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Uncertainty of the Ground Water Fluctuation Based on ANN Approach

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A B S T R A C T

This study pursues to determine the accuracy of the groundwater level fluctuations forecasted at the Kanpur district of India using artificial neural networks (ANNs). The results indicated that performance of multilayer perceptron (MLP) based neural network (M-3, architecture 4-18-1) is satisfactory in the groundwater level fluctuations forecasting. The performance assessment shows that the MLP model performs significantly better. The uncertainty analysis shows that, input of Absent-RF and Absent- ERF, Absent- GWt-1, and Absent- GWt-5 were found more sensitive for GWFs forecasting and can't ignore as input combination & input of Absent- WS and RH were found less sensitive for GWFs forecasting and may be discarded as input combination for GWFs forecasting.

Introduction

A forecast of the fluctuations in the surface water level is the first step to planning conjunctive use in any basin when planning conjunctive use (Saroughi *et al.,* 2023). Furthermore, the depletion of groundwater supplies, conflicts between users of groundwater and users of surface water, and the possibility of ground water contamination will be concerns that will become increasingly important as more aquifer systems are developed in any basin at any time (Nayak *et al.,* 2006). In estimating the status of a hydrologic parameter such as a groundwater level, statistical analysis and mathematical modelling can be used to make predictions about its future status because hydrologic parameters such as groundwater levels are stochastic (Vishwakarma *et al.,* 2023). In order to manage groundwater resources efficiently and effectively, it is necessary to evaluate and forecast groundwater level through specific models (Garcia and Shigidi, 2006). In such a situation, we can make use of time series modeling in order to predict fluctuations in groundwater levels in the future for optimal and proper management of groundwater resources during the upcoming months (Chitsazan *et* *al.,* 2015; Vishwakarma *et al.,* 2018). Due to the fact that groundwater resources are mostly influenced by a number of factors and it is subject to complex fluctuations, it is necessary to decompose this complexity and its variations using mathematical methods (Lu *et al.,* 2014). A number of robust tools are available on the market, and one of them, called artificial neural networks (ANNs), is commonly used to forecast hydro-climatological variables (Shukla *et al.,* 2021; Vishwakarma *et al.,* 2022; Achite *et al.,* 2023). In recent years, artificial neural networks (ANNs) have been used in a number of fields of science and engineering to forecast with great accuracy. As a result of their effectiveness, ANNs have been shown to be able to model virtually any nonlinear function with a high degree of accuracy. As compared to traditional methods, this approach has the major advantage of being able to describe the complex nature of the underlying process in an explicit mathematical manner without requiring the complex nature of the process to be explicitly formulated in terms of mathematics (Shukla *et al.,* 2021; Elbeltagi *et al.,* 2022; Saroughi *et al.,* 2023).

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 comparing the performance of MLP based ANN models in groundwater level fluctuation forecasting at Kanpur District and evaluate the uncertainty for input parameter of ground water fluctuation.

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 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.

Multilayer Feed forward Neural Networks

The multilayer feed forward 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 feed forward 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:

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

Where, x is an input vector, Wji 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; Wkj 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 0 are the activation function for hidden and output layer.

Development of MLP- based ANN models

A hydrological system is essentially dynamic in nature with an inbuilt 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.

Ground water fluctuation (GWF) level produced by rainfall (RF), and effective rainfall (ERF) constantly has a time lag as associated to real ground water level. The following four model were considered to develop model to forecast the GWFs is shown in Table 1.

Uncertainty Analysis

An uncertain analysis seeks to quantify the variation in the output caused by the variability in the input, which results in a variability in the output itself in the absence of any particular input data. In most cases, the quantification process is conducted by estimating statistical quantities of interest, such as the mean, median, quantiles, correlation coefficient, root mean squared error and Nash-Sutcliffe efficiency etc. for the population. It is important to understand the relative contributions of various sources of uncertainty to model performance in order to guide efforts aimed at improving it. There are two factors that determine this: the model's sensitivity to changes in parameter values, as well as the uncertainty level associated with each parameter. The result of input variable was compared with absence of one input parameter to check the uncertainty using by some statistical measures.

Uncertainty analysis in input parameters during AI forecasting refers to the process of quantifying and understanding the uncertainty associated with the input variables used in the forecasting model.

It involves assessing the variability, error, or lack of knowledge in the input data or parameters and considering how these uncertainties propagate through the model to affect the forecasted outcomes.

By performing uncertainty analysis, AI forecasting practitioners can gain insights into the reliability and robustness of the forecasted outcomes. This information is valuable for decision-making processes, risk assessment, and understanding the limitations and potential errors in the forecasting 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.

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

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

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|GWF_i^{Obs} - GWF_i^{Cal}| \quad \ldots(7)$$

$$MBE = \frac{1}{N}\sum_{i=1}^{N}(GWF_i^{Obs} - GWF_i^{Cal}) \quad \ldots(8)$$

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

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

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

Where GWF_i^{Obs} and GWF_i^{Cal} are the observed and models GWF data; $\overline{GWF_i^{Obs}}$ and $\overline{GWF_i^{Cal}}$ are the mean value of the observed and models GWF data.

Results and Discussion

Comparison of MLP based ANNs models M-1, M-2, M-3, M-4

Considering the 4 different 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 2. The values of MAE, MBE, RMSE, d, NSE, PCC and R^2 for selected models (M-1, M- 15, M-3 and M-4) 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-1, M-2, M-3, M-4) based on several statistical indices during the testing period shown in the Table shows that performance of M-3 is better than other models. Among the selected models, M-3 with MAE = 0.090, MBE = 0.000, RMSE = 0.016, d = 0.995, NSE = 0.988, PCC= 1.000and 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.

Uncertainty analysis on Models' Inputs

In the present study, Sensitivity analysis is used for test the Uncertainty analysis. The Table 3 and 4 shows the results of the sensitivity analyses for the M-3 model during training and testing period, respectively at study sites. Fig. 3 and Fig. 4 illustrates an example of variation in sensitivity index during the variations of inputs to the M-3 model during training and testing period, respectively at study sites. It can be observed from Table 3& 4 and Fig. 3& 4, that at site study site, almost all the inputs have reasonably high values of sensitivity index, and hence they significantly affect the groundwater- fluctuations at this site. However, at this study site, based on RMSE, NSE and PCC value, input Absent- GW_{t-1} and Absent- GW_{t-5}has a highest error (i.e., highest value of RMSE), and lowest model efficiency and correlation (i.e., lowest value of NSE and PCC) and sensitivity ranked 1 and 2 respectively as compared to those for the remaining inputs (rank=1–14; Table 3& 4) during training period. Therefore, these input parameters cannot be ignored in GWFs forecasting.

Furthermore, Fig. 3 confirm that these inputs are more sensitive and in the absence of these inputs, predicted GWFs more deviate from the observed GWFs. However, at study site Kanpur city, input Absent- GW_{t-4} and Absent- RH has a lowest error (i.e., lowest value of RMSE), and highest model efficiency and correlation (i.e., highest value of NSE and PCC) and sensitivity ranked 13 and 13 respectively as compared to those for the remaining inputs (rank=1–14; Table 3) during training period. Therefore, input Absent- GW_{t-4} and Absent- RH may be discarded at study site. Thus, it is evident from Table 3 that at study sites, rank 1-4, (i.e., Absent- GW_{t-1}, Absent- GW_{t-5}, Absent- ET and Absent- EV), have a strong influence on groundwater fluctuations, showing greater sensitivity levels during training period.

It can be seen from Table 4 and Fig. 4, that at study site, almost all the inputs have reasonably high values of sensitivity index, and hence they significantly affect the groundwater-fluctuations at this site. However, at this study site, based on RMSE, NSE and PCC value, input Absent-RF and Absent- ERF has a highest error (i.e., highest value of RMSE), and lowest model efficiency and correlation (i.e., lowest value of NSE and PCC) and sensitivity ranked 1 and 2 respectively as compared to those for the remaining inputs (rank=1–14; Table 4) during testing period.

Therefore, these input parameters cannot be ignored in GWFs forecasting. Furthermore, Fig. 4 confirm that these inputs are more sensitive and in the absence of these inputs, predicted GWFs more deviate from the observed GWFs. However, at study site Kanpur city, input Absent- GW_{t-2} and Absent-WS has a lowest error (i.e., lowest value of RMSE), and highest model efficiency and correlation (i.e., highest value of NSE and PCC) and sensitivity ranked 13 and 13 respectively as compared to those for the remaining inputs (rank=1–14; Table 4) during training period. Therefore, input Absent-GW_{t-2} and Absent- WS may be discarded at study site.

Thus, it is evident from Table 4 that at study sites, rank 1-4, (i.e., Absent- RF and Absent- ERF, Absent- RH and Absent- GW_{t-5}), have a strong influence on groundwater fluctuations, showing greater sensitivity levels during testing period. Fig. 3 and 4 shows the same result, observed and estimated GWFs with different input parameters.

Table.1 Details of output-input variables for ANN models

Model	Input variable	Output
M-1	GW_{t-1}, GW_{t-2}, GW_{t-3}	GWF
M-2	RF, GW_{t-1}, GW_{t-2}	GWF
M-3	RF, ERF, GW_{t-1}, GW_{t-2}	GWF
M-4	RF, ERF, GW_{t-1}, GW_{t-2}, GW_{t-3}	GWF

Table.2 Comparison of the selected MLR based M-1, M-2, M-3 and M-4 models.

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

Table.3 Summary of uncertainty analysis during training period.

Input Variable	Training						
	MBE	RMSE	NSE	PCC	Rank*	Rank**	Rank***
RF, ERF, T, RH, SR, WS, EV, ET, GW_{t-1}, GW_{t-2}, GW_{t-3}, GW_{t-4}, GW_{t-5}	0.0609	0.6935	0.5205	0.7476	5	5	5
Absent- GW_{t-5}	-0.0182	1.0119	-0.0208	0.4048	2	2	1
Absent- GW_{t-4}	0.0084	0.4466	0.8012	0.8953	13	13	13
Absent- GW_{t-3}	0.0068	0.4832	0.7672	0.8951	8	8	10
Absent- GW_{t-2}	0.0091	0.4495	0.7985	0.8953	11	11	12
Absent- GW_{t-1}	-0.0029	1.0268	-0.0511	0.4429	1	1	2
Absent- ET	-0.0660	0.9021	0.1887	0.5161	3	3	3
Absent- EV	-0.0243	0.8863	0.2169	0.5560	4	4	4
Absent- WS	0.0115	0.4478	0.8001	0.8947	12	12	9
Absent- SR	0.0076	0.4575	0.7913	0.8952	9	9	11
Absent- RH	0.0084	0.4466	0.8012	0.8953	13	13	13
Absent- T	0.0107	0.4531	0.7953	0.8944	10	10	8
Absent- ERF	-0.0561	0.6538	0.5739	0.7633	6	6	6
Absent- RF	0.0059	0.5592	0.6883	0.8323	7	7	7

Table.4 Summary of uncertainty analysis during testing period.

Input Variable	Training						
	MBE	RMSE	NSE	PCC	Rank*	Rank**	Rank***
RF, ERF, T, RH, SR, WS, EV, ET, GW_{t-1}, GW_{t-2}, GW_{t-3}, GW_{t-4}, GW_{t-5}	-0.0119	0.8663	0.3027	0.5594	7	7	5
Absent- GW_{t-5}	0.0665	0.9203	0.2130	0.5597	4	4	6
Absent- GW_{t-4}	-0.0017	0.7772	0.4387	0.6931	11	11	11
Absent- GW_{t-3}	-0.0893	0.8336	0.3542	0.6043	9	9	9
Absent- GW_{t-2}	-0.0874	0.6803	0.5700	0.7602	14	14	14
Absent- GW_{t-1}	-0.0663	0.7543	0.4713	0.7118	12	12	13
Absent- ET	-0.0568	0.8910	0.2623	0.5867	6	6	7
Absent- EV	-0.0652	0.8514	0.3265	0.5989	8	8	8
Absent- WS	-0.0765	0.7414	0.4891	0.7035	13	13	12
Absent- SR	0.0102	0.7900	0.4200	0.6713	10	10	10
Absent- RH	-0.0356	0.9447	0.1706	0.4916	3	3	3
Absent- T	-0.0501	0.9011	0.2455	0.5431	5	5	4
Absent- ERF	0.0201	1.0484	-0.0214	0.3665	2	2	2
Absent- RF	0.0786	1.1432	-0.2144	0.2692	1	1	1

Location map of the Kanpur District

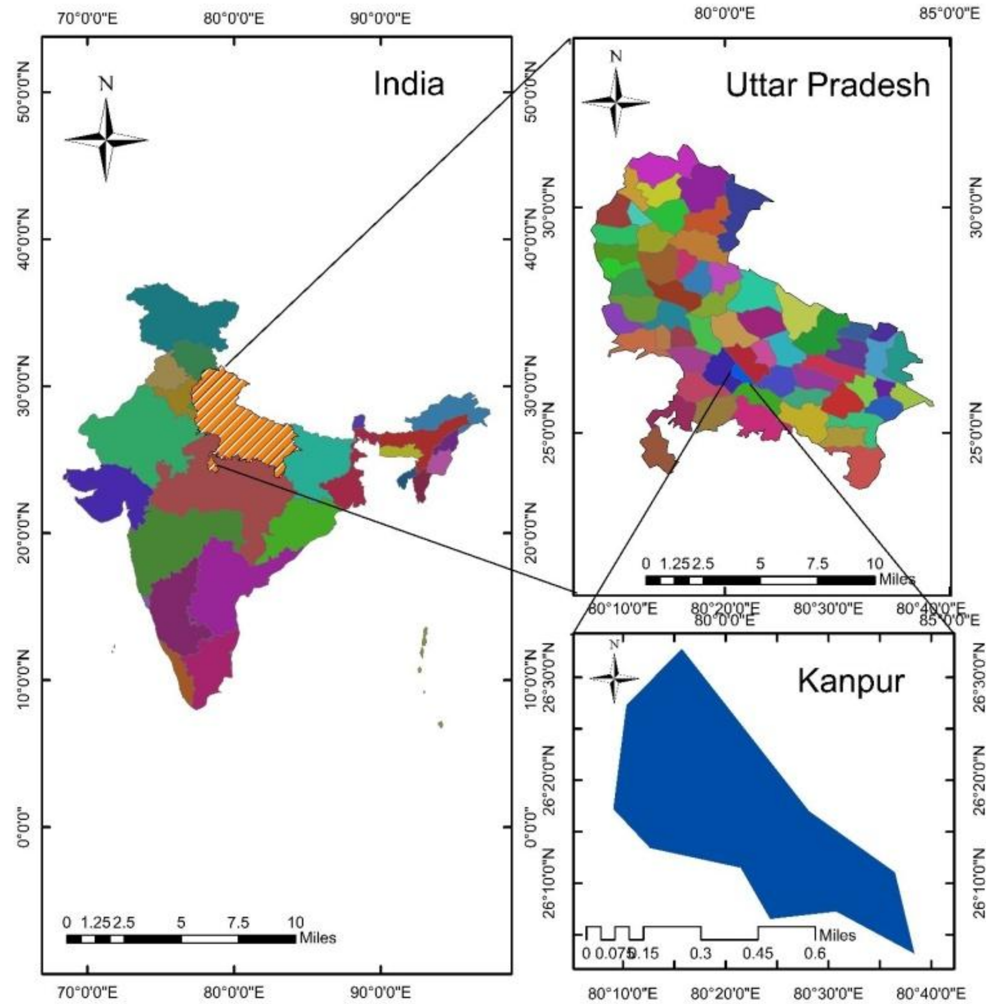


Fig.2 Single layer and multilayer feed forward networks

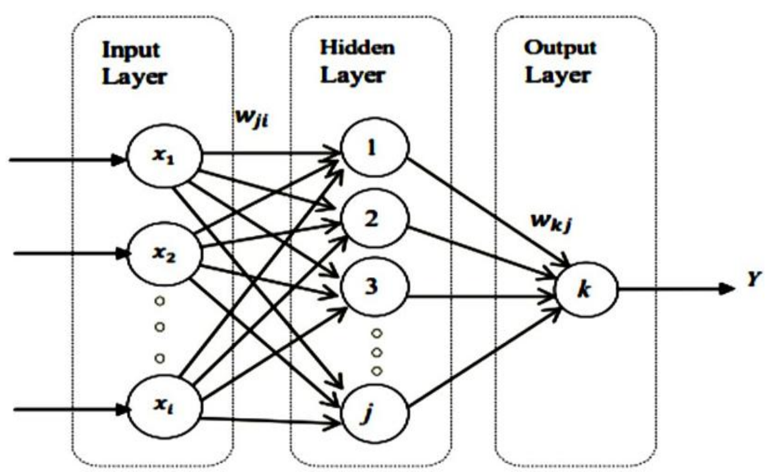


Fig.3 Temporal line diagram of sensitivity analysis during training period.

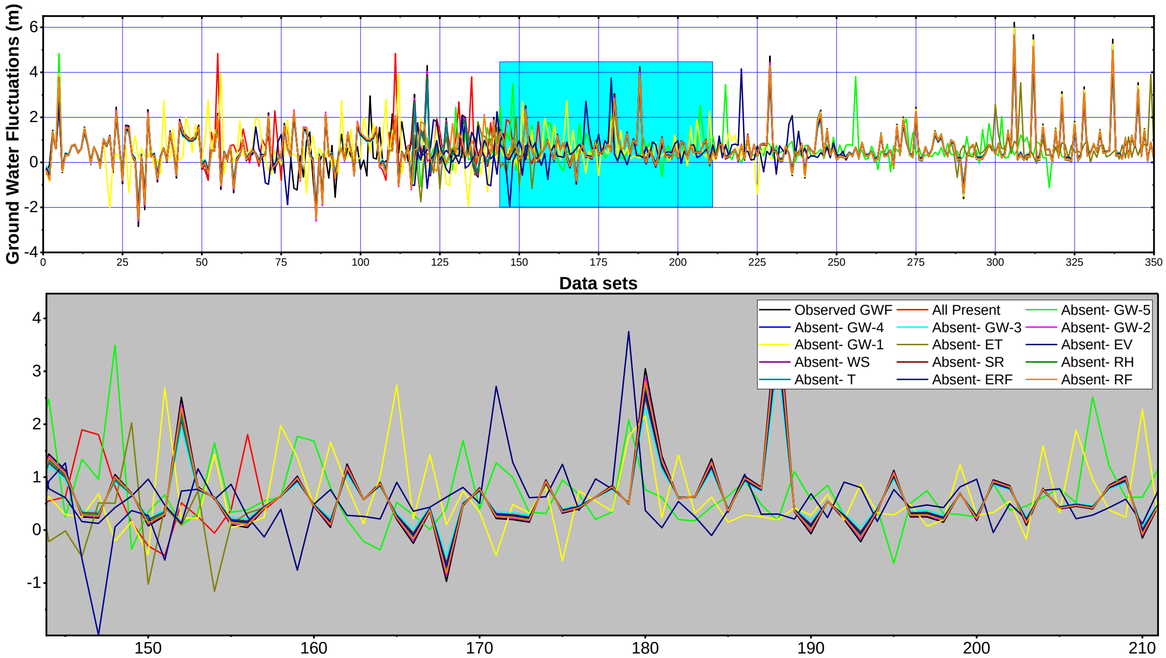
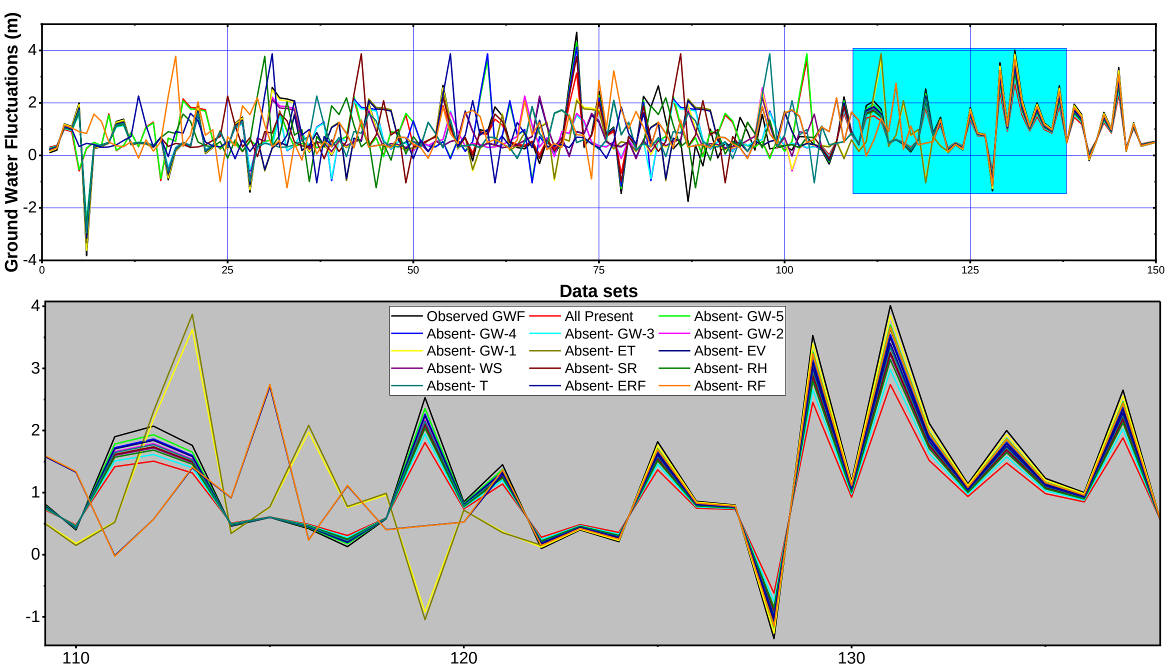


Fig.4 Temporal line diagram of sensitivity analysis during testing period.



Absent- GW_{t-1} deviate more with observed GWFs during training and testing period. As we aware that final decision will be consider based on the values testing period. Thus, it may conclude that input of Absent- RF and Absent- ERF, Absent- GW_{t-1}, and Absent- GW_{t-5} is more sensitive. However, for the remaining, only a small number of inputs have very low sensitivity (rank more than 6), which are highlighted in Table 3 and 4. Therefore, the inputs having 'very high' to 'moderate' sensitivity should be considered with greater accuracy so as to ensure reliable prediction of groundwater fluctuations by the MLP model.

Based on the findings of this study, the following conclusions have been drawn:

The M-3 models (architecture 4-18-1) model performed better than all other models in terms of statistical criterion in the GWF prediction for Kanpur district.

Based on uncertainty analysis, input of Absent- RF and Absent- ERF, Absent- GWt- 1, and Absent- GWt-5 were found more sensitive for GWFs forecasting and cannot be ignored as input combination.

Based on uncertainty analysis, input of Absent- WS and RH were found less sensitive for GWFs forecasting and may be discarded as input combination for GWFs forecasting.

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