshbhuvns@gmail.com

and in order to determine some parameters, one has to solve an inverse problem (Arora *et al.*, 2011), which itself requires running simulation models repeatedly until the values have been determined. This results in a substantial increase in computational costs (Arora *et al.*, 2012).

Guzman *et al.* (2017) applied a dynamic form of a Recurrent Neural Network (RNN) model to forecast groundwater levels in the Mississippi River, US. A daily historical input time series, including precipitation levels, groundwater levels, and the timing of rainfall, were collected for a period of eight years to forecast groundwater levels up to three months in the future. According to their findings, models created with lags of 100 days provided the most precise forecast of groundwater levels in judgement with models generated. Sarangi and Bhattacharya (2005) studied and compare ANN models for sediment loss forecast with a MLR model in order to determine the effectiveness of ANN models in Banha watershed in India. Based on the hydrographs and the silt load data of 1995–1998, two ANN models were developed, one geomorphology-based and the other non-geomorphology-based, to predict sediment yield, and their reliability was tested using the hydrographs and silt load data.

Hence, the purposes of this study are (1) identify the best input combination for multilayer perceptron (MLP) based artificial neural networks (ANN) modeling approach; (2) selecting the best four input combination in the multilayer perceptron (MLP) based artificial neural networks (ANN) models; and (3) comparing the performance of MLP based ANN models in groundwater level fluctuation forecasting at Kanpur District.

MATERIALS AND METHODS

Study area

The Kanpur district lies between 25°55′ and 27° North latitude and 79°30′ and 80°35′ East longitudes in Survey of India Toposheet No. 54N and 63B. Fig. 1 illustrates the location of

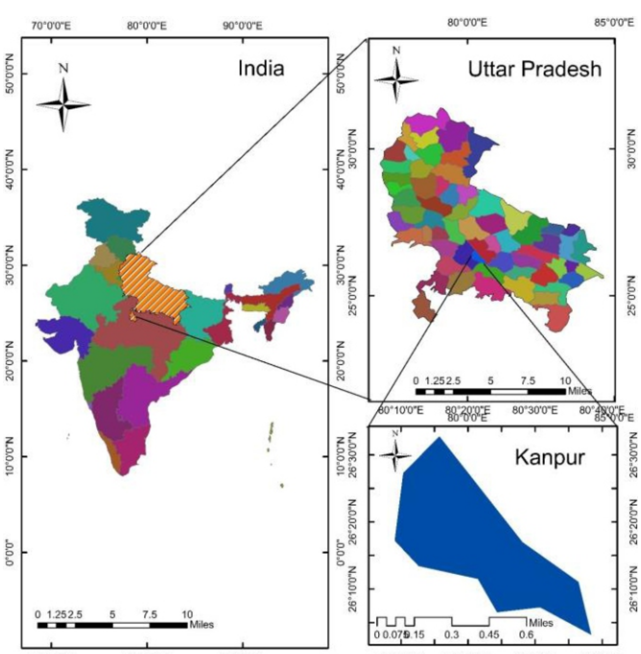

Fig. 1: Location map of the Kanpur District.

the study area. The total geographical area of the district is 3155 km^2. The long-term average annual precipitation of Kanpur district is 821.9 mm.

Data Acquisition

Meteorological and hydro geological data of last 18 year for the duration 1998-2016 were collected from the metrological station of Kanpur District. This includes rainfall, effective rainfall, average temperature, relative humidity, solar radiation, wind speed, evaporation and evapotranspiration. Ground water Level data for the above period from 50 wells of different blocks (Kakwan, Bilhaur, Ghatampur, Shivrajpur, Chaubeypur, Kalyanpur, Vidhnu, Sarsaul, Bhitargaon and Patara) of Kanpur district were obtained from Divisional office of CGWB- Kanpur Nagar, Ministry of Water Resources, RD & GR, Govt. of India.

Analysis of data

Eighteen years data collected for the analysis was divided into two phases, first phase is training (70%) data and second is testing (30%) data. The training was done using the fifteen years data from January 1, 1998 to December 31, 2013, whereas the testing was done using the three years data from January 1, 2014 to December 31, 2016 for validation of developed models. The statistical parameters of ground water level fluctuation data are shown in Table 1.

Table 1: Statistical parameter of ground water level fluctuation data set for training and testing at Kanpur Nagar

Statistical parameters	Ground water level fluctuation	
	Training data set	*Testing data set*
Mean	0.6047	0.8219
Standard Error	0.0536	0.0850
Median	0.4000	0.5500
Mode	0.2500	0.2500
Standard Deviation	1.0029	1.0408
Sample Variance	1.0059	1.0833
Kurtosis	7.6566	3.7127
Skewness	1.7395	0.1603
Range	9.0700	8.5100
Minimum	-2.8500	-3.8200
Maximum	6.2200	4.6900
Count	350	150
Confidence level (95.0%)	0.1054	0.1679

Multilayer Feed forward Neural Networks

The multilayer feedforward neural network is a system that consists of an interconnection of perceptron cells in which communications and computations move from the input to the output of the neural network in a single direction. There are a number of layers in a neural network that correspond to the layer of perceptrons that make up the neural network. One of the simplest neural networks is one based on a single input layer and a single output layer consisting of perceptrons each. The network depicted in Fig. 2 is an example of this type of network. The output layer of the network is the only layer with the functionality of activation calculations, which is why the network is technically referred to as a one-layer feedforward network with two outputs. There are no connections between neurons in the same layer, and there is no feedback between layers as well. In each layer, the inputs from the neurons are applied as the outputs from the neurons in the next layer, and so on. As a result of this network, the following equation can be used to determine the final output:

$$Y = f_0\left[\sum_j W_{kj} f_h\left(W_{ji}x_i + b_i\right) + b_k\right] \tag{1}$$

Where, x is an input vector, W *j i* is the connection weight from the *i* neuron in the input layer to the *j* neuron in the hidden layer; *j* is the threshold value or bias of *j* hidden neuron; W *k j* is the connection weight from the *j* neuron in the hidden layer to the *k* neuron in the output layer; *k* is bias of k^{th} output neuron *f h*and *f* o are the activation function for hidden and output layer.

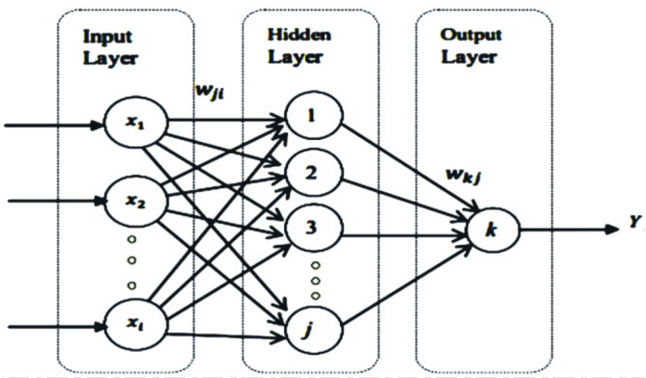

Fig. 2: Single layer and multilayer feed forward networks.

Gamma Test (GT)

The mechanism of evapotranspiration is part of hydrological processes that are typically non- linear, complex, and dynamic. Due to the trial-and-error procedure, looking for the best input combination is a challenging task the optimal for hydrological modelling (Gholami *et al.* 2021; Bajirao *et al.* 2021). This procedure needs calibration and testing to establish the best model based on input combinations. The Gamma test (GT) minimizes the workload needed for model creation by considering all input combinations of input parameters, guiding selecting input parameters for creating a reliable, smooth model (Singh *et al.* 2019, 2022; Kumar *et al.* 2022). GT is a non-parametric test and non-linearity analyzing tool that examines the nonlinear relationship between input and output variables (Malik *et al.* 2018; Singh *et al.* 2018). A major advantage of this tool is its speed in massive data sets because GT takes a few moments to run. The GT algorithm uses a set of M input/output variables as:

$$\{x_i(i), \ldots\ldots\ldots x_m(i), y_i\} = \{x_i, y_i\}[1 \le i \le M] \tag{2}$$

For which "M" is the total number of data, "X" is the input matrix and "Y" is the corresponding output variable, for which a hypothesis for a possible link between X and Y is the available. The gamma coefficient (Γ) is calculated value using simple linear regression between X and Y which is given below:

$$y = f(x_i \ldots\ldots\ldots x_m) + \Gamma \tag{3}$$

Where *f* is a smooth function and Γ is a random variable representing noise. This study selected the best input combination based on the minimum V-ratio and gamma (Γ) value for predicting ground water fluctuation. WinGamma™ software was utilized to apply the gamma test.

Development of MLP based ANN model

Several factors affect the boost of groundwater recharge, including infiltration capacity, rainfall characteristics, and climatic factors, which may distress the recharge of groundwater (Şen, 2015). A hydraulic system is essentially dynamic in nature with an inherent memory, which means that the output of a system (watershed) on any given day will be affected not only by the inputs and outputs of the current day, but also by the inputs and outputs of the day before (Chua and Wong, 2011). Ground water level produced by rainfall, constantly has a time lag as associated to real ground water level. In this case, time series have to be useful for correctly modelling of ground water level. The following equation shows relationships of rainfall (RF), effective rainfall (ERF), average temperature (T), relative humidity (RH), solar radiation (SR), wind speed (WS), evaporation (EV) and evapotranspiration (ET) and ground water level (GW):

$$GWF = f(RF, ERF, T, RH, SR, WS, EV, ET, GW_t, GW_{t-1}, GW_{t-2}, GW_{t-3}, \ldots, GW_{t-n}) \tag{4}$$

Where, GWF = Ground Water Fluctuation, GWt = Ground water level in current season, GWt-1 = Ground water level one season lag, GWt-2=Ground water level two season lag, GWt-3 = Ground water level three season lag, GWt-n =Ground water level in n season lag. Various combinations of input combination with five lag days of ground water level (GWL) data sets were used in the present study to develop a model.

Model Evaluation criteria

In the present study, the accuracy and efficiency criteria that have been used are the distinct criteria. The MLP performance was evaluated by assessing the values of statistical and hydrological indices such as Nash Sutcliffe model Efficiency (NSE), Willmott Index of agreement (d), mean absolute error (MAE), mean bias error (MBE), root mean square error (RMSE), correlation coefficient (PCC), and R-squared correlation (R^2). In addition, line diagram, scatter plot and Taylor diagram were used to visually analyze the diagnostic data.

$$NSE = 1 - \frac{\sum_{i=1}^{N}\left(GWF_i^{Obs} - GWF_i^{Cal}\right)^2}{\left(GWF_i^{Obs} - \overline{GWF_i^{Obs}}\right)^2} \tag{5}$$

$$d = 1 - \frac{\sum_{i=1}^{N}\left(GWF_i^{Obs} - GWF_i^{Cal}\right)^2}{\sum_{i=1}^{N}\left(\left|GWF_i^{Cal} - \overline{GWF_i^{Obs}}\right| + \left|GWF_i^{Obs} - \overline{GWF_i^{Obs}}\right|\right)^2} \tag{6}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|GWF_i^{Obs} - GWF_i^{Cat}\right| \tag{7}$$

$$MBE = \frac{1}{N}\sum_{i=1}^{N}\left(GWF_i^{Obs} - GWF_i^{Cal}\right) \tag{8}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(GWF_i^{Obs} - GWF_i^{Cal}\right)^2} \tag{9}$$

$$PCC = \sqrt{1 - \frac{\sum_{i=1}^{N}\left(Q_i^{Obs} - GWF_i^{Cal}\right)^2}{\sum_{i=1}^{N}\left(Q_i^{Obs} - \overline{GWF_i^{Cal}}\right)^2}} \tag{10}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}\left(GWF_i^{Obs} - GWF_i^{Cal}\right)^2}{\sum_{i=1}^{N}\left(GWF_i^{Obs} - \overline{GWF_i^{Cal}}\right)^2} \tag{11}$$

Table 2: Choice of Input variable based on Gamma Test (GT) and Standard Errors.

Model	Input variable	Gamma	SE
M-1	RF, ERF, T, RH, SR, WS, EV, ET, GW_{t-1}, GW_{t-2}, GW_{t-3}, GW_{t-4}, GW_{t-5}	0.6020	0.0615
M-2	RF, ERF, T, RH, WS, EV, ET, GW_{t-1}, GW_{t-2}, GW_{t-3}, GW_{t-4}, GW_{t-5}	0.6062	0.0608
M-3	RF, ERF, RH, WS, EV, ET, GW_{t-1}, GW_{t-2}, GW_{t-3}, GW_{t-4}, GW_{t-5}	0.6490	0.0586
M-4	RF, ERF, RH, EV, ET, GW_{t-1}, GW_{t-2}, GW_{t-3}, GW_{t-4}, GW_{t-5}	0.6022	0.0598
M-5	RF, ERF, EV, ET, GW_{t-1}, GW_{t-2}, GW_{t-3}, GW_{t-4}, GW_{t-5}	0.6392	0.0561
M-6	RF, ERF, ET, GW_{t-1}, GW_{t-2}, GW_{t-3}, GW_{t-4}, GW_{t-5}	0.5704	0.0615
M-7	RF, ET, GW_{t-1}, GW_{t-2}, GW_{t-3}, GW_{t-4}, GW_{t-5}	0.5052	0.0601
M-8	RF, GW_{t-1}, GW_{t-2}, GW_{t-3}, GW_{t-4}, GW_{t-5}	0.6005	0.0604
M-9	GWt-1, GWt-2, GW t-3, GWt-4, GWt-5	0.6204	0.0595
M-10	GWt-1, GWt-2, GW t-3, GWt-4	0.5034	0.0595
M-11	**GWt-1, GWt-2, GW t-3**	**0.4179**	**0.0501**
M-12	GWt-1, GWt-2	0.6065	0.0598
M-13	GWt-1	0.5859	0.0584
M-14	RF, GW_{t-1}	0.5994	0.0595
M-15	**RF, GW_{t-1}, GW_{t-2}**	**0.4164**	**0.0508**
M-16	**RF, ERF, GW_{t-1}, GW_{t-2}**	**0.4088**	**0.0497**
M-17	**RF, ERF, GW_{t-1}, GW_{t-2}, GW_{t-3}**	**0.3975**	**0.0483**
M-18	RF, ERF, ET, GW_{t-1}, GW_{t-2}, GW_{t-3}	0.5383	0.0610
M-19	RF, ERF, ET, GW_{t-1}, GW_{t-2}, GW_{t-3}	0.5916	0.0591
M-20	RF, ERF, ET, GW_{t-1}, GW_{t-2}, GW_{t-3}, GW_{t-4}	0.5916	0.0596
M-21	RF, ERF, RH, SR, WS, EV, ET	0.5894	0.0589
M-22	RF, ERF, SR, WS, EV, ET	0.5828	0.0614
M-23	RF, ERF, WS, EV, ET	0.6116	0.0570
M-24	RF, ERF, EV, ET	0.6075	0.0597
M-25	RF, ERF, ET	0.6166	0.0619
M-26	RF, ERF	0.5991	0.0583

Where GWF_i^{obs} and GWF_i^{Cal} are the observed and models GWF data GWF_i^{obs} and GWF_i^{Cal} are the mean value of the observed and models GWF data.

RESULTS AND DISCUSSION

Selecting Best Input Variable Using Gamma Test

Choosing the optimal set of input parameters for predicting GW fluctuation and the GWL trend is very challenging which was also used to remove the redundant input constraints that have little or no impact on the forecast. In order to avoid complexity, the most relevant inputs are selected based on their influence on the results. Following that, the results are easy to understand and to analyze since the models have been developed with only the most relevant inputs. Table 2 illustrate the GT results for several input variables and the corresponding GWF data test architecture and the results of running the multilayer perceptron (MLP) based ANNs model after they have been developed.

The best four input-output combinations were selected based on Gamma test. In this study, M-11, M-15, M16 and M-17 models were found as the best input- output combination based on minimum value of gamma and standard error (SE).

Comparison of MLP based ANNs models M-11, M-15, M-16, M-17

Various MLP based ANN models developed for the prediction of ground water fluctuation in various blocks of Kanpur district were assessed based on the statistical evaluation criteria. A number of performance indices were evaluated during the training and testing period for these selected models, and the results are shown in Table 3. In this study, M-11, M-15, M-16 and M-17 models were found as the best combination of input-output based on minimum value of gamma and standard error (SE) (Table 2). The values of MAE, MBE, RMSE, d, NSE, PCC and R^2 for selected models (M-11, M- 15, M-16 and M-17) varied from 0.065 to 0.274 m, -0.079 to 0.006 m, 0.011 to 1 m, 0.937 to 0.998, 0.843 to 0.988, 0.985 to 1, and 0.97 to 1, respectively. The analysis of the selected MLP based ANN models (i.e., M-11, M-15, M-16, M-17) based on several statistical indices during the testing period shown in the Table shows that performance of M-16 is better than other models. Among the selected models, M-16 with MAE = 0.090, MBE = 0.000, RMSE = 0.016, d = 0.995, NSE = 0.988, PCC = 1.000 and R^2 =1.000 respectively during training and MAE = 0.099, MBE = -0.030, RMSE = 0.011, d = 0.994, NSE = 0.934, PCC = 1.000 and R^2 =1.000 respectively during testing, was found to be the best model.

Table 3: Comparison of the selected MLR based M-11, M-15, M-16 and M-17 models

Data sets	Model	Architecture	Statistical parameters						
			MAE	MBE	RMSE	d	NSE	PCC	R^2
Training dataset	M-11	3-36-1	0.243	0.005	0.031	0.948	0.947	0.985	0.970
	M-15	3-25-1	0.065	0.006	0.027	0.995	0.961	0.993	0.986
	M-16	**4-18-1**	**0.090**	**0.000**	**0.016**	**0.995**	**0.988**	**1.000**	**1.000**
	M-17	5-30-1	0.198	0.000	1.000	0.968	0.978	1.000	1.000
Testing dataset	M-11	3-36-1	0.274	-0.079	0.021	0.937	0.874	0.997	0.995
	M-15	3-25-1	0.066	-0.020	0.025	0.998	0.843	1.000	1.000
	M-16	**4-18-1**	**0.099**	**-0.030**	**0.011**	**0.994**	**0.934**	**1.000**	**1.000**
	M-17	5-30-1	0.219	-0.067	0.018	0.966	0.905	1.000	1.000

The visual diagrams between observed and forecasted values of GWF using MLP based ANN models for Kanpur City during the training and testing period are depicted in Fig. 3. It is detected from these graphs and scatter plots that the developed models generally under predict to GWFs. There are no data point have found big deviation between forecatsed and observed runoff for M-16 with architecture 4-18-1 model during training and testing period. It is apparent from these Figures that predicted ground water fluctuations using M-16 with architecture 4-18-1 model during training testing period is quite close to the values of observed GWF. It is clear that selected M-16 with architecture 4-18-1 model give satisfactory results for GWF. The qualitative assessment of the established models in forecasting of GWFs has been found suitable for the Kanpur City.

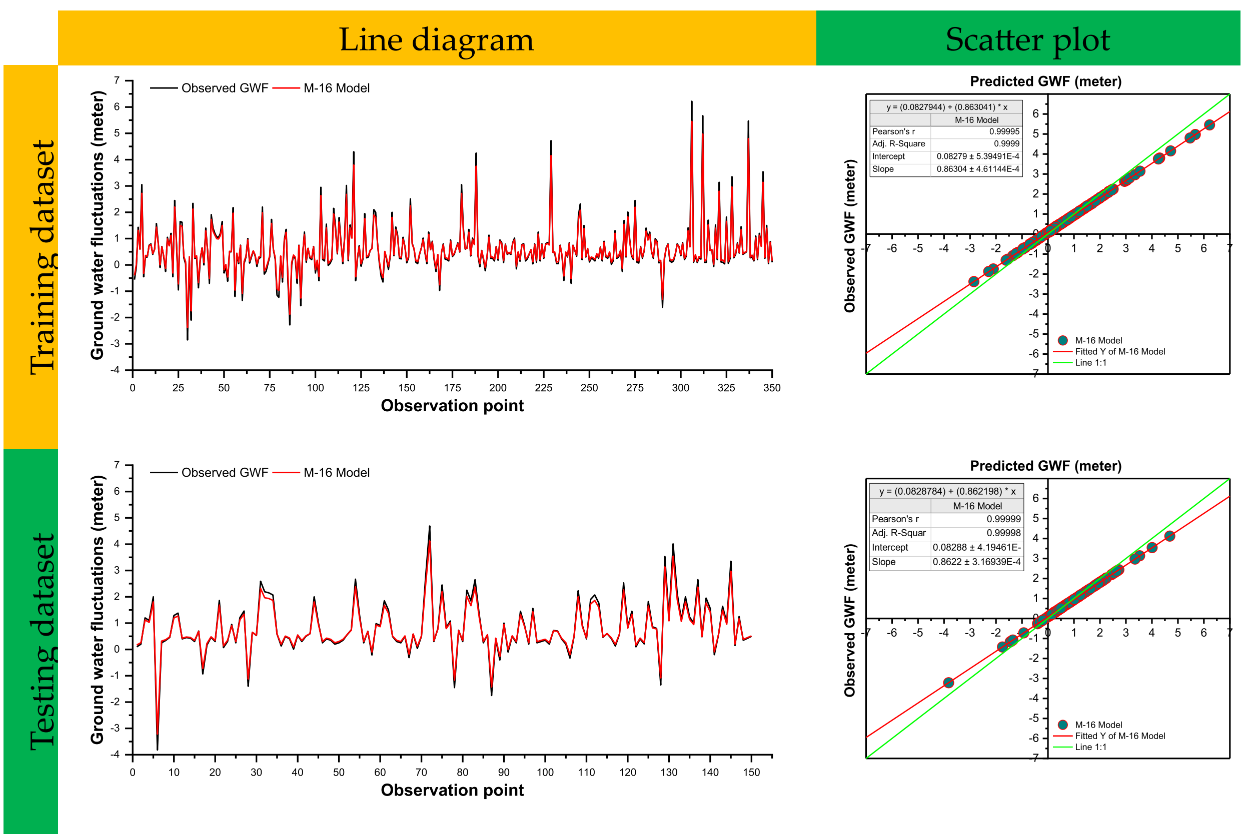

Fig. 3: Line and scatter diagram between observed GWF and predicted GWF model (M-16, architecture 4-18-1) during training and testing data sets

Based on the characteristics of acceptable results ranges for NSE, d and R^2, all model found very good. Based on the input parameters availability, any one of them model could be select for ground water fluctuations forecasting. Furthermore, Taylor diagram confirm that M-16 model was very close to reference line, that shows minimum standard deviation and root mean square error and maximum Pearson's correlation coefficient (Fig. 4).

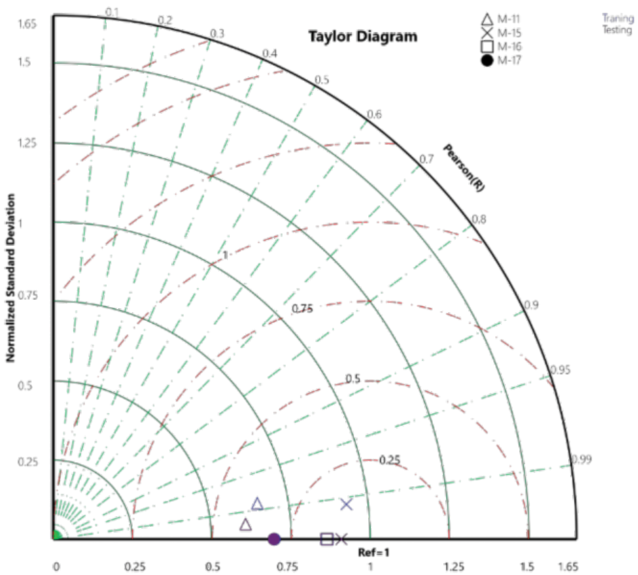

Fig. 4: Taylor Diagram of M-11, M-15, M-16 and M-17 model. Note: red dot-dash line shows RMSE value

CONCLUSIONS

The results of the investigation show that the MLP based ANN models provide good estimating accuracy, and are appropriate for the prediction of GWFs in semiarid regions which have a limited amount of available water. The ability of using Gamma tests to identify the input parameters of the model may turn this technique into an efficient tool for preprocessing the data for predicting groundwater levels using the model. Among all the selected MLP based ANN models, the model M-16, architecture 4-18-1 showed the best performance for ground water fluctuations prediction at Kanpur district.

ACKNOWLEDGMENTS

The writers thank Divisional office of CGWB- Kanpur Nagar, Ministry of Water Resources, RD & GR, Govt. of India for providing necessary data to carry out this work. Special thanks are owed to Professor Arpan Sherring, Department of Irrigation and Drainage Engineering, Sam Higginbottom University of Agriculture, Technology and Sciences, Prayagraj, Uttar Pradesh, for his support and valuable comments. They gratefully acknowledge the anonymous reviewers and editors for their valuable reviews and suggestions.

REFERENCES

Arora B, Mohanty BP, McGuire JT.2012. Uncertainty in dual permeability model parameters for structured soils. *Water Resour. Res.* **48**:. https://doi.org/10.1029/2011WR010500

Mirzania E, Vishwakarma DK, Bui Q-AT, et al.2023. A novel hybrid AIG-SVR model for estimating daily reference evapotranspiration. *Arab J. Geosci.* **16**:301. https://doi.org/10.1007/s12517-023-11387-0

Nayak PC, Rao YRS, Sudheer KP.2006. Groundwater Level Forecasting in a Shallow Aquifer Using Artificial Neural Network Approach. *Water Resour. Manag.* **20**:77–90. https://doi.org/10.1007/s11269-006-4007-z

Rashidi S, Vafakhah M, Lafdani EK, Javadi MR.2016. Evaluating the support vector machine for suspended sediment load forecasting based on gamma test. Arab J Geosci 9:583. https://doi.org/10.1007/s12517-016-2601-9

Sahoo S, Russo TA, Elliott J, Foster I (2017) Machine learning algorithms for modeling groundwater level changes in agricultural regions of the U.S. *Water Resour. Res.* **53**:3878–3895. https://doi.org/10.1002/2016WR019933

Sahu RK, Müller J, Park J, et al.2020. Impact of Input Feature Selection on Groundwater Level Prediction From a Multi-Layer Perceptron Neural Network. *Front Water* **2**:. https://doi.org/10.3389/frwa.2020.573034

Sarangi A and Bhattacharya AK.2005. Comparison of Artificial Neural Network and regression models for sediment loss prediction from Banha watershed in India. *Agric. Water Manag.* **78**:195–208. https://doi.org/10.1016/j.agwat.2005.02.001

Saroughi M, Mirzania E, Vishwakarma DK, et al.2023. A Novel Hybrid Algorithms for Groundwater Level Prediction. *Iran J Sci Technol Trans Civ Eng*. https://doi.org/10.1007/s40996-023-01068-z

Shukla R, Kumar P, Vishwakarma DK, et al.2021. Modeling of stage-discharge using back propagation ANN-, ANFIS-, and WANN-based computing techniques. *Theor. Appl. Climatol.* https://doi.org/10.1007/s00704-021-03863-y

Singh AK, Kumar P, Ali R, et al.2022. An Integrated Statistical-Machine Learning Approach for Runoff Prediction. *Sustainability* **14**:8209. https://doi.org/10.3390/su14138209

Singh VK, Kumar D, Kashyap PS, Kisi O.2018. Simulation of suspended sediment based on gamma test, heuristic, and regression-based techniques. *Environ. Earth Sci.* **77**:708. https://doi.org/10.1007/s12665-018-7892-6

Singh VK, Kumar D, Kashyap PS, Singh PK.2019. Predicting Unsaturated Hydraulic Conductivity of Soil Based on Machine Learning Algorithms. In: Conference: Proceedings of International Conference Opportunities and Challenges in Engineering, Management and Science (OCEMS-2019)At: Bareilly, India

Singh VK, Kumar P, Singh BP.2016. Rainfall-runoff modeling using artificial neural networks (ANNs) and multiple linear regression (MLR) techniques. *Indian J. Ecol.* **43**:436–442

Solgi R, Loáiciga HA, Kram M (2021) Long short-term memory neural network (LSTM-NN) for aquifer level time series forecasting using in-situ piezometric observations. *J. Hydrol.* **601**:126800. https://doi.org/10.1016/j.jhydrol.2021.126800

Steefel CI, Appelo CAJ, Arora B, et al.2015. Reactive transport codes for subsurface environmental simulation. *Comput. Geosci.* **19**:445–478. https://doi.org/10.1007/s10596-014-9443-x

Vishwakarma DK, Kumar R, Kumar A, et al.2022. Evaluation and development of empirical models for wetted soil fronts under drip irrigation in high-density apple crop from a point source. *Irrig. Sci.* https://doi.org/10.1007/s00271-022-00826-7

Vishwakarma DK, Kuriqi A, Abed SA, et al.2023. Forecasting of stage-discharge in a non-perennial river using machine learning with gamma test. *Heliyon* **9**:e16290. https://doi.org/10.1016/j.heliyon.2023.e16290

Citation:

Sachan SK, Sherring A and Denis DM.2023. Gamma test-based MLP based ANN model for groundwater fluctuation forecasting in Kanpur District, Uttar Pradesh. *Journal of AgriSearch* **10**(2): 87-93