Trend analysis of ground-water levels and rainfall to assess sustainability of groundwater in Kamrup Metropolitan District of Assam in Northeast India

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Abstract

Although categorised as "safe" in respect of ground water development and management, the state of Assam in northeast India is found to possess the "highest depleting potential" of usable ground water storage in the country, and to exhibit falling trends of pre-monsoon ground water levels in about 55% of the monitoring Stations. With the second highest population density in the state and with ground water being the major source of water-use, the Kamrup Metropolitan District of the state has already started witnessing water stress, and has been characterised by the maximum falling trend of ground water level in the state. In this study, seasonal and annual trends of ground water level and rainfall in the Kamrup region were analysed from monthly water-level data of 39 stations and concurrent rainfall data from January 2007 till June 2019 by using nonparametric Mann-Kendall test and Sen's Slope estimator. The trends indicate cause of concern, and provide scientific basis for strategizing ground water development and management for sustainable water-use in the region.

Keywords: Groundwater level; rainfall; trend analysis; Mann Kendall; Sen's slope; Kamrup Metropolitan District

INTRODUCTION

Groundwater is a major element for sustenance of life and livelihood in many parts of the world, particularly where the use of surface water is constrained either due to inadequacy of quantity and/or quality or for lack of infrastructure for providing supply from surface sources. However ramifications of increasing population and alterations in the dynamics of groundwater recharge have started exerting pressure on the availability of groundwater in many regions where complacency about continued availability of groundwater have, until recently, masked the need for scientific analysis and assessment for sustainably managing this precious resource.

The state of Assam in the north-eastern part of India is one such region, all 28 districts of which had been designated "safe" by the Central Ground Water Board (CGWB) of India in its National Compilation of Dynamic Ground Water Resources (CGWB, 2017). Here the category "safe" indicates a stage of groundwater extraction that is less than 70% in the area under consideration. However, observations on groundwater levels in bore and dug wells over the last two decade in many parts of the state indicate that the availability of groundwater has begun being stressed. From in-situ and satellite-based estimates of usable groundwater storage across India, Bhanja and Mukherjee (2019) found high rate of depletion (>5 km^3/year) of groundwater storage despite increase in precipitation in the state of Assam, and flagged the state as having the "highest depletion potential" of usable groundwater storage amongst states in India. A general decline in trend of ground water level in the state in the pre-monsoon period and the maximum falling trend of 0.812 m/year in Kamrup Metropolitan District Ground Water Monitoring Stations (GWMS) of the state are reported in the Ground Water Year Book for North Eastern Region in 2016-17 published by the CGWB. The Kamrup Metropolitan District particularly assumes significance in the light of falling trend of groundwater level as because Guwahati, the largest city of Assam and the largest metropolis of the north-eastern part of India lies in this district, and covers about 38% of the area and 76% of the population (as per 2011 census) of the district. Further, despite being located on the bank of the mighty Brahmaputra River having large volume of flow, a major part of the city's population depends on groundwater for meeting the need of potable water (Singh et al., 2017; Bhattacharya and Borah, 2014; Das and Goswami, 2013), and the dependence is likely to increase in future unless adequate infrastructure for supplying water is created. The increasing dependence on groundwater coupled with reducing subsurface infiltration due to increasing urbanization (Schueler, 1987) and a perceivably changing pattern of occurrence of seasonal rainfall have already started showing signs of distress as regards availability of water below ground level in post monsoon and winter seasons in parts of the Guwahati metropolis and the remaining areas of the Kamrup Metropolitan District. It is therefore pertinent to assess the trend of groundwater level in the Kamrup Metropolitan District that would be necessary for devising management options for creating resilience against reduced availability of groundwater in the district.

Although references to very few studies on the trend of groundwater levels in the Kamrup Metropolitan District or in Guwahati Metropolis could be found in literature and are cited in the preceding paragraph, studies conducted for investigating trends in groundwater levels elsewhere in India and abroad abound. Most of the studies use statistical methods varying from simple linear regression to more advanced parametric and nonparametric methods (Helsel and Hirsch, 2002). Among the statistical methods, the classical approaches, such as the Mann-Kendall test, its seasonal variant, Sen's slope estimator, etc. have been widely used for testing trends in climatic and hydrological time series (Hirsch et al., 1982; Aziz and Burn, 2006; Thas et al., 2007). Pathak and Dodamani (2019) applied cluster analysis on long-term monthly groundwater levels and carried out Mann-Kendall tests to investigate annual and seasonal trends of groundwater levels in the groundwater drought-prone Ghataprabha River basin of India. Kumar et al. (2018) used descriptive statistics, Modified Mann-Kendall Test and Sen's Slope Estimator for analysing trend of groundwater levels in alluvial aquifers of Uttar Pradesh in India. Le Brocque et al. (2018) applied a modified Mann-Kendall test and Sen's slope estimator to data of 381 groundwater bores in southern Queensland in Australia from 1989 to 2015 in order to investigate annual trend of groundwater as well as the trend in distinct wet and dry climatic phases. Palte et al. (2015) used Mann-Kendall test and Sen's slope estimator for identifying trends in pre and post-monsoon groundwater levels in Karnal district of Haryana in India over the period from 1974 to 2010. Panda et al. (2012) used non-parametric Kendall slope to assess the magnitude of trend and inverse distance weighted method of interpolation to interpret the spatial behaviour of the trends of groundwater levels in the Gujarat state of India. Thakur and Thomas (2011) applied non-parametric Kendall's rank correlation test in order to identify trends in groundwater level data and linear regression test in order to identify the significance of the slope in the Sagar District of Madhya Pradesh in India. Fenelon and Moreo (2002) used graphical methods employing Locally Weighted Scatterplot Smooths and statistical methods employing Mann-Kendall trend tests on groundwater levels and spring discharge during the years from 1960 to 2000 in the Yucca Mountain Region, Nevada and California in the USA for evaluating the variability and the upward, downward or cyclic trends. Amongst other methods, Shamsudduha et al. (2009) used "Seasonal-Trend decomposition procedure based on Loess (STL)" (Cleveland et al., 1990) for investigating trend and seasonal components in weekly groundwater levels in the Ganges-Brahmaputra-Meghna Delta in Bangladesh by noting the inadequacy of Mann-Kendall and Seasonal Kendall tests in resolving trends in a time series characterized by serial dependence.

Besides investigating trends of groundwater levels, mathematical modelling techniques have also been applied widely for assessing groundwater resources, for investigating relationships between occurrences of groundwater and other hydro meteorological variables and for forecasting groundwater levels. Demirci et al. (2019) used Artificial Intelligence (AI) for modelling groundwater levels in the Reyhanli region of Turkey. Kim and Lee (2019) used a correlation model for groundwater level and river stage considering changes in hydrological and geological conditions, and compared the results with measured values and those obtained from an ANN model. Mirarabi et al. (2019) evaluated the performances of data-driven Support Vector machine Regression (SVR) and ANN models for forecasting groundwater levels of confined and unconfined systems in Hashtgerd plain in Iran at 1-, 2- and 3-month ahead. Nadiri et al. (2019) analysed groundwater level variations in an aquifer in Iran. Balavalikar et al. (2018) used Particle Swarm Optimization based Artificial Neural Network (ANN) model for forecasting groundwater level in Udupi District of Karnataka in India. Brenner et al. (2018) used a process-based semi-distributed Karst model for evaluating simulated groundwater levels and frequencies in a chalk catchment in England. Combining outputs from three fuzzy logic based models by ANN, Demirci et al. (2018) used Neuro-Fuzzy (NF), SVR with radial basis functions and SVR with poly-kernel models to estimate groundwater level fluctuations in Minnesota in the USA. Porte et al. (2018) used ANN model to predict groundwater level in Chhattisgarh in India. Sahoo et al. (2017) used machine learning algorithms for modeling groundwater level changes in agricultural regions of the U.S. Varouchakis (2017) used a Kalman filter adaptation algorithm with exogenous inputs to model groundwater level fluctuations in the island of Crete in Greece. Lohani and Krishan (2015) used ANN for simulating groundwater level in Amritsar and Gurdaspur Districts of Punjab in India. Varalakshmi, V. et al. (2014) used three dimensional groundwater flow model employing visual MODFLOW software to a semiarid hard rock aquifer in India. Sreekanth et al. (2009) used ANN for forecasting groundwater level in Maheshwaram watershed of Telangana in India. Besides the above, many other researchers used machine learning models including ANN (Nourani et al., 2015; Sahoo and Jha, 2013; Adamowski and Chan, 2011; Coulibaly et al., 2001), fuzzy theory (Güler et al., 2012; Kurtulus and Razack, 2010), genetic programming (Kasiviswanathan et al., 2016; Shiri and Kisi, 2011), autoregressive models (Chang et al., 2016; Bidwell, 2005; Knotters and Bierkens, 2001) and SVR (Yoon et al., 2011; Behzad et al., 2010) for groundwater modelling.

In the study reported herein, seasonal trends of occurrence of dynamically available groundwater and rainfall over the Kamrup Metropolitan District have been analysed using statistical methods of trend analysis. Further, the patterns of the seasonal occurrence of groundwater in relation to that of rainfall in the district have been examined using a black-box and a data-driven ANN model, and conclusion drawn on the likely impact of change in the pattern of seasonal rainfall on the groundwater level in the district.

STUDY AREA AND DATA USED

As stated in the previous section, the Kamrup Metropolitan District in the state of Assam in India was chosen as the area of study. The district covers an area of 1,528 km^2, and is bounded by 25°43´ and 26°51´ North latitudes and 90°36´ and 92°12´ East longitudes. The climate of the area is sub-tropical with semi-dry summer and cold winter. The maximum and the minimum temperatures in the district range from 37 to 39 degree and 6 to 7 degree Celsius respectively. The annual rainfall in the district ranges from 1500 mm to 2600 mm with an average precipitation of about 1752 mm. The Bharalu, Digaru and Kolong Rivers flows through the district in generally northerly directions to join the Brahmaputra River flowing along the northern boundary of the district. Recent and older Alluvium and Shillong group of rocks of pre-cambrian age constitute the predominant geological formations of the District. Alluvial sediment is the major water bearing formation underlying the district.

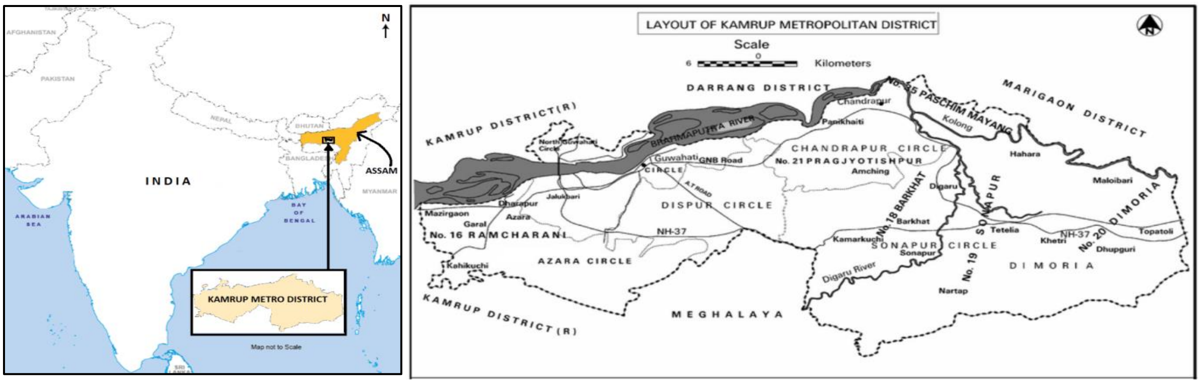


Figure 1: Location map of the Kamrup Metropolitan District[1]

[1] District map source: **source:** http://sdmassam.nic.in/pdf/dmp/Kamrup(M).pdf

As regards the current status of groundwater development, the groundwater draft mainly comprises withdrawals for domestic and irrigation purposes and a negligible amount for industry. Although the district lies on the bank of the Brahmaputra River, it lacks adequate infrastructure to tap, treat and supply surface water from this river to meet the domestic, irrigation and industrial needs. Even only 40% of the population of Guwahati metropolitan area within the district has access to central piped water supply system. Although the Government of Assam is in the process of implementing four major projects for supplying water to the Guwahati Metropolitan Area in the district, the dependence on non-potable water sources, predominantly groundwater is likely to continue outside Guwahati Metropolitan area in the district in the foreseeable future.

The CGWB has 39 groundwater monitoring wells in the district comprising five tube wells and the rest dug wells. Data of monthly groundwater occurrence in metre below ground level (mbgl) at these 39 locations from November 2007 to June 2019 were collected from CGWB. Data of monthly rainfall in millimetre (mm) over the district for the period from 12 water-years from June 2007 to December 2018 were collected from the India Meteorological Department (IMD).

METHODOLOGY

Data processing

In accordance with the classification of months into seasons in India by IMD, the monthly groundwater level data for each well and the monthly rainfall data over the district were grouped into monsoon (June-September), Post-monsoon (October-November), Winter (December-February) and Pre-monsoon (March-May) seasons. The seasonal average of groundwater levels at all 39 wells and that of rainfall over the district were then estimated for each year. Thus series of data of groundwater levels for 12 post-monsoon, winter and pre-monsoon seasons (from 2007-08 to 2018-19) and 11 monsoon seasons (from 2008-09 to 2018-19) were produced; for rainfall, series of seasonal data of 12 water-years (from 2007-08 to 2018-19) were obtained.

Trend analysis

Seasonal data of groundwater levels and rainfall were investigated for trends. Noting that non-parametric Mann-Kendall test and Sen's Slope estimator are widely adopted in climatic and hydrological time series analysis, these two methods have been used in the current study for analysing seasonal trends in groundwater levels and rainfall.

Mann-Kendall test (Mann, 1945; Kendall, 1975; Gilbert, 1987) is a commonly employed non-parametric test to detect monotonic trends in series of environmental, climate or hydrological data. The null hypothesis for this statistical test is that the data come from a population with independently and identically distributed. The alternative hypothesis is that the data follow a monotonic trend. The presence of a statistically significant trend is identified using the values of a test statistic Z, the positive value indicating an upward trend and a negative value indicating a downward trend. In non-parametric statistics, Sen's slope estimator (Sen, 1968) or Theil-Sen is used to robustly fit a linear model $f(t) = Qt + B$, Q and B being the slope and a constant respectively, to n number of sample points by choosing the median of the slopes of all lines through pair of points, and hence to estimate the true slope (change per unit time) if a linear trend is present in a time series. Interested readers may refer published literature (Jain and Kumar, 2012; Drápela and Drápelová, 2010, Kundzewicz, 2004, etc.) for details of the tests. For ease of calculation, a Macro named MAKESENS 1.0 created by Salmi *et al*. (2002) has been used.

Groundwater level simulation

Having detected the seasonal trends of average groundwater levels and rainfall over the district, the relation between occurrence of monthly rainfall and monthly average groundwater level were sought by mathematical modelling in order to explore the influence of rainfall in recharging the aquifers underlying the district. For this purpose, the series of monthly average groundwater levels were simulated with inputs of monthly rainfall. Although it is perceived that other variables, such as quantum of extraction of groundwater, length of spells of zero-rainfall between rainfall events and, hence, antecedent moisture conditions, etc. would influence the variability of the monthly average groundwater levels, these variables were considered extraneous in comparison with rainfall, and were not considered in the modelling exercise for simulation. Further, the consideration of monthly rainfall as the primary and the only trigger for simulating monthly average groundwater levels stemmed from the observation that the hydro meteorological characteristics of the district, being monsoonal, display strong seasonal patterns that may be adequate to simulate the influence of the input over the output to the model. For simulation, two black-box type models, namely a system-theoretic Parametric Simple Linear model (PSLM) and a data-driven non-linear ANN model (Goswami and O'Connor, 2007) were used. For ease of referencing, the models are briefly described below:

Parametric Simple Linear Model

In the Parametric form of Simple Linear Model (PSLM), a Linear Transfer Function type representation of the transformation of the input series x to the output series y for discrete data intervals is formulated as

$$\sum_{j=0}^{r} \alpha_j y_{t-j} = \sum_{j=1}^{s} \omega_j x_{t-b-j+1}$$

where α_j are Auto-Regressive (AR) parameters, with $\alpha_0 = 1$, the ω_j are Moving Average (MA) parameters and b is an integer-valued time delay (Kachroo and Liang, 1992), and r and s are orders of the autoregressive and the moving average components. Writing explicitly for y_t with the incorporation of an error term e_t, the above expression becomes

$$y_t = \sum_{j=1}^{r} \alpha_j y_{t-j} + \sum_{j=1}^{s} \omega_j x_{t-b-j+1} + e_t$$

In this form, the current value of y depends linearly on previous values of y and x. The parameters of the model are estimated by the method of Ordinary Least Squares. The model may be applied both in non-updating as well as in updating modes. In updating mode, past recorded values of y are used as inputs in contrast with the use of past simulated values of y in the case of non-updating mode. In the present study, PSLM was applied in updating mode with the variable x_t, y_t representing the monthly rainfall and the monthly average groundwater level at t^{th} month respectively.

Artificial Neural Network Model

A typical neural network consists of a number of computational elements, i.e. nodes or neurons, and connection pathways linking these nodes reflecting the functioning of the biological neural networks of the human brain. The connection pathways transfer information between various neurons with each connection pathway between a pair of neurons is associated with a 'connection weight'. A neuron usually receives an array of inputs, but it has a single output. The input elements constituting a neuron input array can either be external inputs to the network or outputs of other neurons. The neuron accumulates these inputs and transforms these to a neuron output by means of a mathematical transfer function. This output is distributed to a number of connection pathways thereby serving as inputs to other neurons, with each of these connection pathways transmitting the full value of the contributing neuron. Amongst various types of neural networks, the "multi-layer feed forward network" consisting of an input layer comprising neurons from input series of monthly rainfall, an output layer having single output that produces the output series of simulated monthly average groundwater levels and only one "hidden" layer, having either one or two neurons, between the input and the output layers has been used in this study. A layer is usually a group of neurons having same pattern of pathways connecting other neurons of adjacent layers, and each neuron in a layer has pathways connecting neurons in the next adjacent layer, but none to those of the same layer. A schematic diagram of the ANN model is presented in Figure 2.

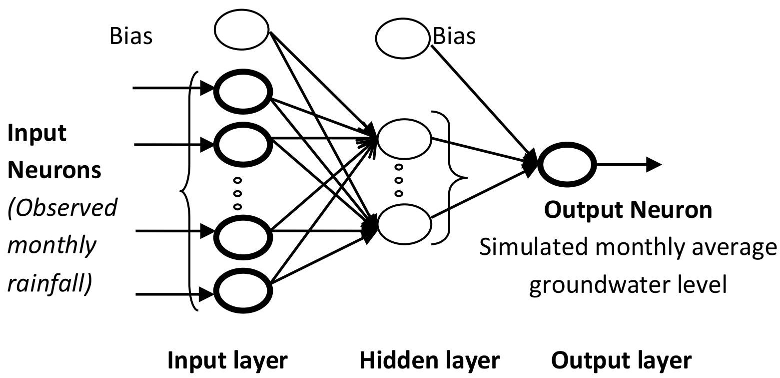


Figure 2: Schematic diagram of ANN model

For a neuron either in the hidden or in the output layer, the received inputs y_i are transformed to its output y_{out} by applying the widely-used logistic function of sigmoid form as the transfer function bounded in the range [0,1] as below

$$y_{out} = \mathrm{f}\left(\sum_{i=1}^{M} w_i y_i + w_0\right) = \frac{1}{1+e^{-\sigma\left(\sum_{i=1}^{M} w_i y_i + w_0\right)}}$$

where *f*() denotes the transfer function, w_i is the input connection pathway weight, *M* is the total number of inputs and w_o is the neuron threshold (or bias), i.e. a base-line value independent of the input. If *l* is the total number of neurons in the input layer and *m* is the total number of neurons in the hidden layer, then the total number of weights to be estimated would be $(l+1)m + (m+1)$. Simplex method is used for automatic optimisation of weights for the ANN model used in this study.

Model calibration

Each model was calibrated first by split-sample calibration using about two-third of the data in the input and output series for calibration and the rest for validation. The widely-used Nash-Sutcliffe model efficiency coefficient R^2 (Nash and Sutcliffe, 1970) was used to evaluate the performance of each model. Noting that the efficiency in validation was comparable with those in calibration, the model was then recalibrated using all data in the series.

RESULTS AND DISCUSSIONS

For visual examination of the pattern of seasonal variation of monthly rainfall and monthly average groundwater level, the series of these two variables and the 3-period moving average for each series are plotted in Figure 3. From this figure, a general decline in the values of rainfall in monsoon represented by the peaks of the lower moving average graph and a general rise in the values of groundwater levels in post-monsoon and winter, albeit small, represented by the troughs of the upper moving average graph may be seen. Being measured in mbgl, a rise in groundwater level indicates a lowering of groundwater availability in wells in the district.

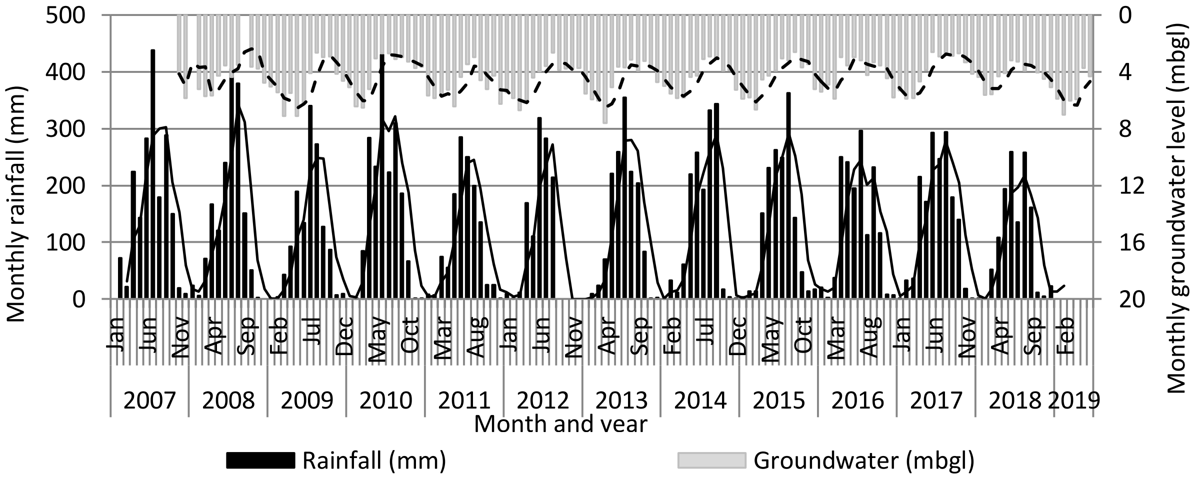
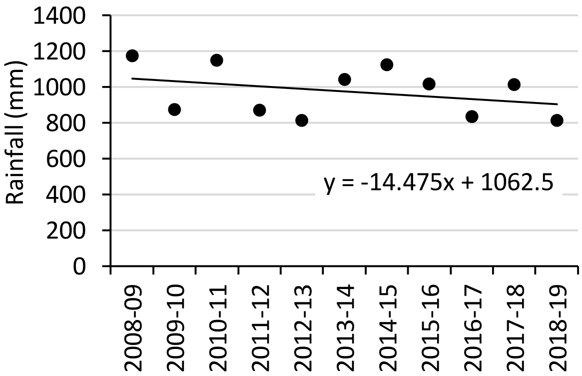
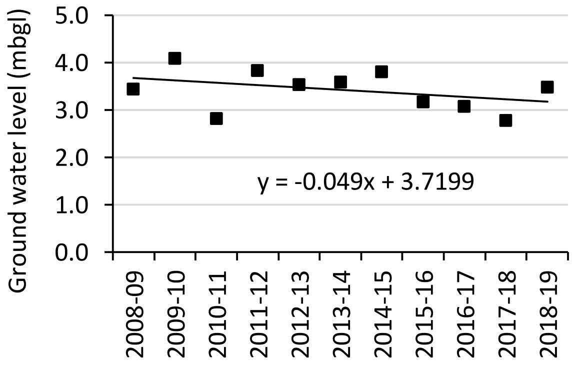


Figure 3: Monthly rainfall and average groundwater levels together with moving average values

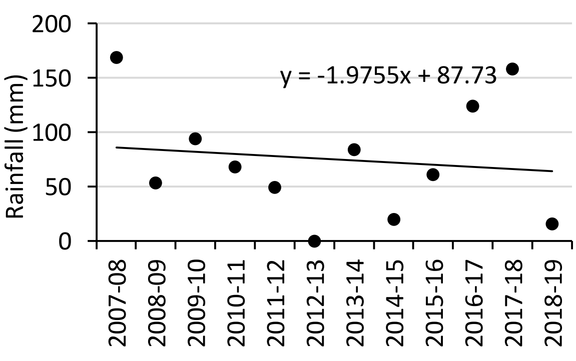
In order to explore seasonal trend in the variables, the seasonal values of rainfall and groundwater levels for the water-years for which data were available were plotted for each of the four seasons. Data in each graph were also presented with a line of best-fit and the equation of the line was given. These plots are shown in Figure 4. From this figure, negative trends of rainfall are found in monsoon and post-monsoon seasons whereas positive trends are visible in winter and pre-monsoon seasons. The declining trend of rainfall that is also represented by a relatively steep slope of the best-fit line is quite strong in monsoon, and is highly significant for the availability of dynamic groundwater in the district. Similar declining trend, although not as strong as that for monsoon, is also present in the rainfall values of the post-monsoon season. In contrast, there are rising trends of rainfall in winter and pre-monsoon seasons. Overall, seasonal redistribution of rainfall appears to occur in the district with time. As for groundwater levels in mbgl, negative trends are found in pre-monsoon and monsoon seasons whereas positive trends are visible in post-monsoon and winter seasons. An overview of the trend clearly brings out patterns of influence of rainfall over groundwater levels, and as expected, shows that the effect of rainfall in a season is reflected in groundwater level in the following season. Thus declining rainfall in monsoon and post-monsoon seasons translates into declining trends of groundwater levels in mbgl in post-monsoon and winter seasons respectively. Similarly increasing rainfall in winter and pre-monsoon seasons are reflected in the falling trends of groundwater levels in mbgl in pre-monsoon and monsoon seasons respectively. The positive trends of groundwater level in mbgl indicating increasing unavailability of groundwater are particularly significant and worrying, and need to be monitored with future data as these become available.

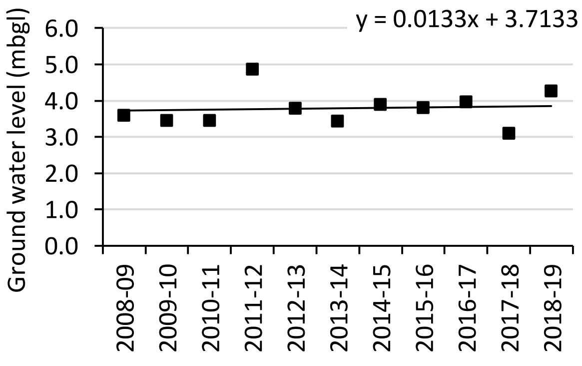
Monsoon (Jun – Sep)





Post-monsoon (Oct – Nov)





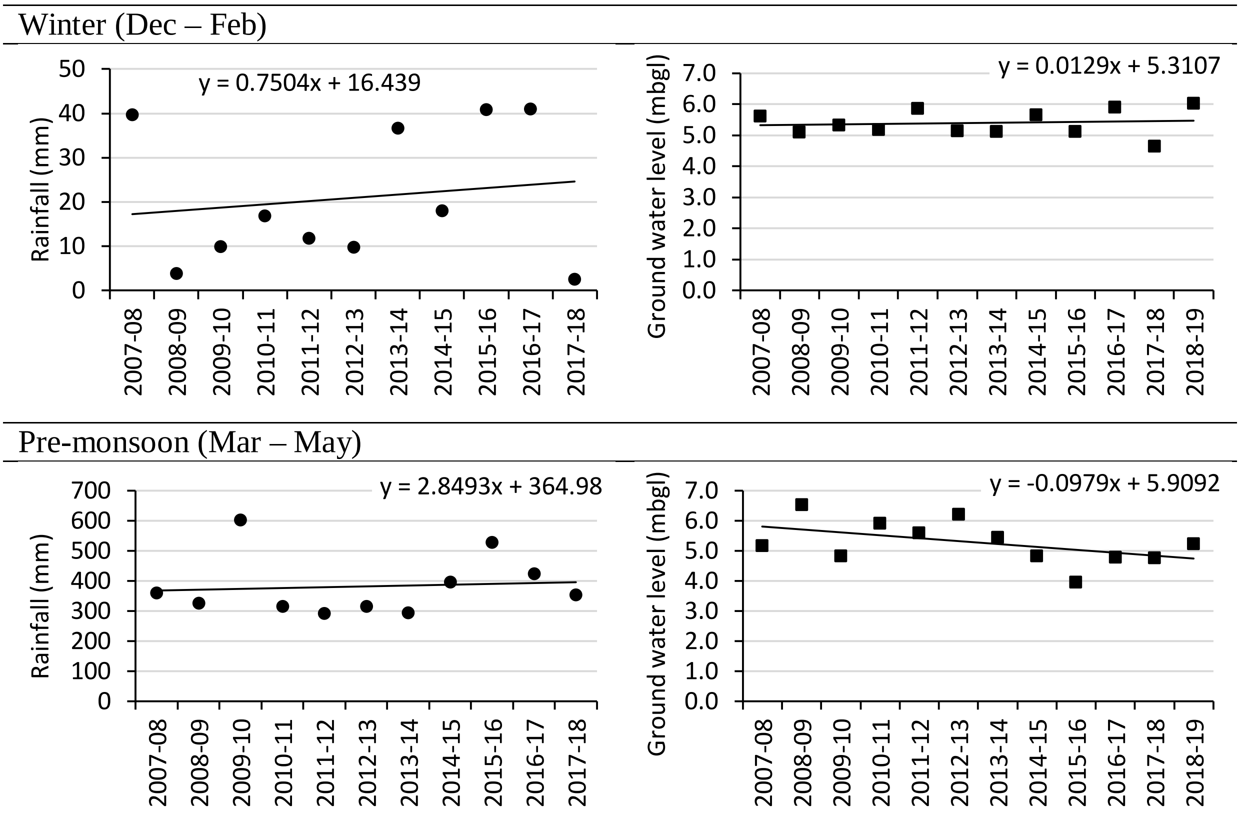


Figure 4: Seasonal values of rainfall and groundwater levels together with lines of best-fit

In order to further detect trends with statistical significance, Mann-Kendall test was undertaken and Sen's slope estimators evaluated for the series of rainfall and groundwater levels for each season. Results of these analyses are presented in Table 1. From this table, a significant increasing trend of winter rainfall and a correspondingly significant declining trend in groundwater level, and hence a significantly rising trend of groundwater availability, in pre-monsoon may be seen. Although trends of the variables in all other seasons are statistically insignificant, a positive Sen's slope could be detected for winter groundwater level in mbgl. For rainfall, it may be seen that the Sen's slope and the Man-Kendall test statistic both exhibit negative trend in monsoon. Overall, it shows that the reducing availability of groundwater in winter might have been the impact of the reducing rainfall in monsoon, and is highly important for sustainable living of the habitants of the Kamrup Metropolitan District.

Table 1: Results of Man-Kendall test and the values of Sen's Slope estimator

Time series	First year	Last Year	n	Test Z	Significance	Q	B
Monsoon rainfall (mm)	*2008-2009*	*2017-2018*	*10*	-1.07		-8.26	1087.44
Monsoon groundwater level (mbgl)	*2008-2009*	*2017-2018*	*10*	-1.43		-0.12	4.17
Post-monsoon rainfall (mm)	*2007-2008*	*2017-2018*	*11*	0.00		1.05	64.97
Post-monsoon groundwater level (mbgl)	*2007-2008*	*2017-2018*	*11*	-0.31		-0.02	3.88
Winter rainfall (mm)	*2007-2008*	*2016-2017*	*10*	1.79	*	2.35	7.48
Winter groundwater level (mbgl)	*2007-2008*	*2016-2017*	*10*	0.18		0.01	5.24
Pre-monsoon rainfall (mm)	*2007-2008*	*2016-2017*	*10*	0.36		5.44	339.42
Pre-monsoon groundwater level (mbgl)	*2007-2008*	*2016-2017*	*10*	-1.79	*	-0.16	6.24

NOTE: * for $p < 0.05$; NS for $p \geq 0.1$.
Q and B represent the variable and the intercept of a trend-line. The 95% and 99% confidence limits are also provided.

For exploring the time-lag of the impact of monthly rainfall on monthly average groundwater level, the linear PSLM and the non-linear ANN models were run a large number of times with different number of the parameters and nodes of the respective models by noting the value of the coefficient of efficiency R^2 of the calibrated model in each run. The results of the simulation of monthly average groundwater levels using monthly rainfall by PSLM and ANN models are presented in Table 2and 3 respectively. In Table 2, the structure of each PSLM model is indicated by $s – r - b$ where s and r are the Moving Average and Auto-Regressive orders and b is the time-delay of the model

From Table 2, it may be seen that in five sets, each with the same AR order varying from one to five, the order of the MA component yielding the highest value of the R^2 model efficiency coefficient corresponds to five. In one set with AR order six, the order of the MA component for highest efficiency works out to six. However, the difference in the values of R^2 coefficient for the structures with the MA order five and six in this set is marginal. From these results, it was concluded that monthly average groundwater levels could be modelled with best fitting performance when the order of the MA components comprising of the monthly rainfall values was five. This indicates that the monthly average groundwater level in the district in a given month is likely to be influenced by the monthly rainfall of five previous months starting from the given month

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Table 2: Results of simulation of monthly average groundwater level by PSLM

Model structure (s - r - b)	R^2 (%)	Model structure (s - r - b)	R^2 (%)	Model structure (s - r - b)	R^2 (%)	Model structure (s - r - b)	R^2 (%)	Model structure (s - r - b)	R^2 (%)	Model structure (s - r - b)	R^2 (%)
1-1-0	45.57	1-2-0	53.62	1-3-0	57.02	1-4-0	58.66	1-5-0	60.87	1-6-0	62.45
2-1-0	51.53	2-2-0	55.32	2-3-0	57.37	2-4-0	58.68	2-5-0	61.47	2-6-0	63.24
3-1-0	52.88	3-2-0	57.63	3-3-0	59.07	3-4-0	59.57	3-5-0	61.47	3-6-0	63.63
4-1-0	55.44	4-2-0	61.01	4-3-0	63.41	4-4-0	63.46	4-5-0	63.87	4-6-0	64.34
5-1-0	**56.73**	**5-2-0**	**62.59**	**5-3-0**	**65.06**	**5-4-0**	**65.37**	**5-5-0**	**65.63**	5-6-0	65.62
6-1-0	56.46	6-2-0	62.49	6-3-0	64.92	6-4-0	65.20	6-5-0	65.54	**6-6-0**	**65.65**

Note: In each set with constant AR order *r*, the structure yielding the highest R^2 is shown in bold

Table 3: Results of simulation of monthly average groundwater level by ANN model

Neurons in input layer	Neurons in hidden layer	*No. of weights optimized*	R^2 (%)	Neurons in input layer	Neurons in hidden layer	*No. of weights optimized*	R^2 (%)
1	1	4	-0.02	1	2	7	28.28
2	1	5	56.91	2	2	9	54.33
3	1	6	64.89	3	2	11	66.94
4	1	7	64.87	4	2	13	68.25
5	**1**	**8**	**70.65**	**5**	**2**	**15**	**70.01**
6	1	9	-0.01	6	2	17	41.60

Note: In each set with constant number of neurons in the hidden layer, the structure yielding the highest R^2 is shown in bold

In the cases of results from ANN model as presented in Table 3, it may be found that the structure with five neurons in the input layer produces the highest value of the R^2 model efficiency coefficient, in either set of models having one or two neurons in the hidden layer. The models with structure having the number of neurons more than two were not tested because of such models being highly non-parsimonious. The structure with five neurons in the input layer indicates that, like in the case of the PSLM, the monthly average groundwater level in a given month is likely to be influenced by the monthly rainfall of five previous months starting from the given month when an ANN model is fitted.

Overall, the results from one linear and one non-linear model consistently indicate that the impact of five previous months' rainfall starting from a given month are likely to be reflected in the monthly average groundwater level, and hence the recharge of the dynamic groundwater resource and, in turn, the availability of ground water in the district, in that month. This corroborates the observations from trend-detection analysis using best-fit straight line described earlier that the impacts of declining monthly rainfall in the monsoon (Jun-Sep) and post-monsoon (Oct-Nov) seasons are likely being reflected in the increasing trend of monthly average groundwater levels mbgl in the post-monsoon (Oct-Nov) and winter seasons (Dec-Feb). Similarly, the observations from model simulation studies also substantiate the observations from the trend-detection analyses using Mann-Kendall test statistic and Sen's slope estimator that reducing availability of groundwater in winter might have been the impact of the reducing rainfall in monsoon. These observations resulting from the study are highly important for sustainable living of the habitants of the Kamrup Metropolitan District.

CONCLUSION AND RECOMMENDATION

The present study was undertaken to investigate seasonal trends, if any, in the occurrence of groundwater in the Kamrup Metropolitan District in Assam, and the presence of trends in seasonal rainfall that might be influencing the former. The study was conducted with available data of monthly average ground water level (mbgl) at 39 stations in the Kamrup Metropolitan District and monthly rainfall in the district over a period from 2007 to 2019. For investigating trends, the slopes of the lines of best-fit, Mann-Kendal test statistic, and Sen's slope estimator were used. For studying the likely influence of previous month's rainfall on the groundwater level at any given month, simulation of monthly average groundwater levels were undertaken by fitting a linear and a non-linear mathematical model of black-box type, namely the system-theoretic PSLM and the data-driven ANN model. From this extensive study, it could be concluded that five months' rainfall starting from a given month are likely to influence the monthly average groundwater level in that month, and hence the availability of ground water in the district.

This conclusion is highly important particularly in the context of declining trend of groundwater level in mbgl that might cause increasing scarcity of groundwater in the district in the post-monsoon and winter months. Suitable options would have to be considered for creating resilience against likely hardship in sourcing groundwater that may result from likely redistribution of seasonal rainfall within a water-year and declines in the amount of rainfall in the monsoon and the post-monsoon seasons in particular in future water-years. A feasible alternative would be adoption of suitable policies and implementation of schemes for sustainable development and management of groundwater and conjunctive use of surface water and groundwater.

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