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Groundwater level estimation in northwest region of Bangladesh using hybrid locally weighted linear regression and Gaussian process regression modeling

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Abstract

The knowledge about the role of the underlying variables on groundwater level (GWL) fluctuation at local scale in the drought-prone urban areas of Bangladesh is still not explored. To better insight into the relative contribution of underlying factors on GWL fluctuation, this study proposed a novel hybrid ensemble modeling framework based on locally weighted linear regression (LWLR) and four Gaussian Process Regressions (GPRs) e.g., poly kernel, Pearson universal kernel (PUK), radian basis function (RBF) and normalized poly kernel. The proposed framework has employed to predict GWL at six wells in the drought-prone local areas of North-western urban region of Bangladesh, where GWL is declining rapidly. The rainfall, temperature (Tave), soil moisture (SM), normalized difference vegetation index (NDVI), Indian Ocean Dipole (IOD), Southern Oscillation Index (SOI), Nina3.4, and population growth rate for the period 1993-2017 were utilized as inputs to developed GWL models. The best input combination was explored using the best subset regression model and sensitivity analysis, and the optimal input combination was applied in LWLR and GPRs to estimate monthly GWL fluctuation. The hybrid LWLR-GPR-PUK model, on average, improves the prediction accuracy from 10 to 50% during the training stage and 20-70% during the testing stage compared to other models. The proposed modeling approach can act as a promising substitute tool to estimate GWL fluctuation, especially in drought-prone local areas in urban regions where groundwater data scarcity hinders the physical law-based model development.

Keywords: Groundwater level estimation, Machine learning, Bangladesh, Locally weighted linear regression, PUK model

1. Introduction

Sustainable use of groundwater is now a prime concern to the decision-makers and practitioners worldwide, especially in an agrarian-based developing country like Bangladesh (Hasanuzzaman et al. 2017). In the recent years, hydro-climatic variabilities, fast population growth and over-exploitation have adversely affected this precious resource in many regions across the globe (Salam et al. 2020a; Wu et al. 2021). This is particularly true for Bangladesh, where water demand is drastically increased (Islam et al. 2021a). As a result, groundwater level (GWL) is declining rapidly, thus raising the water stress. The local areas are not free from this problem too. Reliable local level groundwater fluctuation data in time and space is the primary prerequisite of getting the clear insight about the contemporary condition of groundwater fluctuation at local areas which is very essential to act accordingly to avoid extreme events arising from the withdrawal of groundwater at local areas. Therefore, prediction of local level GWL is essential for the water-stressed drought-prone areas.

The physically-based models are generally used to simulate groundwater quality and quantity (Hosono et al. 2019). However, the traditional groundwater models such as MODFLOW (Harbaugh et al. 2000), HYDRUS (Šimůnek et al. 2003) need extensive data, parameters and sufficient experience. The high cost and long computational time are also other issues of groundwater simulation using traditional models. To overcome these shortcomings, scientists adopted alternative techniques in recent decades, e.g., data-driven (statistical and soft computing machine learning (ML) algorithm) surrogate of the physically-based traditional models for predicting GWL (Rahman et al. 2020).

The data-driven soft computing technique does not depend on the underlying complicated hydrological process. Instead, it solely depends on the statistical associations between

78 explanatory and response parameters. The soft computing models commonly used in GWL
79 prediction include Artificial Neural Network (ANN) (Mirarabi et al. 2019), Support Vector
80 Machine (SVM) (Tang et al. 2019), Adaptive-Network-based Fuzzy Inference System (ANFIS)
81 (Gong et al., 2018), Extreme Learning Machine (ELM) (Alizamir et al., 2018), Random Forest
82 (RF) (Koch et al. 2019) and M5 tree (M5P) model (Kisi 2015). Despite their success in GWL
83 modelling efficiently with less data, these techniques suffer from some shortcomings. For
84 instance, the ANN also exhibits high sensitivity to the trained data, overfitting problem and
85 dependence on hidden neurons and poor forecasting (Shiri et al. 2020). The performance of SVM
86 depends on the optimal selection of kernel functions (Sheikh Khozani et al. 2019). The tree-
87 based models like the Random Tree (RT), M5P tree, and Reduced Error Pruning Tree (REPTree)
88 have weak predictability, limiting their use in robust modelling of GWL (Song et al. 2019).
89 Recently, novel hybrid ensemble algorithms have been used to overcome the difficulties of
90 standalone data-driven algorithms in GWL prediction (Yadav et al. 2020; Wu et al. 2021;
91 Mallick et al. 2021a). Several recent studies employed hybrid ensemble models for different
92 hydro-meteorological applications (Yadav et al., 2020; Sharafati et al. 2020; Mallick et al.
93 2021b). The studies showed promising outcomes using hybrid ensemble models.
94 The highly nonlinear association of GWL with its predictive variables can be explained using a
95 local modeling approach, such as Locally Weighted Linear Regression (LWLR). The main
96 advantage of LWLR is that its training stage occurs at the prediction phase to enhance prediction
97 precision (Cleveland and Devlin 1988). Few studies have applied this novel LWLR algorithm
98 for solving prediction problem (Jamei and Ahmadianfar 2019; Ahmadianfar et al. 2020; Huang
99 et al. 2020). However, it has not been used so far for GWL prediction.

The surrogate models, namely Gaussian Processes Regression (GPR), are among the most potent prediction approaches. The GRP showed excellent performances in hydrological modelling, including forecasting groundwater depth fluctuations (Kumar et al. 2020), groundwater salinity prediction (Lal and Datta 2020), etc. The LWLR has a fast convergence characteristic, but it needs adjustment of many parameters requiring high computational cost. Therefore, high precision at less computation cost is achievable by hybridizing GRP with LWLR. However, hybridizing GRP with LWLR model application in GWL modelling and prediction has not been extensively explored yet in existing literature.

The precision of data-driven prediction models significantly relies on the input datasets utilized (Sahoo et al. 2017). Precipitation, evapotranspiration, surface temperature, and pumping rate are some of the most evident inputs of GWL prediction model (Wunsch et al. 2018). Furthermore, GWL is also partly influenced by intra-annual to decadal climate variability and change, hydro-meteorological factors, soil moisture, urbanization and land-use/land-cover (Kuss and Gurdak 2014).

Groundwater management planning (GMP) is essential to control GWL drop. However, the aquifer system is dynamic and different from location to location depending on several surficial and aquifer related factors. No matter how close the wells are, the dynamic nature of the aquifer system has been made it inconvenient to generalize an idea about the GWL fluctuation of any region by analyzing data of few wells or one well. For this reason, for assessing regional level GWL fluctuation, it needs considering all the wells situated in any specific region. But, in a country like Bangladesh, it is very difficult to collect data from all wells of any region due to it will consume huge money, formalities, and time. This leads the authors to choose only 2 wells from each district (6 wells in total) to predict the local level GWL fluctuation (instead of regional GWL fluctuation) that would give knowledge for a systematic understanding of the local level GWL fluctuation in drought-prone

urban groundwater aquifer influenced by climatological, hydro-meteorological, and human-induced factors. This work has two objectives. First, to estimate the local level monthly GWL using novel hybrid soft computing models in three urban districts of North-western Bangladesh. Second, to determine the best input combination using sensitivity analysis for better prediction accuracy.

2. Data and method

2.1 Study area description

The northern part of the North-western region of Bangladesh covers 23.5% (34,515 km²) of the country's total land. The region consists of 16 administrative districts, of which Dinajpur, Nilphamari and Rangpur districts were selected for this study. Total 6 wells from the 3 districts (2 wells from each district) are considered for this research (Figure 1). The study area, bounded by 23°47' N to 25°50' N latitude and 88°01' E to 89°48' E longitude, is located on the West of the Atrai River and the North of the Teesta River (Islam et al. 2021b). The population of the North-western region is about 61.5 million, with a density of 930/km². The North-western region is networked by several rivers and underlined by distinct oxidized red soils and sediments of Plio-Pleistocene and Holocene ages (Rashid et al. 2015; Das 2021). The elevation of the channel-floodplain complexes is about 8–23 m above mean sea level (AMSL), and the Himalayan piedmont plain is approximately 30–45 m AMSL. There is a wide variation in the sub-surface lithology in the North-western region (Figure 2). Two types of aquifers are found in the North-western region of Bangladesh which are: i) semi-confined shallow aquifer which is found just below the top soil spreading from 10-35 m, ii) lower shallow aquifer spreading from 20-70 m and is made of sand (coarse-medium grained), silt and fine sediment. Nearly 82% of annual rainfall in the area happen during May-October (rainy monsoon period), and only 18% of rain

147 occurs during November-April (dry season) (Ghose et al. 2021). It has a diverse monsoon
148 season, with an annual mean temperature ranged from 19°C in January to 31°C in August with a
149 mean of 26°C (Das and Islam 2021). The notable changes in several monthly climatic parameters
150 confirm that the climate of the North-western region is continuously changing (Salam et al.,
151 2020b).

152

Figure 1: Map showing the northwest region of Bangladesh

Figure 2: Stratigraphic panel diagram of the North-western region of Bangladesh (Source: Jahan et al. 2007)

2.2 Data

The present study used several datasets from different sources for predicting local level GWL fluctuation. The daily (which then converted to monthly) rainfall and average temperature; monthly soil moisture (SM); Indian Ocean Dipole (IOD), Southern Oscillation Index (SOI) and

Nina; population growth; MODIS Normalized Difference Vegetation Index (NDVI) data for Rangpur, Nilphamari and Dinajpur meteorological stations were collected from Bangladesh Meteorological Department (BMD); Bangladesh Water Development Board (BWDB); Food and Agricultural Organization (FAO); National Oceanic and Atmospheric Association (NOAA) Climate Prediction Center (CPC); Bangladesh Bureau of Statistics; National Aeronautics and Space Administration (NASA), respectively and monthly GWL (m) data for 6 selected wells from the Bangladesh Water Development Board (BWDB). The MODIS data was collected in Network Common Data Form (NetCDF) format and then converted to excel format. All the data were collected for the period 1993–2017.

2.3. The Methods used for estimating GWL

2.3.1 Gaussian processes regression

Gaussian process regression (GPR) model is a recently developed ML algorithm. According to Samuleson et al. (2017), the two important properties of GPR are: (1) the stochastic process explained by the multivariable Gaussian probability distribution (GPD), (2) the unbiased forecasting based on the linear combination of previous experimental observation. The covariance-based kernel function and mean function are the most mathematical characteristics of GPR for the inputs (X_i) and outputs (Y_i) domains, where X_i and Y_i are independently and identically distributed. The GPR can be defined as :

$$f(x) \sim GP(m(x), k(x, x')) \quad (1)$$

where $f(x)$ is the regression.

For "y" observation, the Gaussian noise function is:

$$y = f(x) + \varepsilon \quad (2)$$

$$\varepsilon \approx N(0, \sigma_f^2) \quad (3)$$

where ε is the noise of normal distribution function with $N(0, \sigma_f^2)$. The new way for noise combination in covariance function $k(\mathbf{x}, \mathbf{x})$, described according to Akbari et al. (2019) as follow:

$$k(x, x') = \sigma_f^2 \exp\left[\frac{-(x, x')^2}{2\tau^2}\right] + \sigma_n^2 \delta(x, x) \quad (4)$$

$\delta(\mathbf{x}, \mathbf{x})$ is the Kronecker delta function, and n is the observations of y . The choice of the appropriate kernel can give a good map of the input series for processing inputs in high dimensional feature space (Kumar et al. 2019). The most important kernels are described below.

The Poly kernel represents the similarity of vectors in a feature space allowing learning of nonlinear models.

$$k(x_i, x) = ((x_i, x) + 1)^d \quad (5)$$

The normalized kernel version can reduce the sparse data and allow building a better model. It can be expressed as:

$$k(x_i, x) = K(x_i, x) / \sqrt{K(x_i, x_i) K(x, x)} \quad (6)$$

Radial Basis Function (RBF) also known as "squared exponential", is a stationary kernel given by the equation (7).

$$k(x_i, x) = e^{-\gamma \|x_i - x\|^2} \quad (7)$$

Pearson (1895) proposed the Pearson Universal Kernel (PUK) as an alternative to the generic kernel function for curve fitting. The mathematical description of the kernel is as below:

$$k(x_i, x) = \left(1 / \left[1 + (2\sqrt{\|x_i - x\|^2} \sqrt{2^{(1/\omega)} - 1/\sigma^2})^2\right]\right)^\omega \quad (8)$$

Figure 3: Functioning of Gaussian Process Regression or probabilistic graphical model

2.3.2. Locally Weighted Linear Regression (LWLR)

Atkeson et al. (1997) first proposed the LWLR, a classical non-parametric regression approach. LWLR is one of the most classical approaches used in statistical and ML fields. It takes the basic conception of multiple linear regression (MLR). The LWLR covers the drawback of the MLR, which under-fits the data and negatively impacts the prediction process, especially in complex problems (Jamei et al. 2020). It uses the Weight function to define the relationship between the predictand and the training dataset (Ahmadianfar et al. 2020). The loss function $F(\theta)$, explained by equation (4), is used to find the learning model θ . One of the major advantages of the LWLR is the making testing phase in parallel with prediction steps, which can provide the lowest mean-squared error (MSE) in prediction.

$$F(\theta) = \sum_{i=1}^n w_i (y_i - \theta^T x_i)^2 \quad (9)$$

The Gaussian kernel function is written as:

$$W(i) = \exp\left(-\frac{(x_i - x)^2}{2k^2}\right) \quad (10)$$

where, W is a weight matrix used to decrease the function distance between the estimated data corresponds to the test or request point, x_i refers to the i^{th} training example point, k represents the bandwidth parameter that can be modified and adjusted to select the width of the kernel for the best distance between the request and training point. According to Huang et al. (2020), the LWLR kernel function is symmetric. Therefore, it is better to distribute the sample points within the dotted circle area. If the solid circle area A is the training sample, some sample points lost in the solid circle area of B (Figure 4).

Figure 4: Functioning of Locally Weighted Linear Regression model (Huang et al. 2020)

2.4 Statistical error measures

Observed and modeled GWL data were compared for the study period to evaluate the accuracy of the models using five statistical indices: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Relative Absolute Error (RAE), Root Relative Squared Error (RRSE), and Correlation Coefficient (CC). The equations of the statistical indices are noted below.

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (GWL_A^i - GWL_P^i)^2} \quad (11)$$

$$MAE = \frac{1}{N} \sum_{i=1}^N |GWL_P^i - GWL_A^i| \quad (12)$$

$$RAE = \left| \frac{GWL_A - GWL_P}{GWL_P} \right| \times 100 \quad (13)$$

$$RRSE = \frac{\sqrt{\sum_{i=1}^N (GWL_P^i - GWL_A^i)^2}}{\sqrt{\sum_{i=1}^N (GWL_A^i - \overline{GWL})^2}} \quad (14)$$

$$CC = \sqrt{1 - \frac{\sum_{i=1}^N (GWL_P^i - GWL_A^i)^2}{\sum_{i=1}^N (GWL^i - \overline{GWL})^2}} \quad (15)$$

GWL_A^i is the observed or actual GWL, GWL_P^i is the simulated GWL, $\overline{GWL}$ is the mean of observed GWL, and N is the total number of data points.

2.5 Model optimization

There is no ideal consensus on data division. The present study used data from 1993-2017. The first 76% of data (1993–2011) were used for training, and the rest of the 24% data (2012–2017) were used for testing. The nine models developed in this study were first optimized. Different mechanisms are available for optimizing or tuning model hyperparameters. The present study utilized the Grid search technique for optimizing model parameters. The optimized values of

model hyperparameters used in the present study are presented in Table 1. The flowchart for the proposed novel hybrid modeling framework is shown in Figure 5.

Figure 5: Methodological flowcharts for the proposed novel hybrid modeling framework

Table 1: The tuning parameters of the machine learning algorithm used in this study for groundwater level prediction

Model name	Description of parameters
Locally weighted linear regression (LWLR)	Batch size-100, KNN= 0, Nearest neighbor search algorithm= linear NN
Gaussian Process Regression (GPR) based	Kernel=Normalized Poly; Batch size-100, Noise = 1, Seed = 1; Filter type =Normalize training data; Cache size = 250000

on four kernels

Kernel= Poly; Batch size-100, Noise = 1, Seed = 1; Filter
type =Normalize training data; Cache size = 250000
Kernel= PUK; Batch size-100, Noise = 1, Seed = 1; Filter
type =Normalize training data; Cache size = 250000; Omega
= 1, Sigma =1
Kernel= RBF; Batch size-100, Noise = 1, Seed = 1; Filter
type =Normalize training data; Cache size = 250000; Gamma
= 0.01

3. Results

3.1 Multicollinearity assessment and descriptive statistics of conditioning variables

The present study performed a multicollinearity assessment for checking whether the variables are valid enough to build any model for predicting GWL (Table 2). Variance inflation factor (VIF) and tolerance statistics are the common methods used for detecting multicollinearity. The VIF of a variable close to 1 indicates no correlation existed with other variables. SOI and NINA at all stations showed a VIF higher than 2 (less than 2.30), meaning less multicollinearity effects that do not affect the results (Table 2). Soil moisture is mainly affected by rainfall and temperature affects rainfall. So, these variables may have VIF more than 1 which is expected. Rainfall (Rangpur and Nilphamari, VIF is very close to 2 for Dinajpur) and SM (Nilphamari, VIF is very close to 2 for Dinajpur and Rangpur) showed a VIF higher than 2, which cannot much affect the results. The VIFs of the rest of the variables at all stations were less than 2 (close to 1), indicating that they are free from the multicollinearity effect (Table 2). The standard error (SE) of mean, standard deviation (StDev), minimum, first quartile (Q1), middle number (Median), third quartile (Q3) and maximum values of the selected variables during both training and testing period are given in Table 3.

Table 2: Multicollinearity statistics of conditioning variables

Variables	Collinearity Statistics					
	Rangpur		Nilphamari		Dinajpur	
	Tolerance	VIF	Tolerance	VIF	Tolerance	VIF
Rainfall	0.489	2.046	0.454	2.202	0.591	1.693
Tave	0.927	1.078	0.531	1.882	0.947	1.055
NDVI	0.924	1.082	0.92	1.087	0.944	1.059
IOD	0.821	1.218	0.847	1.18	0.837	1.195
SOI	0.478	2.094	0.469	2.132	0.47	2.13
NINA	0.429	2.333	0.449	2.229	0.429	2.33
SM	0.514	1.946	0.483	2.073	0.6	1.665
Population Growth	0.981	1.02	0.97	1.031	0.978	1.023

Table 3: Descriptive statistics of the data during the training (A: 1993-2011) and testing period

(B: 2012-2017) in Rangpur

Variable	Mean	SE Mean	StDev	Minimum	Q1	Median	Q3	Maximum
A. Training	Rangpur							
Rainfall	187.4	13.80	208.0	0.0	6.3	109.0	336.8	913.0
Tave	24.56	0.288	4.347	13.9	21.925	26.400	28.300	29.700
NDVI	0.197	0.005	0.074	0.047	0.138	0.1790	0.252	0.412
IOD	-0.014	0.024	0.361	-0.887	-0.251	-0.027	0.163	1.473
SOI	-0.004	0.746	11.264	-28.6	-7.875	0.200	8.825	27.100
NINA	-0.078	0.057	0.862	-1.79	-0.720	-0.115	0.450	2.420
SM	118.86	3.97	59.89	26.00	54.25	129.00	179.00	179.00
Population Growth	2.039	0.025	0.384	1.06	1.830	1.9500	2.260	4.1500
B. Testing								
Rainfall	176.1	24.4	207.3	0.0	2.0	112.5	309.3	784.0
Tave	32.05	3.90	33.05	15.00	25.63	29.10	31.67	306.00
NDVI	0.19400	0.009	0.072	0.045	0.141	0.183	0.248	0.380
IOD	0.0643	0.033	0.283	-0.486	-0.151	0.041	0.311	0.749
SOI	-2.00	1.04	8.82	-22.00	-7.75	-1.35	4.13	13.90
NINA	0.277	0.101	0.856	-0.930	-0.320	0.095	0.547	2.570
SM	114.24	7.26	61.58	25.00	47.00	125.00	179.00	179.00
Population Growth	2.784	0.107	0.911	1.620	2.120	2.510	3.217	5.250
A. Training	Nilphamari							
Rainfall	186.2	14.6	221.0	0.0	4.0	82.5	306.0	951.0
SM	123.77	4.21	63.56	26.00	57.00	133.50	191.00	191.00
NDVI	0.173	0.003	0.047	0.06560	0.14050	0.170	0.202	0.345
IOD	-0.014	0.024	0.361	-0.8867	-0.2510	-0.027	0.1635	1.473
SOI	-0.004	0.746	11.264	-28.600	-7.875	0.200	8.825	27.100
NINA	-0.078	0.057	0.862	-1.7900	-0.7200	-0.115	0.4500	2.4200
Population Growth	2.039	0.025	0.384	1.0600	1.8300	1.9500	2.2600	4.1500
B. Testing								

Rainfall	151.1	20.9	177.4	0.0	3.3	66.5	245.8	628.0
SM	118.00	7.73	65.56	28.00	50.50	108.0	191.00	191.0
NDVI	0.16814	0.00556	0.0472	0.009	0.139	0.168	0.205	0.277
IOD	0.0643	0.0334	0.283	-0.486	-0.151	0.0413	0.3115	0.749
SOI	-2.00	1.04	8.82	-22.00	-7.75	-1.35	4.13	13.90
NINA	0.277	0.101	0.856	-0.930	-0.320	0.095	0.547	2.570
Population Growth	2.784	0.107	0.911	1.620	2.120	2.510	3.217	5.250
A. Training	Dinajpur							
Rainfall	167.7	13.3	200.2	0.0	3.0	71.0	288.5	1026.0
Tave	25.523	0.881	13.31	13.2	21.50	26.70	28.60	213.20
SM	127.97	4.47	67.49	29.00	60.00	124.0	203.0	203.00
NDVI	0.217	0.005	0.0827	0.063	0.152	0.199	0.270	0.446
IOD	-0.014	0.024	0.361	-0.887	-0.251	-0.027	0.164	1.473
SOI	-0.004	0.746	11.264	-28.6	-7.875	0.20	8.825	27.100
NINA	-0.078	0.057	0.862	-1.79	-0.720	-0.115	0.450	2.420
Population Growth	2.034	0.025	0.384	1.06	1.830	1.95	2.260	4.150
B. Testing								
Rainfall	143.9	20.2	171.5	0.0	1.3	68.0	256.5	640.0
Tave	28.785	0.587	4.981	14.5	25.70	29.75	32.375	37.300
SM	120.85	8.17	69.35	26.00	48.0	115.0	203.00	203.00
NDVI	0.218	0.009	0.082	0.068	0.149	0.205	0.2877	0.392
IOD	0.064	0.033	0.283	-0.486	-0.151	0.041	0.3115	0.749
SOI	-2.00	1.04	8.82	-22.0	-7.75	-1.35	4.13	13.90
NINA	0.277	0.101	0.856	-0.930	-0.32	0.095	0.547	2.570
Population Growth	2.784	0.107	0.911	1.620	2.12	2.510	3.218	5.250

Note: SE Mean: Standard Error of mean, St Dev: Standard deviation, Q1: First Quartile, Median: Middle number, Q3: Third Quartile.

3.2 Selection of best input combination using the sub-set regression and sensitivity analyses

The present study evaluated eight input combinations for exploring the best combination for GWL prediction model. The combinations are: C1) SM; C2) SM, Population Growth; C3) Rainfall, SM, Population Growth; C4) Rainfall, SM, IOD, Population Growth; C5) Rainfall, SM, NDVI, IOD, Population Growth; C6) Rainfall, SM, IOD, SOI, Nina, Population Growth; C7) Rainfall, Tave, SM, IOD, SOI, Nina, Population Growth; C8) Rainfall, Tave, SM, NDVI, IOD, SOI, Nina, Population Growth. The present study employed Mean Square Error (MSE), R^2 , adjusted R^2 , Mallow's CP, Akaike Information Criterion (AIC), Amemiya Prediction Criterion (PC), and Schwarz Bayesian Criterion (SBC) statistical tools for finding the best input combination for predicting GWL. Table 4 presents the results obtained using different methods. On average, the combination, C1, showed the lowest performance at all the wells. The input combination, C8, showed the best performance with higher values of R^2 , adjusted R^2 ,

Amemiya's PC and lower values of MSE, Mallows' Cp, AIC, SBC at all the wells (Table 4). The results indicate a significant influence of all input variables on GWL in the study. Therefore, all the variables are required for reliable prediction of GWL in the study area.

Table 4: Statistical assessment of eight input combinations on model performance

Input parameters	MSE	R square	Adjusted r square	Mallows' Cp	AIC	Schwarz's SBC	Amemiya's PC
Rangpur 27							
C1	0.61	0.22	0.217	9.996	-147.534	-139.052	0.783
C2	0.599	0.236	0.231	5.455	-150.941	-139.83	0.774
C3	0.595	0.243	0.236	4.785	-151.629	-136.814	0.772
C4	0.593	0.249	0.239	9	-151.923	-133.404	0.771
C5	0.592	0.252	0.24	5.271	-151.202	-128.98	0.773
C6	0.594	0.257	0.238	5.306	-151.219	-125.292	0.773
C7	0.592	0.258	0.24	7.004	-149.53	-119.9	0.777
C8	0.59	0.258	0.242	4.524	-146.46	-114.2	0.785
Rangpur 28							
C1	0.756	0.199	0.196	7.657	-76.191	-68.784	0.806
C2	0.764	0.209	0.204	5.894	-77.932	-66.821	0.802
C3	0.76	0.215	0.207	5.533	-78.304	-63.488	0.8
C4	0.758	0.22	0.209	9	-78.043	-59.524	0.801
C5	0.757	0.224	0.211	6.163	-77.721	-55.498	0.802
C6	0.755	0.229	0.213	6.337	-77.589	-51.662	0.802
C7	0.754	0.232	0.214	7.186	-76.772	-47.142	0.805
C8	0.771	0.233	0.211	5.813	-74.964	-41.63	0.809
Nilphamari 30							
C1	0.312	0.127	0.124	8.409	-346.994	-339.586	0.879
C2	0.307	0.145	0.14	3.824	-351.555	-340.444	0.866
C3	0.306	0.162	0.142	9	-355.443	-340.627	0.855
C4	0.302	0.164	0.153	1.406	-354.09	-335.571	0.859
C5	0.303	0.164	0.15	3.192	-352.311	-330.088	0.864
C6	0.304	0.165	0.148	5.088	-350.418	-324.492	0.869
C7	0.305	0.165	0.145	7.037	-348.471	-318.841	0.875
C8	0.302	0.165	0.154	0.036	-346.509	-313.175	0.881
Nilphamari 44							
C1	0.861	0.309	0.307	78.415	-104.506	-71.172	0.601
C2	0.742	0.407	0.403	27.392	-86.704	-75.593	0.578
C3	0.711	0.434	0.428	14.919	-98.527	-83.712	0.563
C4	0.685	0.451	0.444	7.219	-106.162	-87.643	0.559

C5	0.683	0.46	0.45	9	-108.613	-86.39	0.559
C6	0.681	0.462	0.451	5.263	-108.235	-82.308	0.563
C7	0.683	0.463	0.45	7.041	-106.463	-76.833	0.566
C8	0.69	0.463	0.448	4.842	-42.893	-35.486	0.696
Dinajpur 34							
C1	0.585	0.171	0.168	39.348	-187.272	-153.938	0.759
C2	0.548	0.226	0.221	18.997	-177.411	-166.299	0.784
C3	0.528	0.257	0.249	8.546	-187.588	-172.773	0.758
C4	0.52	0.278	0.268	9	-194.278	-175.759	0.741
C5	0.516	0.279	0.267	3.702	-192.549	-170.327	0.746
C6	0.517	0.28	0.265	5.394	-190.866	-164.939	0.75
C7	0.519	0.28	0.263	7.126	-189.142	-159.512	0.754
C8	0.515	0.281	0.261	1.966	-158.718	-151.31	0.835
Dinajpur 38							
C1	1.959	0.122	0.119	78.663	203.675	211.083	0.719
C2	1.753	0.217	0.212	40.108	171.306	182.418	0.794
C3	1.571	0.3	0.293	6.567	139.566	175.198	0.714
C4	1.561	0.307	0.298	5.599	138.569	157.088	0.712
C5	1.558	0.313	0.302	9	141.864	160.1	0.71
C6	1.549	0.317	0.299	5.313	138.186	164.113	0.711
C7	1.553	0.318	0.302	7	139.864	169.494	0.715
C8	1.552	0.318	0.303	4.96	137.878	154.381	0.884

3.3 Comparison of nine data-driven models in groundwater level prediction

Figure 6 represents the scatter plot of monthly observed and predicted GWL (m) estimated using nine ML models (both standalone and hybrid) at the six selected wells in the study area in the training stage. The predicted GWL (m) by the hybrid model LWLR- GPR-PUK showed the highest alignment with the diagonal line of the scatter plot, indicating the best performance of the model in replicating observed GWL (m). Among the six wells, Dinajpur-34 showed the least scattered points in the scatter plot for all the predicted models. The Nilphamari-44 and Dinajpur-38 wells showed the most scattered points for all the predicted models.

Figure 7 depicts the scatter plots for the testing stage. Like the scatter plot of the training stage, the predicted GWL (m) for the hybrid model LWLR-GPR-PUK showed the closest position to

311 the observed GWL (m) at the testing stage (Figure 7). The predicted GWL at Dinajpur-34 well
312 showed the least scattered points along the diagonal line.

313

Figure 6: Scatter plots of predicted GWL (m) using nine machine learning models against the

316 corresponding observed GWL (m) at six selected wells in the training stage

317

Figure 7: Scatter plots of predicted GWL (m) using nine machine learning models against the

corresponding observed GWL (m) at six selected wells in the testing stage

Figure 8 shows the long-term mean monthly time series plot of both observed and predicted GWL (m) during training and testing stages. GWL showed an abrupt increase in the year 2014 at all wells during model testing. Overall, the GWL showed the highest fluctuation (generally 3-4.5 m) at Nilphamari-30 and the lowest fluctuating, from 1-5 m, at Rangpur-27, Rangpur-28, and Nilphamari-44 wells. Besides, GWL showed very high fluctuation (1–6.5 m) at the rest of the two wells. All the models could replicate the observed GWL at all the stations with reasonable accuracy during training and testing periods. However, there were few exceptions. All the ML models underestimated observed GWL during 1999-2002 at Nilphamari-30 (Figure 8). Overall, the least performance in reconstructing the GWL time series was by GPR-RBF during both the training and testing stage at all wells. On the other hand, LWLR- GPR-PUK showed the highest performance in replicating GWL time series, followed by GPR-PUK, LWLR, LWLR- GPR-NPK, LWLR- GPR-Poly Kernel, GPR-NPK, GPR-Poly Kernel and LWLR- GPR-RBF.

Figures 9 and 10 show the Violin plots displaying the error GWL data distribution estimated by nine models at six different wells during the training and testing stage. Like the previous statistical results, violin plots also indicated the LWLR- GPR-PUK as the best model, with fewer errors than the other models at all the wells during both training and testing stages. The error values were fewer at the testing stage compared to the training stage.

342

343

Figure 8: The time series plot of GWL (m) for both the observed and predicted values during the training and testing stage at six selected wells of the northern part of North-western Bangladesh

Figure 9: Violin plot displaying an error (observed-predicted) for nine models (1. LWLR, 2. GPR poly kernel, 3. GPR-PUK, 4. GPR-RBF, 5. GPR-NPK, 6. LWLR- GPR-poly kernel, 7. GPR-PUK- GPR-RBF, 8. GPR-PUK- GPR-NPK, 9. GPR-RBF- GPR-NPK)

350 LWLR- GPR-PUK, 8. LWLR- GPR- RBF, 9. LWLR- GPR-NPK) at six different wells during
 351 the training stage

352
 353 Figure 10: Violin plot displaying an error (observed-predicted) for nine models (1. LWLR, 2.
 354 GPR-poly kernel, 3. GPR-PUK, 4. GPR-RBF, 5. GPR-NPK, 6. LWLR- GPR-poly kernel, 7.

LWLR- GPR-PUK, 8. LWLR- GPR- RBF, 9. LWLR- GPR-NPK) at six different wells during the testing stage

3.4 Statistical evaluation model performance

Table 5 shows the performance of the models in predicting monthly GWL during both the training and testing stage at six selected wells based RMSE, MAE, RAE, RRSE and CC. All models showed an RMSE below 1, except at Dinajpur-38 during both the training and testing stage. All the models showed the least error at Nilphamari-30 during both the training and testing stage. Overall, the results obtained using statistical metrics were very similar to those obtained using scatter plots and time series plots (Figures 5, 6 and 7). The results established the best performance of LWLR- GPR-PUK model. The RMSE of LWLR- GPR-PUK model ranges from 0.36 to 0.65, MAE from 0.23 to 0.47, RAE between 24.67 and 36.35% and RRSE between 27.79 and 36.78% during training. In the testing period, the RMSE were between 20 and 39, MAE from 0.14 to 0.30, RAE between 34.98 and 58.38% and RRSE between 42.13 and 61.35%. The highest CC (0.97-0.98 at the testing stage and 0.82-0.92 at training stage) was obtained for GPR-PUK Kernel, followed by LWLR, LWLR- GPR- NPK, LWLR-GPR-Poly Kernel, GPR-NPK, GPR-Poly Kernel, LWLR- GPR- RBF and GPR-RBF.

The results presented above indicate hybrid model LWLR- GPR-PUK as the best performed and GPR-RBF as the least performed model in predicting local level GWL fluctuation in the study area. Therefore, the LWLR-GPR-PUK model can be suggested for reliable prediction of local level GWL fluctuation in the study area.

376

377 Table 5: Statistical performance of the selected models during training and testing stage at six

378 selected wells

Models	Training period					Testing period				
	RMSE	MAE	RAE (%)	RRSE (%)	CC	RMSE	MAE	RAE (%)	RRSE (%)	CC
Rangpur 27										
1	0.62	0.47	65.12	71.96	0.70	0.52	0.38	48.80	56.33	0.84
2	0.69	0.53	74.56	80.92	0.59	0.79	0.64	81.05	85.34	0.54
3	0.52	0.39	54.33	60.54	0.82	0.52	0.43	54.74	56.57	0.94
4	0.77	0.63	88.41	89.56	0.53	0.91	0.76	97.04	97.86	0.42
5	0.68	0.51	72.05	79.18	0.61	0.75	0.60	76.25	80.69	0.64
6	0.67	0.50	69.97	77.28	0.64	0.68	0.54	69.07	73.56	0.73
7	0.43	0.31	43.21	49.89	0.89	0.33	0.27	34.92	36.11	0.97
8	0.74	0.60	83.67	85.70	0.57	0.86	0.72	91.79	93.22	0.62
9	0.65	0.49	67.96	75.68	0.66	0.64	0.51	64.67	68.70	0.79
Rangpur 28										
1	0.69	0.54	65.69	72.68	0.69	0.52	0.42	56.85	53.09	0.86
2	0.74	0.58	70.11	78.27	0.62	0.90	0.70	93.76	90.67	0.45
3	0.56	0.43	52.14	59.39	0.83	0.54	0.40	54.36	54.33	0.94
4	0.85	0.72	86.97	88.87	0.55	0.98	0.74	98.93	98.78	0.43
5	0.74	0.57	69.16	77.49	0.63	0.83	0.64	84.92	84.03	0.63
6	0.72	0.55	66.37	75.45	0.66	0.74	0.58	77.14	75.43	0.76
7	0.47	0.34	41.77	49.16	0.89	0.36	0.27	36.35	36.78	0.97
8	0.81	0.68	81.82	84.81	0.59	0.93	0.71	94.88	93.48	0.73
9	0.71	0.54	65.42	74.41	0.67	0.69	0.54	71.85	70.18	0.81
Nilphamari 30										
1	0.45	0.32	80.64	82.42	0.57	0.33	0.23	58.13	53.53	0.86
2	0.50	0.33	83.31	90.98	0.41	0.51	0.36	88.86	81.31	0.60
3	0.39	0.28	69.43	72.03	0.72	0.33	0.22	54.67	53.64	0.94
4	0.51	0.34	85.67	92.16	0.46	0.61	0.39	97.30	97.66	0.51
5	0.49	0.33	83.77	88.87	0.46	0.49	0.34	85.03	78.89	0.66
6	0.49	0.32	81.10	88.17	0.47	0.44	0.31	76.56	69.82	0.76
7	0.34	0.23	58.38	61.35	0.82	0.20	0.14	34.28	32.30	0.98
8	0.49	0.33	83.19	89.62	0.48	0.58	0.38	92.50	92.03	0.71
9	0.47	0.32	81.64	85.86	0.52	0.41	0.29	72.75	66.59	0.81
Nilphamari 44										
1	0.72	0.54	59.80	67.28	0.74	0.62	0.46	45.15	52.55	0.86
2	0.73	0.54	59.97	68.61	0.73	0.82	0.67	65.37	69.95	0.74
3	0.55	0.40	44.49	51.69	0.87	0.58	0.47	45.76	49.93	0.93
4	0.89	0.74	82.13	83.48	0.67	1.14	0.99	96.58	96.83	0.70
5	0.72	0.53	59.23	67.86	0.73	0.82	0.67	65.35	70.31	0.74
6	0.70	0.51	57.34	66.28	0.75	0.72	0.57	55.55	60.99	0.82
7	0.44	0.31	34.98	42.13	0.92	0.37	0.29	28.14	31.47	0.97
8	0.83	0.68	75.17	77.75	0.70	1.06	0.92	89.40	89.80	0.80
9	0.69	0.50	55.69	64.82	0.76	0.72	0.57	55.52	61.06	0.82
Dinajpur 34										
1	0.49	0.37	61.54	65.72	0.76	0.67	0.52	70.30	68.72	0.74
2	0.61	0.47	77.25	80.53	0.59	0.83	0.64	85.46	85.04	0.54
3	0.44	0.33	55.00	58.69	0.83	0.53	0.41	55.92	54.17	0.93
4	0.67	0.54	88.82	89.23	0.55	0.96	0.74	98.68	98.25	0.51
5	0.58	0.44	72.08	76.69	0.64	0.79	0.60	80.19	80.79	0.63

6	0.56	0.43	71.21	75.06	0.66	0.73	0.56	74.68	74.03	0.71
7	0.36	0.26	43.70	47.40	0.90	0.33	0.26	35.03	34.22	0.98
8	0.64	0.52	84.68	85.29	0.59	0.91	0.70	94.15	93.08	0.70
9	0.54	0.41	67.36	72.12	0.70	0.68	0.52	69.05	69.63	0.77
Dinajpur 38										
1	0.96	0.74	64.47	69.98	0.73	0.80	0.66	54.37	56.34	0.84
2	1.13	0.90	78.57	82.15	0.57	1.07	0.85	70.27	75.08	0.68
3	0.81	0.61	53.52	59.15	0.83	0.66	0.52	42.65	46.85	0.95
4	1.26	1.05	91.81	91.68	0.50	1.36	1.16	95.42	96.11	0.58
5	1.07	0.82	71.58	77.73	0.63	1.00	0.78	64.63	70.78	0.74
6	1.04	0.81	70.61	75.86	0.66	0.89	0.70	57.98	63.18	0.80
7	0.65	0.47	41.69	47.29	0.90	0.39	0.30	24.67	27.79	0.98
8	1.20	1.01	87.94	87.89	0.55	1.25	1.05	86.60	88.46	0.72
9	1.00	0.75	65.68	72.84	0.69	0.83	0.64	52.77	58.98	0.85

Note: Models: (1) LWLR, (2) GPs-poly kernel, (3) GPs-PUK, (4) GPs-RBF, (5) GPs-Normalized poly kernel, (6) LWLR- GPs-poly kernel, (7) LWLR- GPs-PUK, (8) LWLR- GPs- RBF, (9) LWLR- GPs- Normalized poly kernel

5. Discussion

Though advanced models and soft computing tools have been extensively utilized in GWL prediction studies, the hydrogeological processes should not be ignored. In the present study, the findings of this study imply that the LWLR-GPR-PUK is a robust algorithm for the prediction of GWL at local scale in a humid climatic region like Bangladesh. The models developed in this study should be compared with other soft computing models, i.e., ANN, ANFIS, ELM and RF and their ensemble with metaheuristic models to evaluate the models' relative performance. Furthermore, the proposed modeling algorithms can be also for predicting groundwater contamination, groundwater vulnerability and managed aquifer recharge (Islam et al. 2020).

In recent times, the drought-prone humid region of northern Bangladesh has experienced severe scarcity of GW due to the declination of GWL. The present research revealed that the declination of GWL is much greater in the wells of Rangpur than that of Dinajpur and Nilphamari. The main reason is that the flow of the Teesta River occurs at the upper part of the Rangpur district, and the base flow happens in the SW direction because of the normal slope, triggering the minimum possibility of aquifer recharge from river water in this region. Besides, soil texture in this region

is dominated by silty clay soil, which belongs to relatively lower hydraulic conductivity characteristics (Zinat et al. 2020). Consequently, groundwater recharge from rainfall is very low. On the other hand, the possibilities of groundwater recharge from river and precipitation are comparatively higher in Dinajpur district, as the flow of Atrai River.

The decreasing trend of precipitation, consistent with a widespread and prevailing decreasing trend in GWL over the North-western region, cannot be ignored as a responsible factor. Local geology characterizes shallow aquifers in Bangladesh and largely controls the timing and pathways of groundwater recharge to aquifers (WARPO 2000). The declining shallow groundwater storage in North-western Bangladesh relates to the intensity of abstraction and areas of the high thickness of surface clay where rainfall-fed recharge rates are low due to the low hydraulic conductivity of this subsurface geology (Shamsudduha et al. 2011). Hence, earlier evidence indicates that rigorous abstraction of groundwater for irrigation, decreasing precipitation that is one of the impacts of climate change and local geology of the study region, can be attributed to rapidly declining GWL in the drought-prone urban area.

In this region, the rainfall has reduced 10–45 mm/year over the past 12 years, leading to decreased natural recharge (Jahan et al. 2010). The abuse of existing GWL, mostly being extracted for paddy farming, rice mill operations, domestic and other industrial purposes, is an alarming issue where groundwater provides 80% of the water needed for rice irrigation. Here, random use of water in industry and agriculture is causing GWL declination. On average, GWL varies between 1 and 6 m in the northern region, which is consistent with the Master Plan Organization (MPO 1987) claim, which stated that groundwater is mainly available within 5 m of ground within alluvial aquifers. Evidence suggests that due to low rainfall in the short monsoon season and less available soil moisture, aquifer replenishment slowly ends during the

dry season (Jahan et al., 2010). In the last ten years, the rate of GWL in Rangpur, Niphamari and Dinajpur urban regions has dropped by 0.05 m, 0.03 m, and 0.01 m, respectively, which is also consistent with the result of Dey et al. (2017). Besides, silty loam, the predominant soil type, has a medium permeability, which may be partly responsible for replenishing the depleted GWLs. On the other hand, loamy soil, the dominant soil type in the Dinajpur district, has an elevated permeability level. Therefore, the potential of groundwater recharge from rainfall and surface water sources is a lesser amount here and decrease in the wetland region resulting in a significant declination of GWL in the Rangpur district.

River water use, aquifers' safe yields management, natural and artificial aquifers recharging, rainwater harvesting, and wastewater use are the likely choices for reducing pressure on groundwater and prevent declination of GWL. Also, practices such as mulching can increase the water-holding capacity of field soils and decrease evaporation. Organic mulching, by increasing soil organic matter, can also aid groundwater recharge. Population growth, rapid urbanization, climate change, and poor water management policy have threatened groundwater resources in the study area (Salam et al. 2020a). Thus, strategies such as artificial recharge of aquifers, rainwater harvesting, water-saving technologies and integrated water resources management need to be implemented.

Some of the vital indicators of GWL fluctuations, including bore-well depths closeness of well from sink or source and hydrogeological features, e.g., aquifer porosity and permeability, are ignored in this study due to unavailability data. Further investigation is essential by incorporating these important hydrogeological parameters in data-driven tools to enhance short and mid-term prediction accuracy and confirm these hybrid methods agree well with the theoretical and numerical-based methods.

6. Conclusion

The GWL in the study area has gradually declined over the last two decades because of rapid urbanization and over-exploitation to meet the demand of the growing urban population. The results showed all the factors considered in this study are important for the reliable estimation of GWL at local scale. This indicates that complex interactions of various atmospheric variables and land features determine GWL fluctuation in the local areas of North-western region. The performance assessment of the nine data-driven models developed in this study suggests LWLR-GPR-PUK as the best model for GWL estimation. The estimated average GWL fluctuation varied from 0.4 to 1.25 m. The outcomes obtained from the present work would help detect the reasons for GWL declination at local level situated in urban regions under different hydro-climatic settings. The proposed model would be useful, especially in the drought-prone areas where the physical flow-based model implementation is difficult due to the lack of data. This research would create new knowledge for sustainable groundwater management and aquifer protection in the study areas for safeguarding the groundwater resources.

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Ethical approval

Not applicable

Consent to Participate

466 Not applicable

467 **Consent to Publish**

468 Not applicable

469 **Data available**

470 Data are available upon request on the corresponding author

471 **Code availability**

472 Not applicable

473 **Author contributions**

474 A.R.M.T.I., A.E., and R.S., designed, planned, conceptualized, drafted the original manuscript, and R.S, M.
475 S.I was involved in statistical analysis, interpretation; S.C.P, J.M., and A.E., contributed instrumental setup,
476 data analysis, validation; B.Z., and R.S., contributed to editing the manuscript, literature review, proofreading;
477 S.S., R.S., J.M., and A.R.M. T.I., were involved in software, mapping, and proofreading during the manuscript
478 drafting stage.

479 **Conflict of interest**

480 There is no conflict of interest to publish this work

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