# MODELLING GROUNDWATER LEVEL FLUCTUATION WITH EXOGENOUS INPUT

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## Abstract

Groundwater is one of the major sources of water supply for domestic, industrial and agricultural sectors in Bangladesh. The continued declining of groundwater level (GWL) due to the uncontrolled withdrawal of groundwater causes several problems such as drinking water shortages, reduction in crop yields, water quality degradation and impact on human health. Therefore, accurate prediction of GWL fluctuation is indispensable for the effective management of groundwater resources in Bangladesh. In this study, a GWL fluctuation modelling framework using time series models is presented and demonstrated through a case study. Kushtia district of Bangladesh is selected as the case study area and five GWL monitoring stations and one rainfall station are selected. Weekly GWL and daily rainfall data are collected for the 1999-2006 period, which is used for the analysis and modelling purposes. Since upper shallow aquifers in Bangladesh is unconfined in nature, GWL fluctuation is highly influenced by rainfall. For this reason, both GWL and rainfall data are required to be taken into account to predict GWL fluctuation accurately. In this study, autoregressive integrated moving average with exogenous input (ARIMAX) and autoregressive integrated moving average (ARIMA) time series models are developed in the MATLAB platform for modelling and prediction of GWL fluctuation. In order to formulate the ARIMA-based univariate time series models, only GWL data is used as the input. However, the rainfall data is used as an exogenous input along with the GWL data to develop the ARIMAX-based multivariate time series models. Finally, the estimation of GWL fluctuation is carried out using the adopted models and the performance of each model is assessed. The results indicate that ARIMAX models produce the best prediction of GWL fluctuation over the ARIMA models. This study conclusively proves that the inclusion of rainfall as exogenous input is viable for the enhanced prediction of GWL fluctuations.

## Keywords

Groundwater Level; Exogenous Input; Time Series Model; Seasonality; ARIMAX.

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## 1. Introduction

Globally, groundwater is one of the main sources of water supply for drinking and irrigation purposes in rural and urban areas and has many benefits over surface water in terms of quality and quantity. The overexploitation of groundwater and consequently the continuous depletion of groundwater has become a serious concern globally, particularly in developing countries [1-2]. Prediction of groundwater level (GWL) fluctuation is one of the most important stages for the estimation of sustainable yield and effective management of groundwater systems [3]. Therefore, to exploit and manage groundwater systems, models are necessary to predict GWL fluctuations.

In Bangladesh, groundwater occurs extensively in alluvial aquifers at shallow depths, which is the main source of drinking and agricultural water supplies. Development of the groundwater resource for irrigation and other purposes is an indispensable component of the government's agricultural strategy to achieve the food self-sufficiency of Bangladesh. This is also highlighted in the national water management plan of the country [4]. At present, about 80% of population in Bangladesh depends on the groundwater source for their freshwater supplies [5] while more than 70% of the total irrigated area is served with groundwater [6]. Rapid growth of population, fast increase of agricultural activities and growing industrialization impose extreme pressures on the groundwater resource of the country. Furthermore, the occurrence of arsenic pollution in groundwater makes its management more challenging. Therefore, detailed analysis and prediction of GWL fluctuation is crucial for the effective management of groundwater resource in Bangladesh.

Many natural and anthropogenic factors caused by human activities affect the aquifers at different chronological levels that lead to groundwater fluctuations. Therefore, exact estimation of groundwater fluctuation rate is a challenging task [7]. Nowadays, mathematical models simulated by advanced computing technology are used in exploiting groundwater systems. Among variety of techniques adopted for prediction of GWL fluctuation, time series and artificial neural network (ANN) models are widely applied [8-10]. The main benefit of time series models is that they are comparatively easier to develop and able to generate new sequence time series having identical statistical parameters with observed time series and predicting future time series. Irvine and Eberhardt [11] developed multiplicative, seasonal ARIMA models for Erie and Ontario lakes for predicting up to 6 months ahead levels. However, traditional Box-Jenkins time series or ARIMA models assume that a given time series is generated from an underlying linear process. For this reason, they may not always perform well when applied for modelling hydrologic time series that are usually nonlinear [12]. In order to overcome these shortcomings, hybrid models are often developed by researchers. For example, Vaziri [13] combined ARIMA and ANN models to predict water levels in the Caspian Sea, and Faruk [14] developed a hybrid neural network and ARIMA model for water quality prediction.

In the case of the poor performance of model, the complexity of the model structure could be increased. Ultimately, the simplest model that describes the system dynamics well is preferred. A number of researches have been carried out using these models. The comparative performance of ANN model with the traditional ARMAX model in forecasting 1 month-ahead lake levels was shown in [14]. Dalcin [16] used autoregressive with exogenous variable (ARX) model to appropriately predict the short-term river flows. Perera [17] developed a multivariate time series model using autoregressive moving average with exogenous variable (ARMAX) model to forecast daily irrigation demand for lead times of up to 5 days. Taweesin [18] used ARIMAX model to identify climate influence on groundwater and to forecast GWL in the lower Chao Phraya basin of Thailand. It is evidenced from the aforementioned studies that ARIMAX model offers several advantages including high accuracy, inclusion of exogenous variable, less or no requirement of large amount of data and inexpensive implementation that makes it one of the effective modelling tools to predict GWL fluctuation. It is widely recognized that like many other factors, GWL fluctuation in shallow unconfined aquifers of Bangladesh is highly influenced by rainfall [2, 19-20]. Hence, it is perceived that inclusion of rainfall variable as an exogenous variable in GWL time series modelling using ARIMAX model could give better prediction of GWL fluctuation. Furthermore, to the best knowledge of the authors, ARIMAX model has not been used for the prediction of GWL fluctuation in Bangladesh in the past. Therefore, the aim of the current study is to develop time series model of GWL fluctuation using ARIMAX model and evaluate its performance for modelling and prediction of GWL fluctuation.

## 2. Study Area and Data Description

Kushtia district of Bangladesh, covering an area of 1621 $km^2$, is selected as the study area in the current study. Location of the study area with GWL monitoring and rainfall stations is shown in Figure 1. The study area covers a major part of the command area of the Ganges-Kobadak (G-K) irrigation project. The mean annual rainfall of the study area is 1472 mm and about 72% of rainfall occurs in the monsoon season. The average maximum and minimum temperature of the study area are 37.7 $^0$C and 11.3 $^0$C, respectively. The groundwater extraction rate, like other parts of the country, is relatively higher in the study area. Inadequate water availability during the dry season in the nearby Ganges-Padma River due to the upstream water diversion at Farakka Barrage causes immense pressure on groundwater resources in order to satisfy the irrigation activities in addition to the municipal and commercial uses of groundwater.

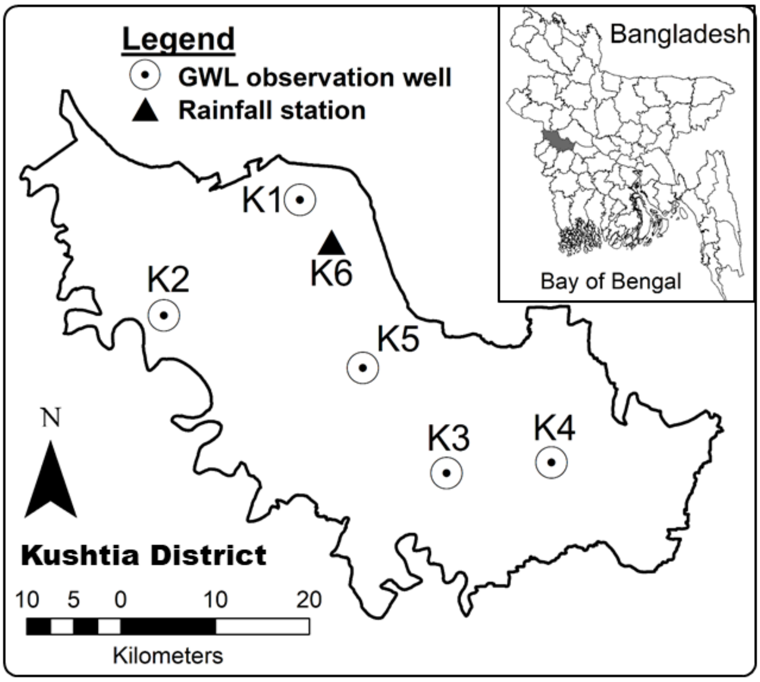


Figure 1: Location of the study area with groundwater level and rainfall monitoring stations

The fluctuation of groundwater flow can be demonstrated and visualized from the observed groundwater levels. Since upper shallow aquifers in Bangladesh is unconfined in nature, GWL fluctuation is highly influenced by rainfall [2, 19-20]. For this reason, rainfall data is used as an exogenous input in the current study for accurate prediction of GWL fluctuations. Five GWL monitoring stations and one rainfall station located within the study area are selected to carry out the study. Approximate locations of the monitoring stations are shown in Figure 1 and details of the monitoring stations are provided in Table 1. Time series GWL and rainfall data are collected from the Bangladesh Water Development Board (BWDB) for a period from 1999 to 2006. The frequency of GWL data collection is one week and rainfall data is available on daily basis in BWDB database. Hence, collected daily rainfall data are converted to weekly rainfall data in order to use with the collected weekly GWL data.

Table 1: Details of groundwater level and rainfall monitoring stations

| SL No | Station ID | Station Type | Upazila | Latitude (Deg) | Longitude (Deg) |
|---|---|---|---|---|---|
| 1 | K1 | Groundwater Level | Bheramara | 24.09 | 88.96 |
| 2 | K2 | Groundwater Level | Daulatpur | 23.98 | 88.83 |
| 3 | K4 | Groundwater Level | Kushtia Sadar | 23.83 | 89.10 |
| 4 | K3 | Groundwater Level | Kumarkhali | 23.84 | 89.20 |
| 5 | K5 | Groundwater Level | Mirpur | 23.93 | 89.02 |
| 6 | K6 | Rainfall | Mirpur | 24.05 | 88.99 |

## 3. Modelling Tools and Techniques: ARIMA and ARIMAX Models

Numerous techniques are available for modelling GWL fluctuation including time series techniques, multiple regression, group theory, synthetic data generation, pattern recognition and artificial intelligence techniques. However, the choice of a modelling technique for a particular problem depends of several factors including data availability, target accuracy, modelling costs, model complexity, ease of interpretation of results etc. It is widely established that the time series modelling technique is advantageous for the cases wherein the available hydrological data is limited. A time series model can be defined as an empirical model to simulate and predict the behavior of uncertain hydrologic systems. An inherent advantage of the time series models is that only few model parameters can describe the time series and hence less computational effort is sufficient for modelling exercise.

In the current study, two-time series models including autoregressive integrated moving average with exogenous input (ARIMAX) and autoregressive integrated moving average (ARIMA) models are adopted for modelling and prediction of GWL fluctuation. ARIMA models are one of the most important time series models for hydrologic data analysis and forecasting, which have been originated from the combination of autoregressive (AR) and moving average (MA) models. In ARIMA modelling technique, the future value of a variable is assumed to be a linear function of several past observations and random errors. ARIMA models use correlational approach and can be applied to model patterns that may not be noticeable in plotted time series data. Seasonal ARIMA, which is generally known as the SARIMA model, is used when the time series exhibits a seasonal variation or seasonality. A multiplicative SARIMA model can be described as ARIMA(p, d, q)(P, D, Q)s, where (p, d, q) indicates the non-seasonal part of the model and (P, D, Q)s represents the seasonal part of the model where p is the order of non-seasonal auto-regression, d is the number of regular differencing, q is the order of non-seasonal MA, P is the order of seasonal auto-regression, D is the number of seasonal differencing, Q is the order of seasonal MA, and s is the seasonality. Since ARIMA models are univariate, it cannot incorporate exogenous variables. However, an ARIMAX multivariate time series model is the combination of ARIMA model with one or more exogenous variables, X. The ARIMAX models offer certain benefits over ARIMA models and therefore they are widely used for model development and prediction purposes.

In the current study, the methodological steps are similar for all the time series models adopted in modelling GWL fluctuation. In general, ARIMA(p, d, q) time series model has no seasonality effect, which can be expressed by

$$\phi(L)(1-L)^d Y_t = C + \theta(L)\varepsilon_t \qquad (1)$$

where, p = order of auto-regression, d = order of integration (differencing), q = order of moving average, L = lag operator, $\phi(L) = (1-\phi_1 L-\phi_2 L^2-\text{........}-\phi_p L^p)$, the autoregressive polynomial, $\theta(L) = (1+\theta_1 L+\theta_2 L^2+\text{........}+\theta_q L^q)$, the moving average polynomial, C is the constant and $\varepsilon_t$ indicates the error term. As indicated earlier, the seasonality is introduced in the ARIMA model formulation to demonstrate the seasonable characteristics presence in the time series data, which is referred to as the SARIMA time series models. SARIMA model is used when the time series shows a seasonal variation. Multiplicative SARIMA(p, d, q)(P, D, Q)s can be expressed by

$$\phi(L)\Phi(L)(1-L)^d(1-L^S)^D Y_t = C + \theta(L)\Theta(L)\varepsilon_t \qquad (2)$$

where, $\phi(L)$, degree $p$ autoregressive operator polynomial, and $\Phi(L)$, degree $P$ autoregressive operator of the same form. $\theta(L)$, degree $q$ moving average operator polynomial, and $\Theta(L)$, degree $Q$ moving average operator of the same form.

For multivariate models, exogenous variable or input is used as an auxiliary input in model development along with the primary variable. The general form of an ARIMAX(p, d, q) time series model with exogenous input is given by

$$\phi(L)Y_t = C^* + X_t\beta + \theta^*(L)\varepsilon_t \qquad (3)$$

where, $C^* = C/(1-L)^d$ and $\theta^*(L) = \theta(L)/(1-L)^d$. If the time series data exhibits the presence of seasonal variation, the multiplicative SARIMAX(p, d, q)(P, D, Q)s model can be expressed by

$$\phi(L)\Phi(L)Y_t = C + X_t\beta + \theta(L)\Theta(L)\varepsilon_t \qquad (4)$$

Time series modelling using ARIMA and ARIMAX models are involved with some iterative steps including identification of the ARIMA model structure, estimation of the model parameters, diagnostic checking of the model residuals, and finally prediction of hydrologic data series, which are also adopted in the current study. Since ARIMA models are univariate in nature, only GWL time series data is used as the input to develop and simulate the ARIMA-based univariate time series models. However, the rainfall data is used as an exogenous input along with the GWL time series data to develop and simulate the ARIMAX-based multivariate time series models. The development and execution of ARIMA and ARIMAX models for simulating GWL fluctuation are performed using the econometric modeller toolbox in MATLAB platform. A number of techniques including linear least squares method, maximum likelihood method, method of moments etc. are available to estimate the parameters of the aforementioned time series models. In the current study, maximum likelihood method is adopted for parameter estimation using the econometric modeller toolbox in MATLAB platform. The maximum likelihood method begins by writing a probability distribution that defines the likelihood of the observed sample as a function of population and distribution parameters. The main advantage of the maximum likelihood method is that it provides a consistent approach to parameter estimation problems. The econometric modeller toolbox is the most widely used tools for time series modelling and parameter estimation, which provides function for analyzing and modelling time series data along with the estimation of model parameters using the maximum likelihood method. Moreover, it offers a wide range of visualizing and diagnostics for the selection of best model.

In the current study, one week ahead prediction of GWL fluctuation is carried out using the developed ARIMA and ARIMAX models. Finally, the performance of each model is assessed in order to identify the best model for GWL fluctuation modeling and prediction. Different model performance evaluation criteria including root-mean-squared-error (RMSE), Akaike information criterion (AIC) and Bayesian information criterion (BIC) have been used in this study to assess the efficacy of the adopted modelling techniques. The model with the lowest RMSE, AIC and BIC values indicates the best model.

## 4. Results and Discussion

The initial step of the time series modelling using ARIMA and ARIMAX is to check the stationarity of the hydrologic data series. It is also necessary to check if there is a presence of seasonality in the data series. For simplicity, modelling and prediction of GWL fluctuation of one observation well (K1 as given in Table 1) is detailed and results of the other observation wells (K2 to K5 in Table 1) are summarized.

In order to make the observed time series stationary, the differencing of the observed data for K1 observation well is done. It is observed from the analysis that the differencing value d=2 is sufficient and adopted for further analysis. After differencing, it is found that the mean of the GWL series decreases to approximately zero after performing the differencing operation, which demonstrates that the differenced series is a stationary series. The orders (p, d, q) of the time series is selected before starting of the model identification. In order to identify the model structure, autocorrelation function (ACF) and partial autocorrelation function (PACF) are often useful, which is also adopted in this study. ACF and PACF are also used to detect the seasonality of the observed data series and the order of the model as preliminary identification. After identification of the ARIMA model structure and seasonality, the model parameters are estimated by the method of maximum likelihood using the econometric modeller toolbox in the MATLAB platform.

ACF and PACF plots for K1 is shown in Figure 2. The ACF analysis indicates a strong seasonal variation of 52 weeks (or one year). The PACF plot indicates that there is no significant correlation after lag 3. Therefore, a total of 48 ARIMA models from ARIMA(0,0,0) to ARIMA(3,2,3) using different combinations of p, d and q parameters are formulated and the corresponding parameters of each model are estimated using the maximum likelihood parameter estimation method available in the econometric modeller toolbox of MATLAB. Then the performance of each model is assessed using the different performance criteria indicated in Section 3. Finally, the model that gives the lowest values of RMSE, AIC and BIC values is selected as the best model.

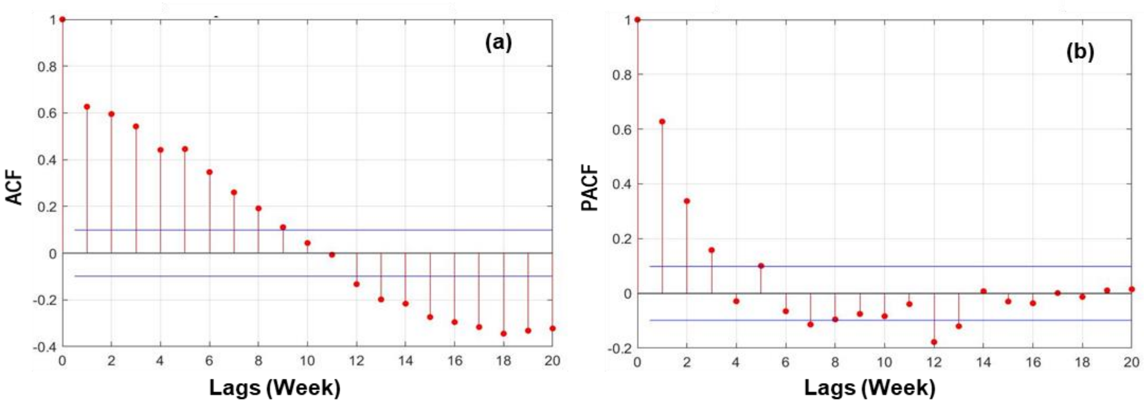


Figure 2: ACF and PACF plots for K1 observation well

From this study or the modelling of the groundwater level fluctuation the best time series model is obtained. The outcome is the best model that can predict the GWL fluctuation more accurately.

The performance of selected 10 models from 48 models for K1 observation well is summarized in Table 2. As can be seen from Table 2, ARIMA (2,0,1) gives the lowest values of RMSE, AIC and BIC and hence it is identified as the best ARIMA model for K1 observation well.

Table 2: Selected ARIMA models for K1 observation well

| **Sl. No.** | **Model Structure** | **Model performance** | | |
|---|---|---|---|---|
| | | **RMSE** | **AIC** | **BIC** |
| 1 | ARIMA (0,1,3) | 0.231 | -27.57 | -7.44 |
| 2 | ARIMA (0,2,3) | 0.224 | -54.37 | -34.24 |
| 3 | ARIMA (1,0,3) | 0.229 | -33.09 | -8.94 |
| 4 | ARIMA (1,1,2) | 0.218 | -75.79 | -55.66 |
| 5 | ARIMA (1,2,2) | 0.224 | -54.87 | -34.74 |
| 6 | ARIMA (2,0,0) | 0.231 | -32.15 | -16.04 |
| 7 | **ARIMA (2,0,1)** | **0.204** | **-131.62** | **-111.49** |
| 8 | ARIMA (2,0,3) | 0.204 | -128.94 | -100.76 |
| 9 | ARIMA (3,0,2) | 0.204 | -128.90 | -100.72 |
| 10 | ARIMA (3,0,3) | 0.204 | -127.35 | -95.14 |

In the similar way, the best ARIMA models for other observation wells from K2 to K5 are identified and presented in Table 3. The identified seasonal ARIMA models are also shown in Table 3, where 52 weeks seasonality is used with seasonal and non-seasonal model parameters. It can be seen from Table 3 that ARIMA model performs better compared to the seasonal ARIMA (or SARIMA) model to predict the GWL fluctuation.

Table 3: Details of the best ARIMA and seasonal ARIMA models for all observation wells

| **Station ID** | **Model Structure** | **Model performance** | | |
|---|---|---|---|---|
| | | **RMSE** | **AIC** | **BIC** |
| **ARIMA model** | | | | |
| K1 | ARIMA (2,0,1) | 0.204 | -131.62 | -111.49 |
| K2 | ARIMA (2,0,1) | 0.255 | 52.80 | 72.93 |
| K3 | ARIMA (3,0,1) | 0.395 | 417.70 | 441.86 |
| K4 | ARIMA (2,0,3) | 0.261 | 76.76 | 104.94 |
| K5 | ARIMA (2,0,1) | 0.200 | -147.10 | -126.97 |
| **ARIMAX model** | | | | |
| K1 | ARIMAX (3,0,3) | 0.193 | -166.49 | -130.32 |
| K2 | ARIMAX (3,0,2) | 0.213 | -87.19 | -55.04 |
| K3 | ARIMAX (2,0,0) | 0.393 | 411.94 | 436.06 |
| K4 | ARIMAX (1,0,3) | 0.248 | 35.11 | 63.27 |
| K5 | ARIMAX (3,0,2) | 0.191 | -174.48 | -138.31 |
| **Seasonal ARIMA model** | | | | |
| K1 | SARIMA $(1,0,0)(1,0,1)_{52}$ | 0.200 | -148.76 | -128.64 |
| K2 | SARIMA $(1,0,0)(1,0,1)_{52}$ | 0.263 | 77.96 | 98.09 |
| K3 | SARIMA $(1,0,1)(1,0,1)_{52}$ | 0.411 | 451.34 | 475.50 |
| K4 | SARIMA $(1,0,1)(1,0,1)_{52}$ | 0.263 | 82.26 | 106.41 |
| K5 | SARIMA $(1,0,0)(1,0,1)_{52}$ | 0.201 | -141.69 | -121.56 |
| **Seasonal ARIMAX model** | | | | |
| K1 | SARIMAX$(1,0,1)(1,0,1)_{52}$ | 0.207 | -77.919 | -51.785 |
| K2 | SARIMAX$(1,0,0)(1,0,1)_{52}$ | 0.266 | 72.720 | 95.120 |
| K3 | SARIMAX$(1,0,1)(1,0,1)_{52}$ | 0.438 | 380.947 | 407.080 |
| K4 | SARIMAX$(1,1,1)(1,1,1)_{52}$ | 0.286 | 116.100 | 142.211 |
| K5 | SARIMAX$(1,0,0)(1,0,1)_{52}$ | 0.214 | -64.120 | -41.720 |

The results of the ARIMAX and seasonal ARIMAX models are also shown in Table 3. It can be seen from the table that the ARIMAX model gives better performance than that given by the seasonal ARIMAX model for the prediction of GWL fluctuation. It is also evident from Table 3 that the best performance for the prediction of the GWL fluctuation is achieved by the ARIMAX model when comparing all univariate and multivariate models.

The results indicate that the addition of rainfall variable as an exogenous input in the ARIMAX model causes the reduction in error and gives the best performance. This is likely to be because the moving average of the white noise has a higher potential to absorb prediction errors when comparing with other modelling methods. This conclusively proves the fact that the inclusion of rainfall input as an exogenous variable in the time series modelling process is viable to enhance the prediction accuracy of GWL fluctuation. Therefore, it is suggested to use the ARIMAX model structure to model and prediction of the GWL fluctuation using the rainfall variable as an exogenous variable for best estimation of the GWL fluctuation.

## 5. Summary and Conclusions

In the current study, modelling and prediction of GWL fluctuation of Kushtia district in Bangladesh is carried out using different univariate and multivariate time series models including ARIMA, SARIMA ARIMAX, and SARIMAX models. The modelling exercise is performed using the econometric modeller toolbox in MATLAB platform, which is the most widely adopted tools in time series modelling and parameter estimation. Only GWL time series data is used as the primary variable to develop ARIMA-based univariate time series models that include ARIMA and SARIMA models. On the other hand, both GWL and rainfall time series data are used to develop ARIMAX-based multivariate time series models that include ARIMAX and SARIMAX models. In the multivariate models, rainfall variable is used as an exogenous input or variable in addition to the GWL time series data to be used as the primary variable in the current study. Such inclusion of rainfall as an exogenous input is justified because the groundwater in the upper unconfined aquifer in Bangladesh is highly influenced by rainfall. In regard to this, it is worth mentioning that other relevant variables such as groundwater extraction data can also be considered as an exogenous variable other than rainfall (used in the current study) based on the data availability. It is believed that the current study is expected to be supportive to explore such inclusions in similar studies in future. After model development and parameter estimation, the performance of each model is assessed through different performance evaluation criteria. The results indicate that the ARIMAX-based multivariate models gives the best prediction of GWL fluctuation compared to the ARIMA-based univariate time series models. The result of this study conclusively proves that the inclusion of rainfall variable as an exogenous input is viable for the enhanced prediction of GWL fluctuations.

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