


GRNN Model for prediction of groundwater fluctuation in the state of Uttarakhand of India using GRACE data under limited bore well data

Dilip Kumar  and Rajib Kumar Bhattacharjya

ABSTRACT

Springs, the primary source of water in the Indian state of Uttarakhand, are disappearing day by day. A report published by United Nations Development Program in 2015 indicates that due to deforestation, and forest fire, the groundwater of the state has been reduced by 50% between 2007 and 2010. As such, for taking proper adaptation policies for the state, it is necessary to monitor the state's groundwater fluctuation. Unfortunately, the bore well data are very limited. Thus, we are proposing two general regression neural network (GRNN)-based models for fast estimation of groundwater fluctuation. The first model evaluates and predicts the groundwater fluctuation in the five known bore well data districts of the state, and the second model, which is based on the first model along with a correlation matrix, predicts the groundwater fluctuation in the districts where no bore well data are available. The assessment of the results shows that the proposed GRNN-based model is capable of estimating the groundwater fluctuation both in the areas where bore well data are available and the areas where bore well data are not available. The study shows that there is a sharp decline in the groundwater level in the hilly districts of the state.

Key words | ANN, GRACE, GRNN, groundwater, groundwater fluctuation, Uttarakhand

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HIGHLIGHTS

- A methodology has been proposed to obtain the regional groundwater fluctuation using GRACE data.
- The model is also capable of deriving the groundwater fluctuation for the areas where bore well data is not available.
- The model uses GRACE data along with rainfall and temperature for the prediction of groundwater fluctuation.

INTRODUCTION

Groundwater has been extensively used in many parts of India (Khan *et al.* 2014; Iqbal *et al.* 2017) and is considered as the backbone resource for agricultural activities of the country. However, the groundwater table has been depleted

rapidly in many parts of the country as a result of unplanned exploitation of groundwater (Tiwari *et al.* 2009; Mohanty *et al.* 2010; Iqbal *et al.* 2017). Uttarakhand is a mountainous state of India where springs are a lifeline for the people. The annual replenishable groundwater resource of the state is 2.27 billion cubic meters (BCM), and the net yearly groundwater availability is 2.10 BCM. The annual groundwater drift in the state is 1.39 BCM (Singhal *et al.* 2010;

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Yadav & Pandey 2017). The people of the state mostly rely on spring water for their agricultural and domestic purposes. As per a United Nations Development Programme (UNDP) report, about 260,000 springs provide 90% of the drinking water sources in the state (Sayers *et al.* 2015; Shukla *et al.* 2016; Frappart & Ramillien 2018; Khaki *et al.* 2019). However, the number of springs in the mountainous parts of the state is decreasing day by day, and several villages face problems related to the supply of drinking water. As such, there is a need to study the fluctuation of the groundwater level of the state. The groundwater fluctuation study will also help in visualizing the effect of climate change (Gonzalez *et al.* 2016; Yang *et al.* 2017).

Uttarakhand has 13 districts. The Central Groundwater Board, Govt. of India, has 167 wells for monitoring the groundwater fluctuation. However, these monitoring wells are only in five districts of the state, i.e., in Dehradun, Haridwar, Udham Singh Nagar, Nainital, and Champawat (Mishra 2017; Dottori *et al.* 2018; Pankaj 2018). Since the bore well data are not available in other districts of the state, especially in hilly areas, there is a need to have a model for estimating the groundwater fluctuation of those unmonitored areas. As such, the present study attempts to provide a model for estimating groundwater fluctuation for the mountainous region of the state.

GRACE, a space mission launched by NASA in March 2002, captures data related to temporal change in the gravity of the Earth. The data can be used for observations of terrestrial water storage changes, ice-mass variations, ocean-bottom pressure changes, and sea-level variations. GRACE data have been used to estimate the depletion of groundwater in different parts of the world (Gouweleeuw *et al.* 2017; Yin *et al.* 2017; Scanlon *et al.* 2018; Opie *et al.* 2020). However, the mass anomaly data cannot be used directly to estimate the change in groundwater of an aquifer as it gives the terrestrial water storage changes (Chen *et al.* 2014; Ahmed & Abdelmohsen 2018; Zhang *et al.* 2019). As such, we proposed to use the generalized regression neural network (GRNN) model to estimate the groundwater fluctuations of the state of Uttarakhand. It has been observed that the fluctuation of groundwater also depends on the rainfall and the temperature. Therefore, rainfall and temperature data are also used along with the GRACE anomaly data to estimate the fluctuation of rainfall. The input to the

GRNN model is, therefore, the GRACE anomaly data, average rainfall, and the average temperature of the area, and the model output is the fluctuation of the groundwater level. For developing the GRNN model, we need the observed groundwater fluctuation data. However, for some parts of the state of Uttarakhand, we do not have the observed groundwater fluctuation data. As such, we proposed a correlation-based GRNN model to estimate the groundwater fluctuation of those districts. The validation of the model shows that the proposed GRNN model is capable of estimating the groundwater fluctuation and can be considered as a reliable model.

STUDY AREA AND MODEL DEVELOPMENT

Study area

Uttarakhand lies between 28°43'–31°27'N latitude and 77°34'–81°02'E longitude (Figure 1). The state spreads over an area of about 53,483 km² and has a diverse hydrogeological structure. The whole region of the state is divided into two distinguishing hydrogeological regimes, i.e., the Gangetic alluvial plain and the Himalayan mountain belt. The Gangetic alluvial plain is covered with a wide range of alluvium and unconsolidated sedimentary material of different size fractions (ranging

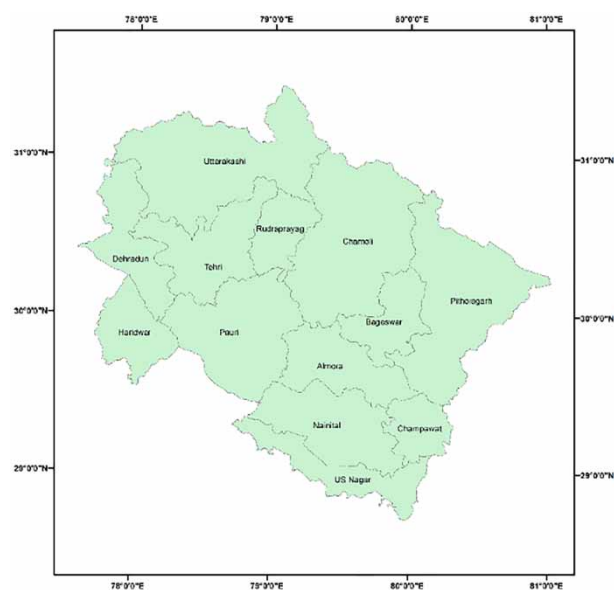


Figure 1 | The study area.

from boulder to clay) and is a likely zone for groundwater development. The Himalayan mountain belt, being largely hilly, has less capacity for large-scale development of groundwater. Groundwater in the hilly region occurs mostly in fractures and rises as springs.

There are 13 districts in Uttarakhand, and out of these 13 districts, only 5 districts have groundwater observation data. The locations of the groundwater observation wells and the districts where no bore well data are available are shown in Figure 2.

The data related to water fluctuation in these wells are downloaded from India-WRIS (Water Resource Information System). The groundwater data are available season-wise, and the data have been classified into four seasons, as shown in Table 1.

General regression neural network (GRNN)

We used the GRNN model to estimate the groundwater fluctuation by using the GRACE anomaly data, rainfall, and temperature. GRNN, as explained by Specht (Chinnasamy *et al.* 2015), is a neural network-based function predicting algorithm (Meena 2012; Joshi 2016). It requires no data for the iterative training, which makes GRNN a more preferable algorithm than other neural network models (Mohanty *et al.* 2010; Akhter & Ahmad 2017). GRNN has the capability to approximate any arbitrary continuous nonlinear functions

Table 1 | Groundwater recording season and their corresponding months

S. no.	Season Name	Months
1.	Post monsoon Kharif	October
2.	Post monsoon Rabi	January
3.	Pre monsoon	April
4.	Monsoon	July

by using the training data. The model is consistent with nature and works on the nonlinear regression concept (Nyatuame *et al.* 2014; Yang *et al.* 2017). The regression of a dependent variable y on an independent variable x estimates the most probable value for y , given x and a training set. The training set consists of pairs of matches x and y .

The fundamental principle of a neural network is that it needs training data to train the network. During the training, the network learns the hidden relationship associated with the input and output data. The training data should contain input-output datasets (Kannan & Ghosh 2011; Andrew *et al.* 2017). The network is then tested using a different dataset. Once the training and testing of the network are over, the model can be used to predict the output based on the given input to the network. In the case of GRNN, the new output is determined using a weighted average of the outputs of the training dataset. The weight of a particular pattern of the training dataset is estimated using the Euclidean distance between the pattern and the training data. If the distance is large, then the weight will be less, and if the distance is small, the pattern will have more weightage to the output. A GRNN model consists of four basic layers. They are the input layer, pattern layer, summation layer, and output layer (Hannan *et al.* 2010; Lv *et al.* 2017; Abou Zaki *et al.* 2018). Figure 3 shows a GRNN network.

The input layer consists of all input data required for the simulation. The pattern layer computes the Euclidean distance and decides the relevant weight. The summation layer consists of two parts, the first one is the numerator, and the second is the denominator. The numerator part contains the summation of the product of weight and the corresponding output. The denominator is the summation of all the weights. The output layer contains one neuron, which estimates the output by dividing the numerator of the summation layer by the denominator.

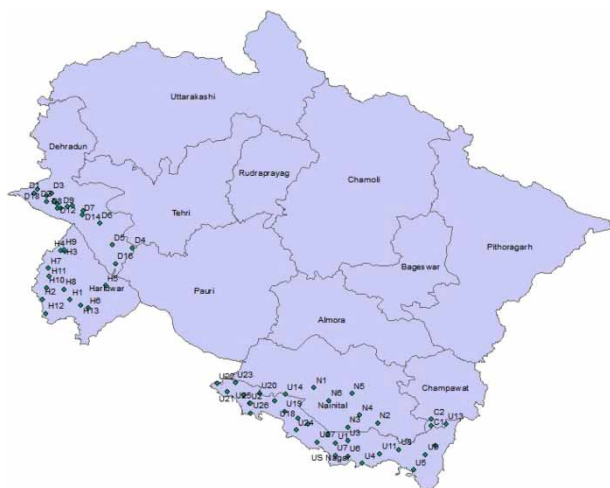


Figure 2 | Map of Uttarakhand showing location of groundwater observation wells.

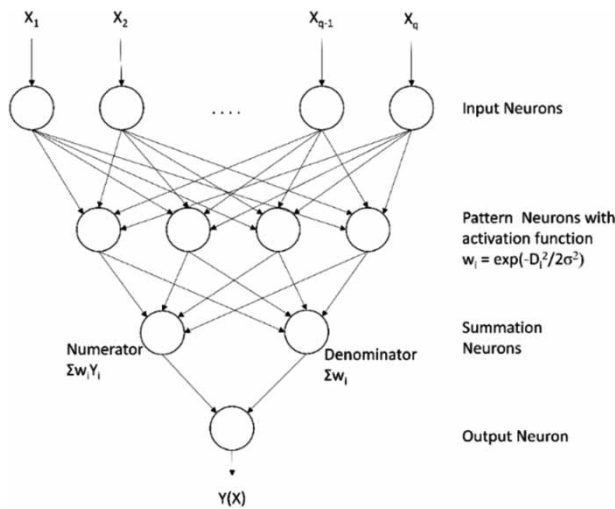


Figure 3 | The basic network diagram of a GRNN model.

As discussed above, the Euclidean distance of the inputs is the basis for calculating the weight to be assigned to a particular pattern. The equation for calculation of the new output according to the new input, as based on training data-sets, is given in Equation (1):

$$Y(X) = \frac{\sum Y_i e^{-\left(\frac{d_i^2}{2\sigma^2}\right)}}{\sum e^{-\left(\frac{d_i^2}{2\sigma^2}\right)}} \quad (1)$$

where d_i is the Euclidean distance between new input (X) and the training input (X_i), σ is the spread, which enhances the distance factor such that the increase in the value of σ decreases the chance of output near to the extreme values of the inputs and vice versa. Hence, σ is called the spread of the network. If the value of the distance d_i is small, the weight term returns a relatively large value and vice versa. If d_i is zero, the weight term returns 1, which means test data will be equal to the training sample, and the output of test data will be the output of the training sample.

The GRNN model has only one parameter to be estimated, i.e., the spread value (σ). The training procedure is to find out the optimum value of σ . The best practice for finding the spread value is the use of an optimization algorithm by minimizing the mean squared error (MSE). For obtaining the optimal value of spread, the whole dataset is divided into two parts, the training sample, and the test sample. Then, GRNN is applied to the test data based on training data, and the optimal value of the spread is obtained by minimizing the MSE.

Model 1: GRNN model for the area where groundwater data are available

The first model is developed for estimation of groundwater fluctuation for the districts having seasonal variation of groundwater data. The concept of the GRNN model, as described above, is applied to five districts of Uttarakhand, namely, Dehradun, Haridwar, Nainital, Champawat, and US Nagar, to predict the groundwater fluctuation, taking GRACE TWS, average temperature, and precipitation as input to the model. The output from the model is the groundwater fluctuation. The GRACE TWS data are available on a monthly scale. However, the groundwater level data are available only four times a year. As such, we have considered the monthly GRACE TWS, average temperature, and average precipitation of the previous three months to predict the groundwater level for the current month. The input months and the corresponding output month are given in Table 2. For example, when January, February, and March are the input months, the output month is April. Thus, an input pattern (k) can be represented as:

$$X_k = [G_k^t, G_k^{t-1}, G_k^{t-2}, T_k^t, T_k^{t-1}, T_k^{t-2}, P_k^t, P_k^{t-1}, P_k^{t-2}] \quad (2)$$

The corresponding output pattern can be represented as:

$$Y_k = [GW_k^{t+1}] \quad (3)$$

The GRNN model used in this study is shown in Figure 4. The input pattern X_k^i represents any arbitrary pattern k for the district i where recorded groundwater data are available. The distance (d_n^i) between the input and training patterns are calculated in the pattern layers and also calculated is the weight (w_n^i) of the particular pattern. There is N number of training patterns. As such, there will be N

Table 2 | Input months and corresponding output months for GRNN model

Input months	Output months
January, February and March	April
April, May and June	July
July, August and September	October
October, November, December	January

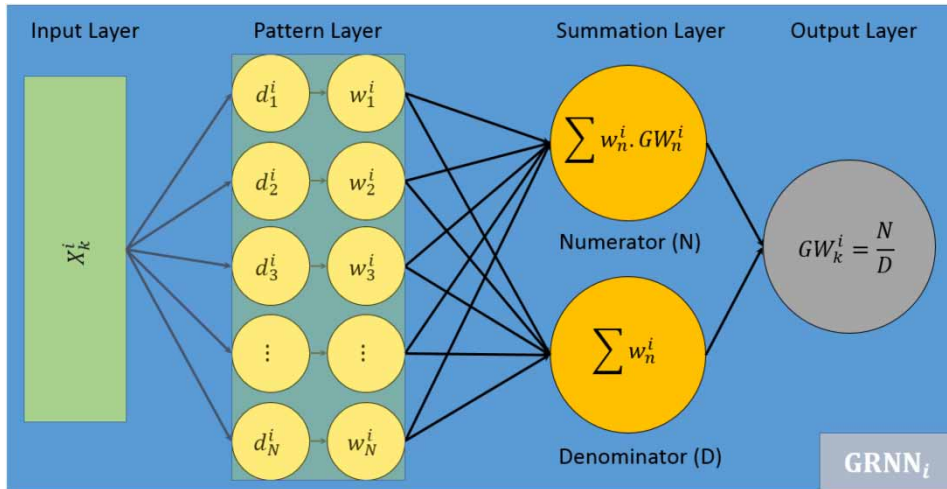


Figure 4 | GRNN architecture of Model I.

neurons in the pattern layer. In the summation layer, the weight of the pattern calculated will be multiplied to the corresponding output, and the result will be summed up at the numerator neuron, and all the weights will be added up at the denominator neuron. The output for the arbitrary vector will be calculated in the output neuron using Equation (1). The model has only one parameter, i.e., the spread value σ , which can be estimated using an optimization algorithm. Once the model is trained, i.e., the optimal spread value is obtained, the model can be used for estimating the groundwater fluctuation. This model is constructed for the i^{th} district of the state. As such, we have named the model $GRNN_i$. We have developed five GRNN models for the five districts where groundwater data are available, named $GRNN_1$, $GRNN_2$, $GRNN_3$, $GRNN_4$, and $GRNN_5$.

Model II: GRNN model for the area where groundwater data are not available

As discussed earlier, there are some areas of Uttarakhand where groundwater data are not available. As such, we proposed a correlation-based GRNN model for estimating the fluctuation of the groundwater for the areas where there are no groundwater monitoring wells. The following sections discuss the correlation matrix and then the GRNN model for estimating the groundwater fluctuation.

The correlation matrix model: A bridge between model I and model II

Here, we have established a relationship between the parameters of known bore well data districts to an unknown one. The correlation matrix between the input parameters (GRACE TWS (G), monthly average temperature (T), and monthly average precipitation (P)) of the districts where the groundwater data are available, and the input parameters of the districts where groundwater data are not available is prepared. As an example, a correlation network is established between Dehradun, where groundwater data are available and all eight districts, i.e., Uttarkashi, Rudrapur, Tehri, Pauri, Chamoli, Pithoragarh, Bageswar, and Almora, where there are no observation wells. The same relationship was also established for all five districts having groundwater data, as shown in Figure 5.

Table 3 shows the correlation matrix for the parameters GRACE TWS (G), monthly average temperature (T), and monthly average precipitation (P) of the district where groundwater data are available to the district where the groundwater data are not available. The R is Pearson's correlation coefficient value. Table 3A represents the values for GRACE TWS (G), 3B represents the values for monthly average temperature (T), and 3C represents the values for the monthly average precipitation (P).

After obtaining the correlation matrix between each known groundwater known data districts to a known one,

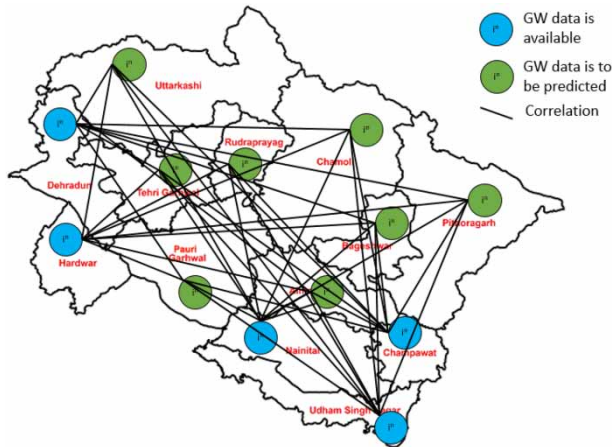


Figure 5 | The correlation network between the different districts of Uttarakhand.

Table 3 | The correlation matrix

A.	$j = 1 \text{ to } J$				
$i = 1 \text{ to } I$	R_{11}^G	R_{12}^G	R_{1J}^G	
	R_{21}^G	R_{22}^G	R_{2J}^G	
	\vdots	\vdots	\vdots	\vdots	
	R_{I1}^G	R_{I2}^G	R_{IJ}^G	
B.	$j = 1 \text{ to } J$				
$i = 1 \text{ to } I$	R_{11}^T	R_{12}^T	R_{1J}^T	
	R_{21}^T	R_{22}^T	R_{2J}^T	
	\vdots	\vdots	\vdots	\vdots	
	R_{I1}^T	R_{I2}^T	R_{IJ}^T	
C.	$j = 1 \text{ to } J$				
$i = 1 \text{ to } I$	R_{11}^P	R_{12}^P	R_{1J}^P	
	R_{21}^P	R_{22}^P	R_{2J}^P	
	\vdots	\vdots	\vdots	\vdots	
	R_{I1}^P	R_{I2}^P	R_{IJ}^P	

an average correlation is calculated by taking the average of all the correlation values. The average correlation value can be calculated using the following equation:

$$R_{ij}^{av} = \frac{1}{3}(R_{ij}^G + R_{ij}^T + R_{ij}^P) \quad (4)$$

where i represents the known district and varying 1–5, j represents the unknown district and varying 1–8, R_{ij}^G is the correlation between GRACE data of the i^{th} known district and the j^{th} unknown district, R_{ij}^T is the correlation between temperature data of the i^{th} known district and the

j^{th} unknown district, R_{ij}^P is the correlation between precipitation data of the i^{th} known district and the j^{th} unknown district. We provide equal weightage to prevent the domination of one input over another.

Correlation-based GRNN (CGRNN) model for the unknown groundwater data districts

For the districts where groundwater table data have not been observed so far, a correlation-based GRNN model is developed to find out the groundwater fluctuation. The correlation-based GRNN model is shown in Figure 6. This model is similar to Model 1; however, we have replaced the weight by the average correlation value obtained by Equation (4). X_j^n is an arbitrary pattern, as described in Equation (2), for the j^{th} district where groundwater data has not been observed. This pattern will now move to all the five GRNN models developed earlier, and the output from the GRNN model will be GW_{ij}^n . Now, the output of the GRNN model will move to the numerator neuron after multiplying the value by the average coefficient of correlation between i and j calculated earlier. Similarly, the average coefficient of correlation between i and j will also be passed to the denominator neuron. The signal received from the numerator and denominator neurons will be summed up, and the output will be calculated at the output neuron.

Different input used in the formation of the GRNN model

The underlying assumption of this study is that the GRACE TWS may work as a valuable predictor for water level changes in the absence of consistent field-based observation data for water level. Now, the critical point was the selection of input data and their correlation. In the present study, we used frequently available data like temperature, precipitation and then established an association with GRACE.

GRACE data

The measurement of water storage in a comprehensive way for different storage compartments is a challenging one. With the development of remote sensing techniques, the space-based observations of the Earth system have provided

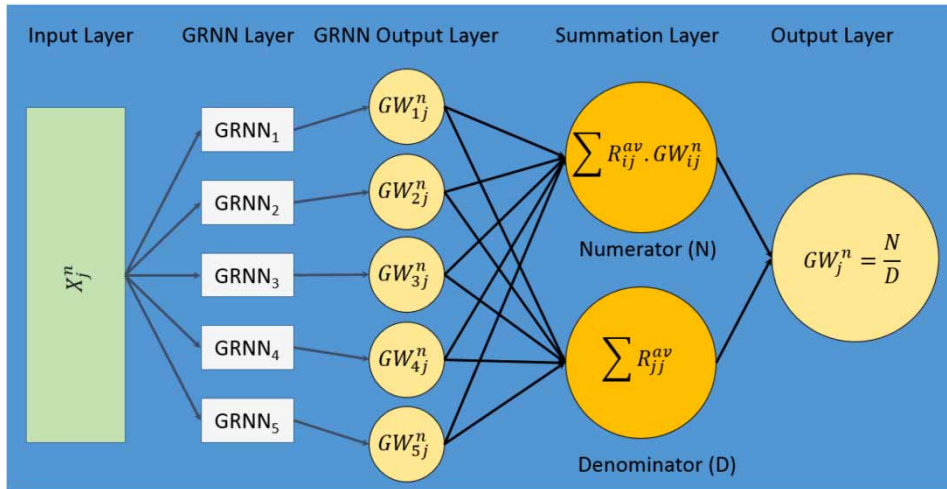
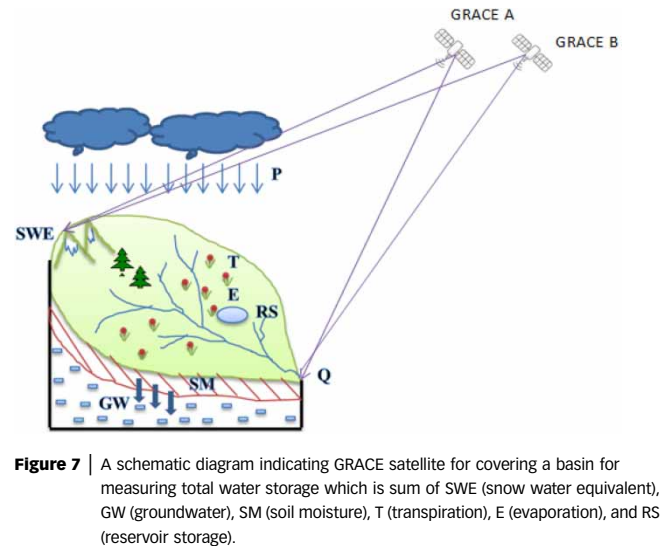


Figure 6 | CGRNN model to predict the groundwater fluctuation for the district where groundwater data are not available.

the capacity to retrieve information across a wide range of land surface hydrological components and also provide the opportunity to characterize terrestrial processes in space and time (Mohanty *et al.* 2010; Frappart & Ramillien 2018). One such successful mission of NASA, i.e., 'GRACE MISSION,' gives us information about total water storage changes occurring on the Earth's surface (Ramillien *et al.* 2014; Gouweleeuw *et al.* 2017). Since March 2002, GRACE has provided first estimates of land water storage variations by monitoring the time-variable component of Earth's gravity field, which has proven to be an excellent complement to ground-based hydrologic measurements to monitor water mass storage variation within the Earth's fluid envelopes (Houborg *et al.* 2012; Chen *et al.* 2014; Tian *et al.* 2018). While comparing the GRACE signal with other satellite data, we can see that other satellites can capture soil moisture only up to a limited depth, i.e., near the land surface only, while the GRACE signal, as shown in Figure 7, provides vertical variation in the total water storage from soil moisture, groundwater at all depths, snowpack, and surface water (Xiao *et al.* 2015; Gonzalez *et al.* 2016; Li *et al.* 2018). It is to be noted that GRACE provides terrestrial water storage anomaly (TWSA) and does not have a vertical resolution, i.e., cannot distinguish between water stored as snow, soil moisture, and groundwater (Chinnasamy *et al.* 2015; Singh *et al.* 2016). GRACE data have been widely used to monitor changes in water mass redistribution for various basins globally. Gridded TWSA data with a spatial resolution



of $1^\circ \times 1^\circ$ and temporal resolution of one month was downloaded from <https://grace.jpl.nasa.gov/data/get-data/monthly-mass-grids-land/> (Sun 2013; Long *et al.* 2017). Each monthly GRACE grid represents the surface mass deviation for that month relative to the baseline average over January 2004 to December 2009 (Forootan *et al.* 2019; Khaki *et al.* 2019). We noticed that there was missing data for a few months, which were calculated using linear interpolation. For getting TWSA of a catchment we used weighted average method to get the TWSA time series (Tian *et al.* 2018). Figure 7 shows the schematic diagram of the GRACE satellite covering an arbitrary watershed.

GRACE data are widely used by hydrologists to analyze various hydrological responses. The (P-ET) describes the amount of water between the atmosphere and the Earth's surface and therefore provides important information regarding the interaction of the atmosphere and the land surface (Syed *et al.* 2008; Li *et al.* 2018). The paper describes large-scale changes in continental water storage projects, which are combined with river discharge data to obtain an estimate for P-ET. Further, Rodell *et al.* (2007) studied satellite observations of Earth's gravity field from GRACE and suggested a method to derive variations in terrestrial water storage, which includes groundwater, soil moisture, and snow. If we have the information of soil moisture and snow data, the groundwater storage variation can be found (Long *et al.* 2013; Hassan & Jin 2016; Nie *et al.* 2018). Reager *et al.* (2014) developed an autoregressive model for flood prediction using GRACE TWSA and discharge (Andrew *et al.* 2017; Long *et al.* 2017).

The total water storage (TWS) data for the different districts of Uttarakhand were downloaded. Figure 8 shows the variation of TWS of the 13 different districts of Uttarakhand.

Figure 9 shows the variation in TWS for the entire state of Uttarakhand. The graph shows that in Uttarakhand, there is an overall loss in TWS @ $(-)$ 0.342 mm/year for the period 2002–2015. Figure 10 shows the average annual

change in TWS, and Figure 11 shows the average monthly change in TWS for the state. The graph of the monthly average change in TWS shows a positive value during the rainy season. It also shows that there was a significant positive change in TWS in 2013 and 2015. In these two years, some flash flood events occurred in the state.

Temperature data

In Uttarakhand, there are 13 districts. Out of these 13 districts, eight districts are hilly, and the remaining five districts are in the plain area, along with some hilly parts (Mishra 2017). In the hilly districts, snowfall is a common phenomenon in the winter season. If we see the average temperature range, we found that the extent of minimum to maximum average temperature varies from 2.3 °C to 36.4 °C for the years from 2005 to 2016 (Government of Uttarakhand 2014). Figure 12 shows the variation of average temperature from 2005 to 2016 in the state.

Monthly average precipitation data

The Uttarakhand state encounters massive precipitation in the form of a flash flood, especially from June to August (Joseph *et al.* 2013). Generally, the climate of Uttarakhand

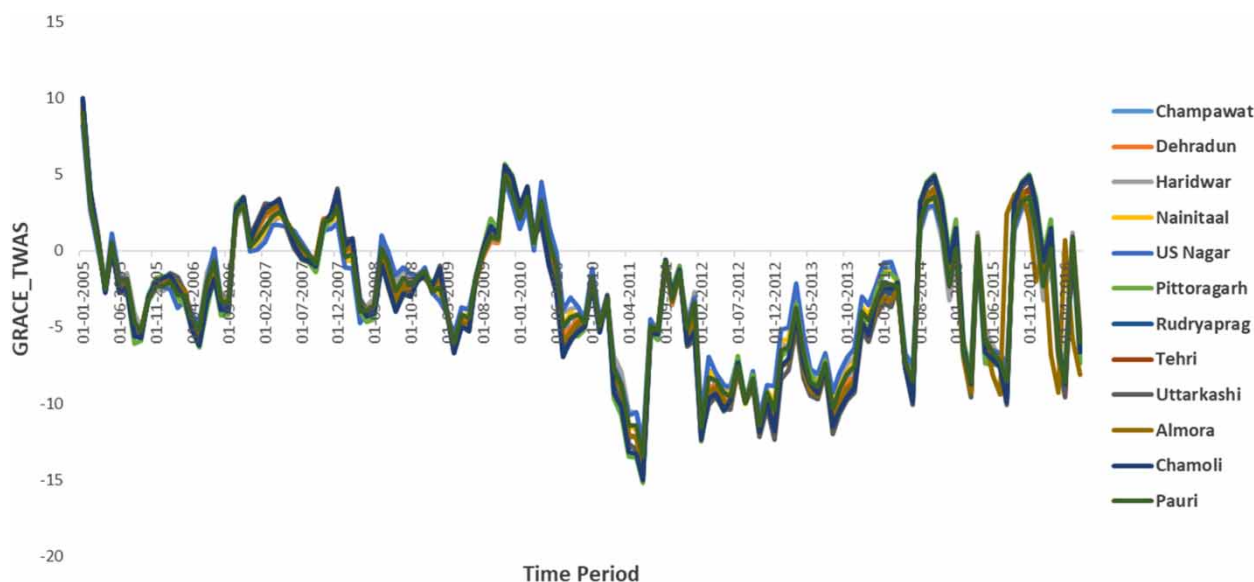


Figure 8 | Variation of TWS in nine districts of Uttarakhand.

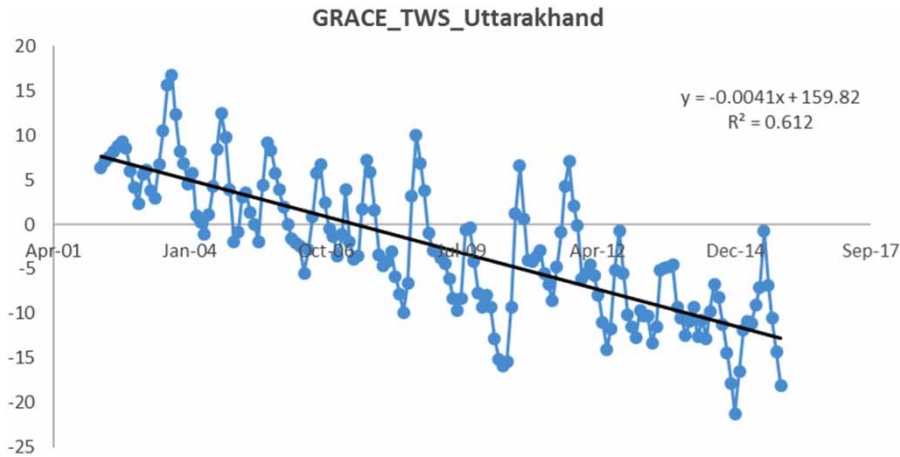


Figure 9 | Variation of TWS of Uttarakhand.

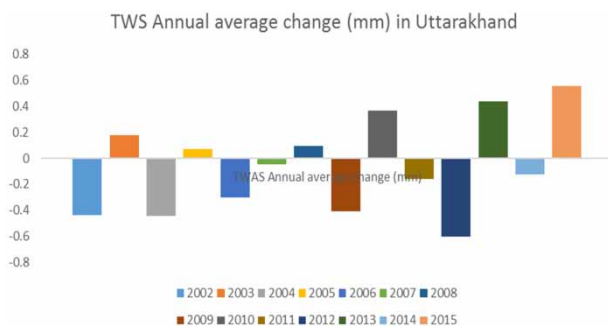


Figure 10 | Annual average change in TWS in Uttarakhand from 2002 to 2015.

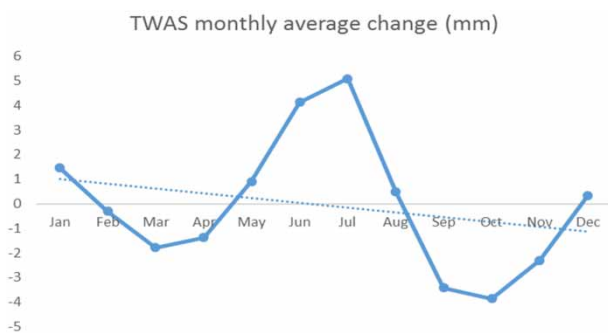


Figure 11 | Monthly average change in TWS in Uttarakhand.

is cold, with a high wind velocity throughout the year. In the state, normal annual rainfall is about 1,800 mm (Ministry and Government 2014). Figure 13 shows the variation of average monthly precipitation in different districts of Uttarakhand. The rainfall and temperature data were collected

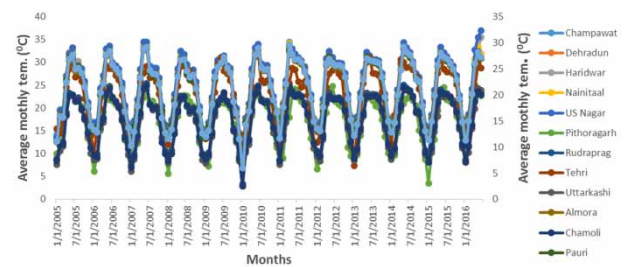


Figure 12 | The variation of average monthly temperature in different districts of Uttarakhand.

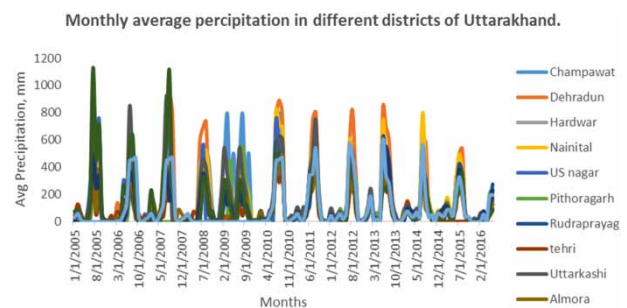


Figure 13 | The variation of average monthly precipitation in different districts of Uttarakhand.

from the Indian Meteorological Department (IMD) for all 13 districts of Uttarakhand, and the normal annual rainfall of the state is about 1,800 mm. The IMD data are available at 0.25×0.25 grid size.

The peak monthly rainfall varies from 1,155 to 250 mm, and there is less rainfall in winter.

RESULTS AND DISCUSSION

Model I: districts where groundwater data are available

A correlation analysis was performed to evaluate the capability of the GRNN model in predicting groundwater fluctuation. For the first model, out of 46 datasets, 25 sets are used for training purposes, and the rest testing and validation. The results show a satisfactory performance of the model in predicting the groundwater fluctuation for all the districts where we have groundwater data, except for the Champawat district. Figure 14 shows the value of R^2 between observed and GRNN-predicted groundwater fluctuation in five districts of Uttarakhand, where bore well fluctuation data are available.

Since the number of wells is greater in Dehradun, Haridwar, and US Nagar (as shown in Figure 2), the prediction of the model is quite good in these districts. Figure 15(a)–15(e) shows the groundwater fluctuation obtained by the model and the actual value. The groundwater fluctuation obtained was in reference to April, 2005 groundwater level, and since we have seasonal-wise groundwater data we tried to maintain the same reference line for each analysis, i.e., April, 2005. The fluctuation we obtained was then converted into a percentage term for better visualization. It can be observed that the predicted data are well matched with the actual groundwater fluctuation value, and as such, the value of R^2 is more than 0.65. In the case of Champawat, there are only two observation wells, and as a result, the GRNN model is not able to predict the output very well and has an R^2 of 0.47.

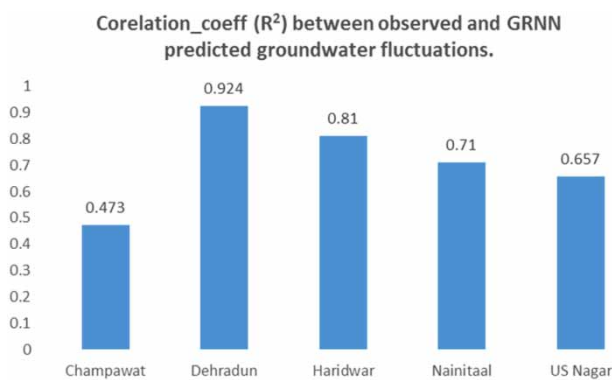


Figure 14 | R^2 between observed and GRNN-predicted groundwater fluctuation in five districts of Uttarakhand.

Model II: GRNN model for the area where groundwater data are not available

A correlation matrix was prepared between the parameters of the districts with known groundwater data to the unknown ones. Table 4 shows the correlation values of different districts for the GRACE data. Similarly, Tables 5 and 6 show the correlation values for temperature and precipitation. It may be observed that, except for the precipitation data, there is a good correlation between the parameters.

After calculation of the correlation value for each input of the GRNN model for each district, the average value is calculated and given in Table 7.

Using the correlation matrix value given in Table 8, the correlation-based GRNN model is executed, and groundwater fluctuation is obtained for districts having no groundwater records. Before applying the model to those districts, the performance of the model is initially evaluated for a district having known groundwater data. There are five districts where groundwater records are available. Four districts were considered for preparing the model, and the result of the model was evaluated using the fifth district. This was performed for all the five districts where there is groundwater fluctuation data. The performance of the model has been evaluated by using the scatter plot between known groundwater fluctuation and predicted groundwater fluctuation obtained using the CGRNN model (Figure 16(a)–16(e)). The corresponding R^2 values are shown in Table 8. As observed, all R^2 values are more than 0.6, and hence it can be stated that the CGRNN model is capable of predicting groundwater fluctuation for the districts without groundwater records. To check the feasibility of the model, other statistical parameters like RMSE, NSE were also used, and the results are shown in Table 9. Each term is explained below.

Root mean square error (RMSE)

The root mean square deviation (RMSD) or root mean square error (RMSE) is commonly used to measure the deviations between sample or population values predicted by a model and the observed values (Xiao *et al.* 2015):

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (X_{obs,i} - X_{model,i})^2}{n}} \quad (5)$$

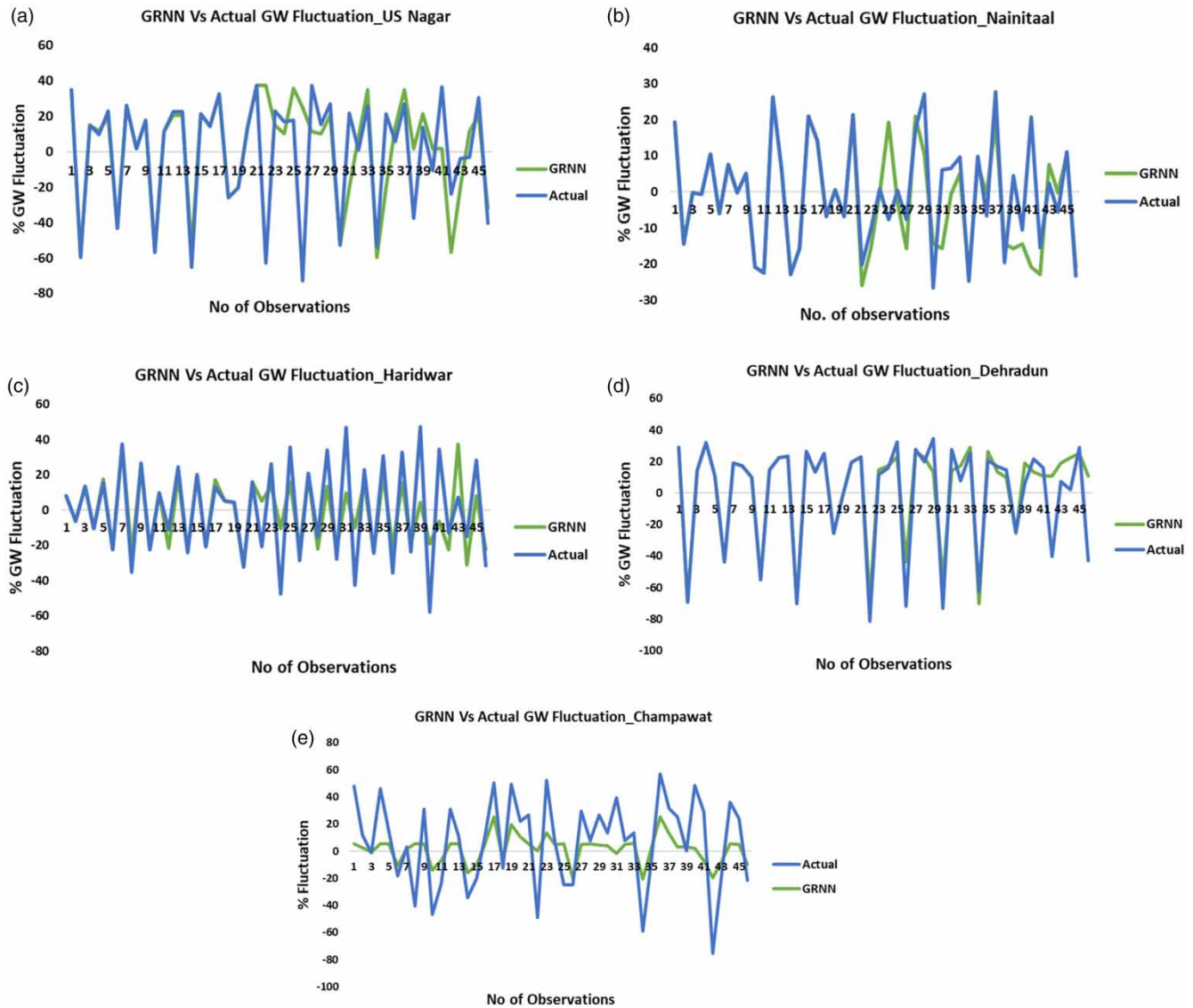


Figure 15 | The comparison of groundwater fluctuation between observed data and GRNN model output: (a) US Nagar, (b) Nainital, (c) Haridwar, (d) Dehradun, and (e) Champawat.

Table 4 | Correlation between GRACE data of the districts where GW data are available and the districts where GW data are unavailable

Districts/ R^2	Pithoragarh	Rudrayaprag	Tehri	Uttarkashi	Almora	Chamoli	Pauri	Bageswar
Champawat	0.993	0.991	0.988	0.983	0.928	0.991	0.994	0.965
Dehradun	0.977	0.992	0.998	0.993	0.933	0.988	0.995	0.986
Haridwar	0.965	0.979	0.987	0.976	0.925	0.973	0.996	0.988
Nainital	0.986	0.989	0.990	0.982	0.929	0.987	0.998	0.998
US Nagar	0.971	0.973	0.976	0.964	0.918	0.970	0.991	0.987

Table 5 | Correlation between temperature data of the districts where GW data are available and the districts where GW data are unavailable

Districts/R ²	Pitthoragarh	Rudrayaprag	Tehri	Uttarkashi	Almora	Chamoli	Pauri	Bageswar
Champawat	0.945	0.994	0.956	0.988	0.999	0.993	0.998	0.992
Dehradun	0.954	0.994	0.963	0.994	0.996	0.992	0.998	0.994
Haridwar	0.955	0.992	0.963	0.991	0.995	0.991	0.997	0.991
Nainital	0.945	0.994	0.956	0.988	0.999	0.993	0.998	0.997
US Nagar	0.946	0.989	0.955	0.986	0.996	0.988	0.995	0.991

Table 6 | Correlation between precipitation data of the districts where GW data are available and the districts where GW data are unavailable

Districts/R ²	Pitthoragarh	Rudrayaprag	Tehri	Uttarkashi	Almora	Chamoli	Pauri	Bageswar
Champawat	0.717	0.798	0.672	0.819	0.747	0.772	0.721	0.721
Dehradun	0.715	0.852	0.835	0.852	0.853	0.899	0.807	0.848
Haridwar	0.699	0.844	0.829	0.848	0.838	0.841	0.804	0.784
Nainital	0.847	0.922	0.844	0.784	0.914	0.899	0.713	0.811
US Nagar	0.606	0.733	0.768	0.811	0.842	0.804	0.894	0.746

Table 7 | Average correlation value between the districts where GW data are available and the districts where GW data are unavailable

Districts/R ²	Pitthoragarh	Rudrayaprag	Tehri	Uttarkashi	Almora	Chamoli	Pauri	Bageswar
Champawat	0.885	0.927	0.872	0.930	0.891	0.919	0.904	0.877
Dehradun	0.882	0.946	0.932	0.946	0.927	0.960	0.934	0.906
Haridwar	0.873	0.938	0.927	0.938	0.919	0.935	0.932	0.881
Nainital	0.926	0.968	0.930	0.918	0.948	0.960	0.903	0.928
US Nagar	0.841	0.898	0.901	0.920	0.918	0.921	0.960	0.917

Table 8 | Correlations between the actual and model-predicted GW data

Sl. No.	District name	R ²
1.	Champawat	0.696
2.	Dehradun	0.769
3.	Haridwar	0.672
4.	Nainital	0.619
5.	US Nagar	0.711

where X_{obs} are observed values, and X_{model} are modeled values at time/place i .

Coefficient of determination (R²)

The coefficient of determination (R²) shows the intensity and control of a linear relationship between two variables (Kazmi *et al.* 2014). The correlation is +1 in the case of a

perfect increasing linear relationship and –1 in the case of a decreasing linear relationship:

$$R^2 = \frac{\left[\sum_{i=1}^n (O_i - \bar{O}_i) * (P_i - \bar{P}_i) \right]^2}{\left[\sum_{i=1}^n (O_i - \bar{O}_i)^2 * \sum_{i=1}^n (P_i - \bar{P}_i)^2 \right]} \quad (6)$$

where, O_i and P_i is observed and simulated value, n is the total number of test data and \bar{P}_i , \bar{O}_i are the mean value.

Nash–Sutcliffe coefficient (E)

The Nash–Sutcliffe model efficiency coefficient (E) is commonly used to assess the predictive power of hydrological discharge models (Moriassi *et al.* 2007; Chen *et al.* 2012). It

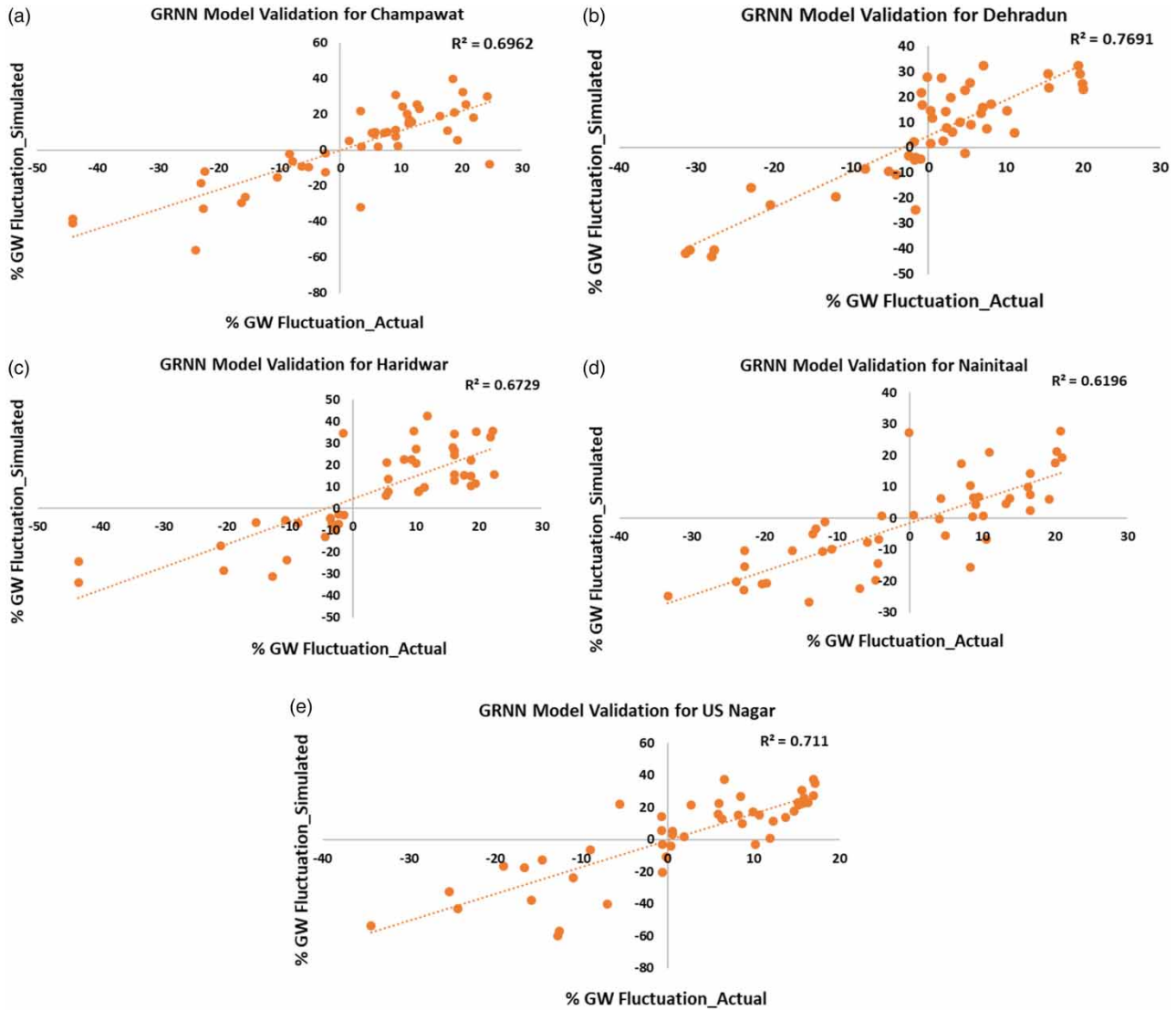


Figure 16 | The scatterplots between actual groundwater fluctuation and predicted one by GRNN model for five districts where groundwater fluctuation data are known.

Table 9 | Correlations, RMSE and NSE value between the actual and model-predicted GW data

Station/District name	Parameters in the training phase			Parameters in the validation phase		
	R^2	RMSE	E	R^2	RMSE	E
Dehradun	0.77	11	0.45	0.78	15	0.83
Haridwar	0.68	2.07	0.75	0.73	2.95	0.66
US Nagar	0.71	12.61	0.84	0.72	12.69	0.82
Champawat	0.70	2.02	0.49	0.65	2.15	0.59
Nainital	0.62	2.39	0.33	0.65	2.29	0.35

is defined as:

$$E = 1 - \frac{\sum_{i=1}^n (X_{obs,i} - X_{model})^2}{\sum_{i=1}^n (X_{obs,i} - \overline{X_{obs}})^2} \quad (7)$$

where X_{obs} are observed values, and X_{model} are modeled values at time/place i . Nash–Sutcliffe efficiencies can range from $-\infty$ to 1. An efficiency of 1 ($E = 1$) corresponds to a perfect match between model and observations.

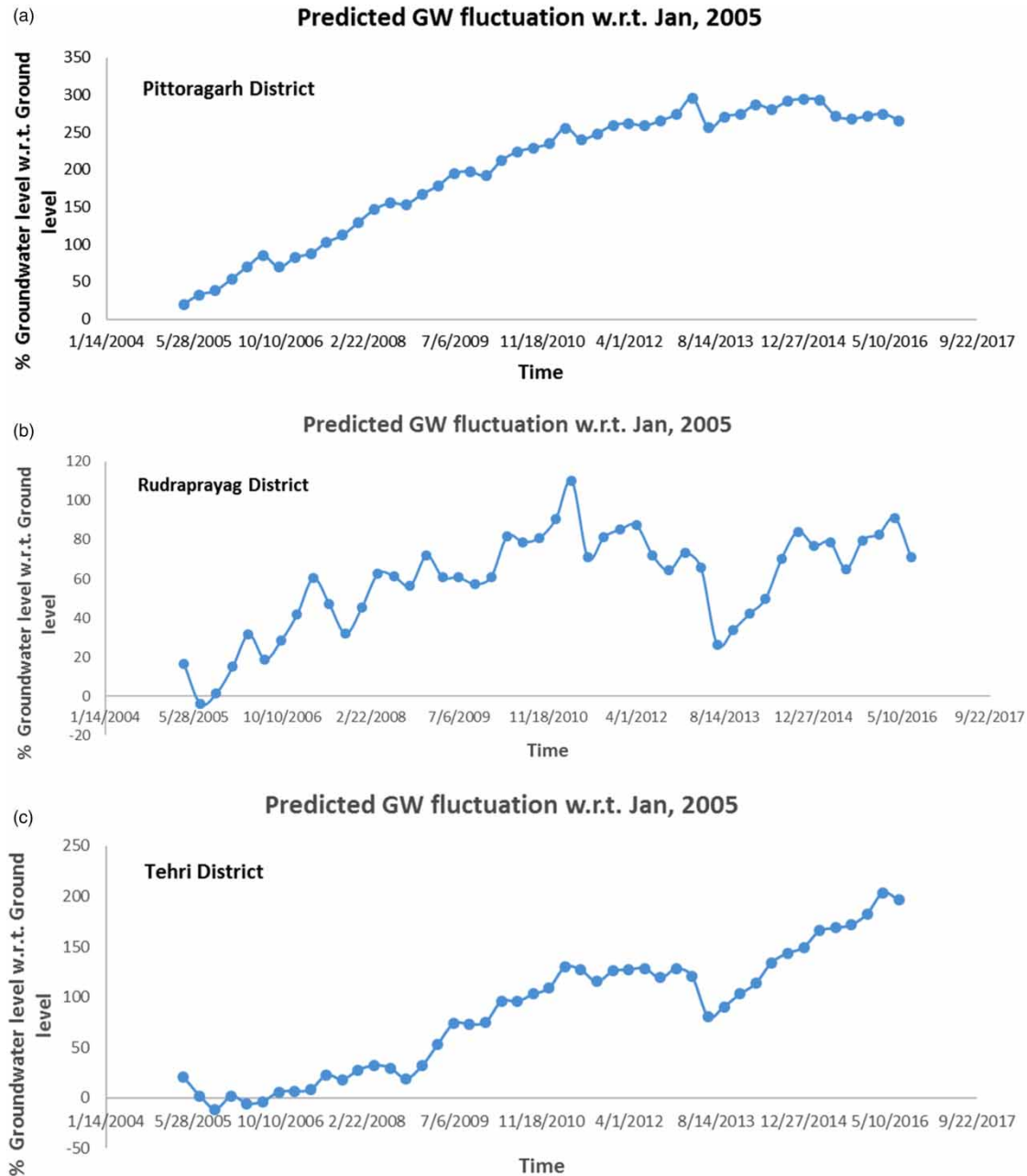


Figure 17 | Groundwater fluctuation as predicted by GRNN model for three hilly districts: (a) Pithoragarh, (b) Rudrapur, and (c) Tehri.

The analysis shows that the model is validated well in those districts where more wells are situated like in Haridwar, US Nagar, and Dehradun. In other districts, the results are also satisfactory as the coefficient of correlation is more than 0.6 and hence can be applied for estimating the groundwater fluctuation for the area where groundwater records are not available.

Comparative groundwater study in Uttarakhand

Figure 17(a)–17(c) show the groundwater fluctuation as a percentage for the three hilly districts of Uttarakhand from 2004 to 2017. The results show that the groundwater level is decreasing day by day in different hilly districts, mainly Pithoragarh, Rudrapur, and Tehri.

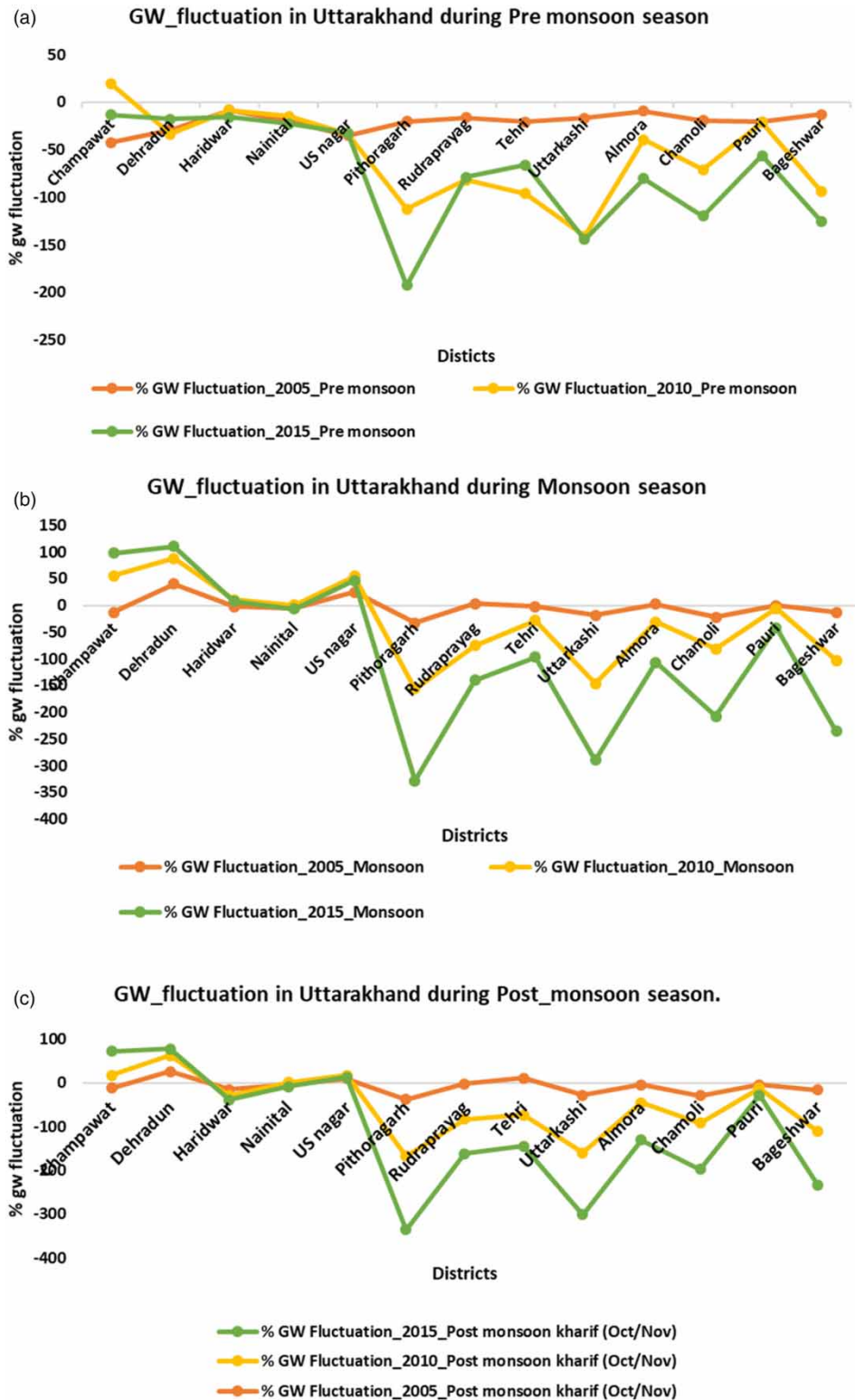


Figure 18 | Pre, post and during monsoon season the variation in groundwater in different district of Uttarakhand.

Figure 18 shows the variation of groundwater in three different seasons, i.e., post-monsoon, monsoon, and pre-monsoon for the years 2005, 2010, and 2015. The figures show the groundwater fluctuation is greater in the year 2015 compared to 2005 and 2010.

The results obtained using the GRNN and CGRNN model are plotted (Figures 19–22) in ArcGIS to visualize the seasonal as well as the decadal change in the groundwater fluctuation. The results show that the groundwater is depleting day by day in different districts of Uttarakhand.

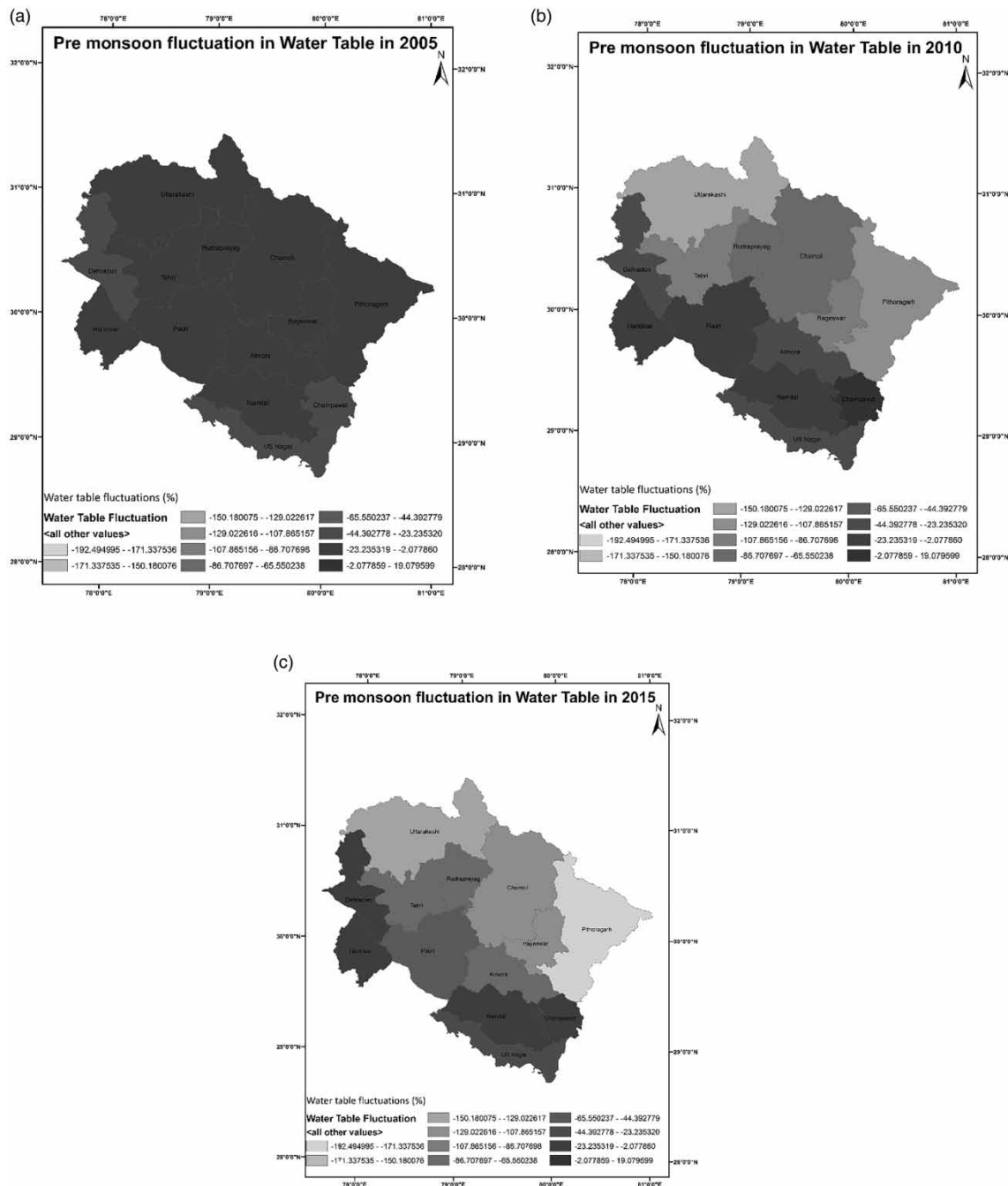


Figure 19 | The variation in groundwater in different districts of Uttarakhand in the pre-monsoon season for the years (a) 2005, (b) 2010, and (c) 2015.

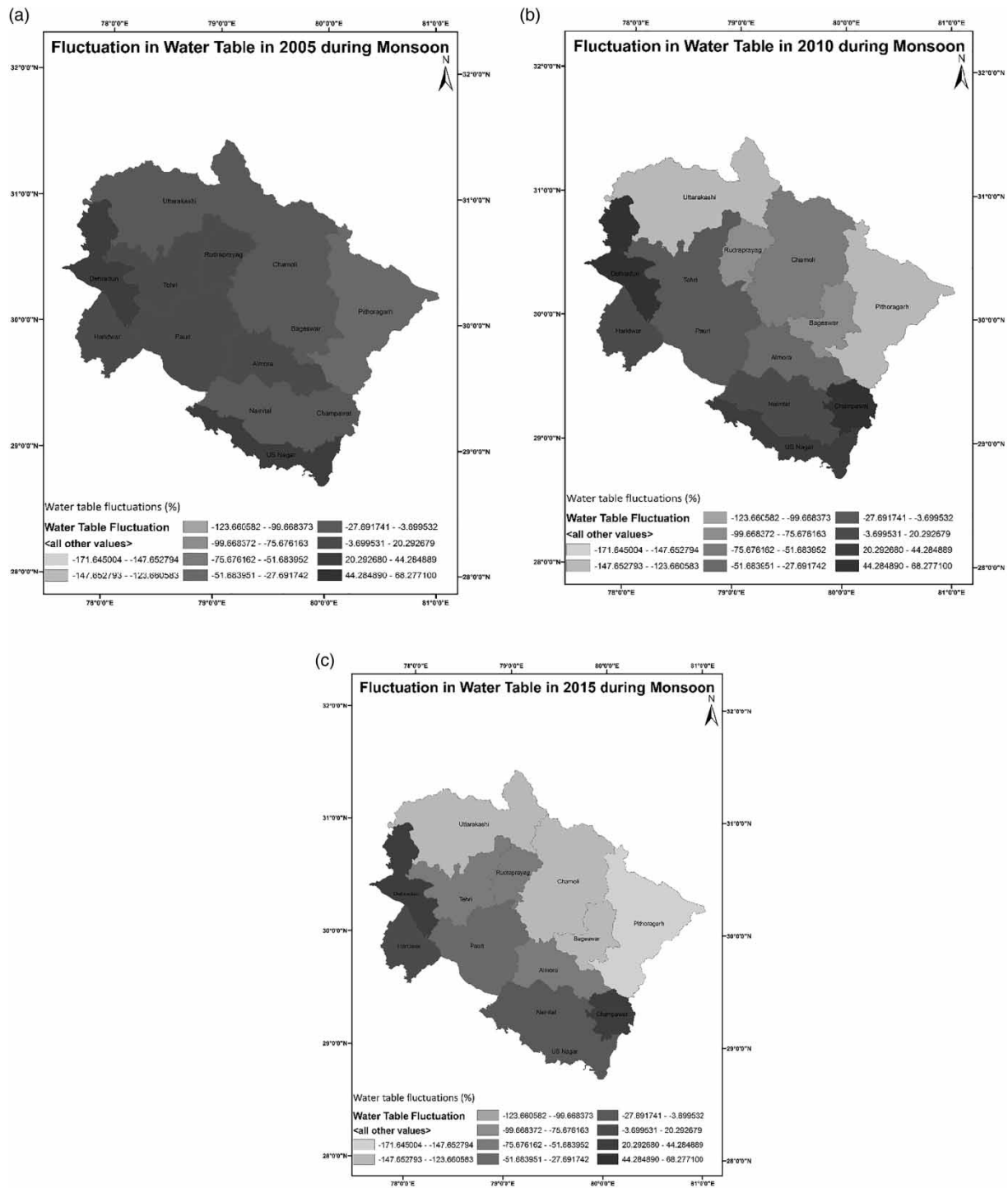


Figure 20 | The variation in groundwater in different districts of Uttarakhand in the monsoon season for the years (a) 2005, (b) 2010, and (c) 2015.

It can be observed from the plots that the groundwater level is decreasing continuously in hilly areas, especially in the border areas with Nepal and China. In plain areas like

Dehradun and Haridwar, the depletion of groundwater is not so fast. This shows that there is sufficient recharge along with the withdrawal of water from the aquifer. As

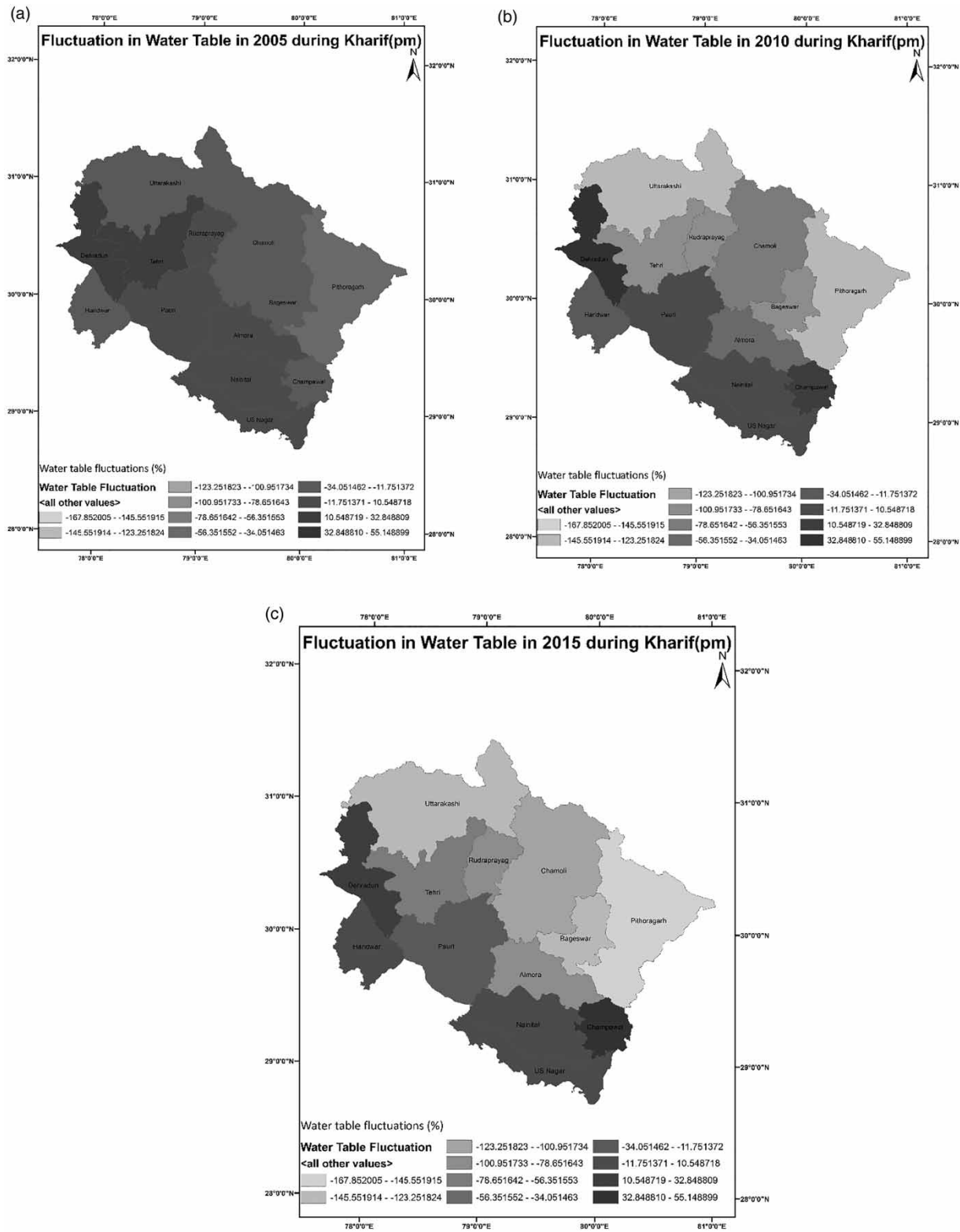


Figure 21 | The variation in groundwater in different districts of Uttarakhand in the post-monsoon (Kharif) season for the years (a) 2005, (b) 2010, and (c) 2015.

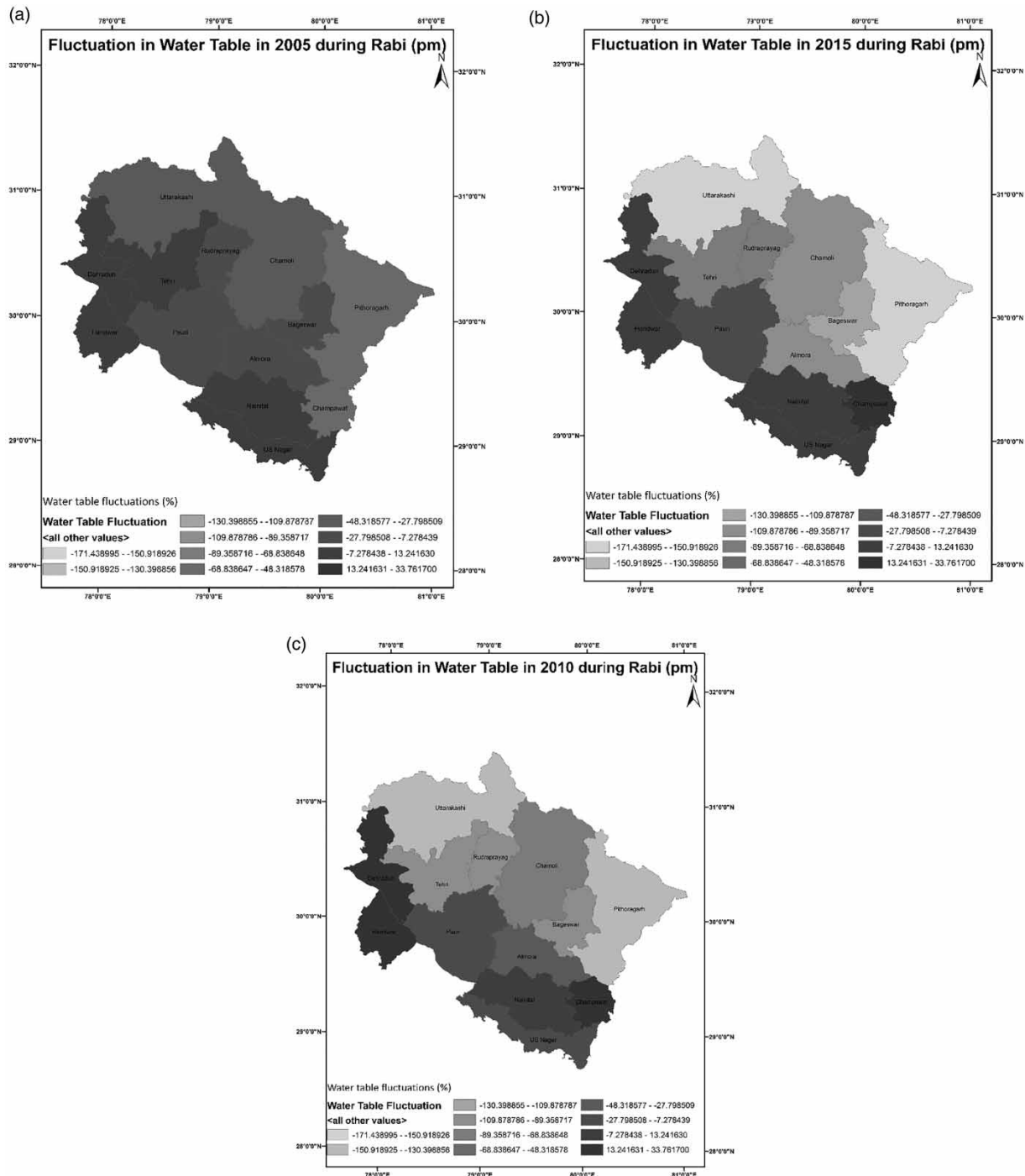


Figure 22 | The variation in groundwater in different districts of Uttarakhand in the post-monsoon (Rabi) season for the years (a) 2005, (b) 2010, and (c) 2015.

per a report published by the UNDP in January 2017, Uttarakhand, which has been recognized as the reservoir state of the Indian subcontinent, has been suffering from drought in 10 out of 13 districts between 2007 and 2009. The report

also says that about 2.6 lakh springs are providing 90% of the drinking water sources in Uttarakhand as per data of 2010. However, due to deforestation, urban development, and forest fires, the discharge of 35% of these springs,

streams, ponds, etc., have reportedly reduced by more than 50%. It was remarked that the situation is going to be worse in the future due to climate change. It has been seen that the result of the present study also matches with the findings of the UNDP report. In the present study, we classified the study period in three divisions, particularly for the years 2005, 2010, and 2015 for the pre-monsoon, monsoon, and post-monsoon season for visualization of change in groundwater level at an interval of five years. In the case of pre-monsoon in the year 2005 (Figure 19), most of the districts have groundwater fluctuation up to 16%. In the year 2010, the water fluctuation goes up to –80% in a major part of the state, whereas in the year 2015, it has gone up to –120% in much of the state. In the case of monsoon in the year 2005 (Figure 20), most of the districts have groundwater fluctuation varying from 20 to 40%. In the year 2010, the water fluctuations go up to –120% in a major part of the state, whereas in the year 2015, it goes up to –150% in the hilly part of the state. A similar trend has also been observed during the post-monsoon (Kharif and rabi) season, as shown in Figures 21 and 22, respectively.

The variation of groundwater, as shown in Figures 19–22, suggests that the groundwater levels have drastically come down in the past decade. Results from all four seasons suggest that groundwater recharge is not occurring as compared to groundwater withdrawal.

CONCLUSIONS

The proposed model and methodology presented in the present study have a uniqueness in terms of the study area since there are no groundwater observation data in the hilly parts of Uttarakhand. The proposed GRNN, as well as the CGRNN model developed by utilizing GRACE TWS, temperature, and precipitation data, can predict the groundwater fluctuation. Testing of the proposed model shows that it is reasonable to obtain a good prediction for groundwater table fluctuations. Therefore, the developed model could be used for further prediction of seasonal water table variations for hilly regions of the state. The model provides the change in water level instead of actual water level since we have GRACE anomaly data,

and the available groundwater data are also in terms of fluctuation. However, once the groundwater fluctuation is known, the groundwater level can be approximated. It can be concluded that the proposed GRNN-based model is a better option for the prediction of groundwater fluctuation when there is no continuous monitoring of the groundwater table. The GRNN model, as explained in this study, can be used by scientists, practicing engineers, and researchers for carrying out a well-organized study of groundwater fluctuations. The study shows that groundwater is depleting in hilly areas of the state, which is alarming in nature. On the other hand, in plain areas, the groundwater fluctuation is not significant. The findings of the study are in accordance with the findings made by a study conducted by UNDP.

DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

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