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Spatiotemporal Analysis and Forecasting of Groundwater Level Fluctuations with Sectoral Water Demand Assessment in Shahjadpur, Sirajganj, Bangladesh

Md. Nazmul Islam Hasan[1*], Khondaker Emamul Haque[1], Shamim Ahmed[2], and Md. Mahedi Hasan[1]

[1]Department of Geology and Mining, University of Rajshahi, Rajshahi 6205, Bangladesh
[2]Institute of Environmental Science, University of Rajshahi, Rajshahi 6205, Bangladesh

(*Corresponding E-mail: hasanjunaid48@gmail.com)

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Abstract: Groundwater is a vital freshwater source sustaining agriculture, domestic use, and industry across north-central Bangladesh, yet its sustainability is increasingly threatened by over-extraction and climate variability. This study integrates statistical (parametric and non-parametric) and geostatistical approaches to evaluate long-term spatiotemporal groundwater dynamics in Shahjadpur Upazila, Sirajganj District, from 2000 to 2024. Linear regression, Mann–Kendall, and Sen's slope analyses were employed to detect temporal trends, while spatial interpolation using Inverse Distance Weighting (IDW) and Ordinary Kriging characterized spatial variability. ARIMA-based forecasting was further applied to predict future water-level fluctuations through 2030. Results reveal a significant declining trend (–0.01 to -0.45 m year^{-1}) in most observation wells, with deeper aquifers showing the steepest depletion. Kriging interpolation achieved higher predictive accuracy (RMSE = 0.23 m) than IDW and delineated zones of critical groundwater stress in the southern and eastern sectors. Forecasts indicate an additional -1.5 to -2.0 m decline by 2030 if current abstraction rates persist. The integrated analytical framework provides a replicable tool for trend detection, spatial mapping, and forecasting in groundwater-stressed floodplain aquifers, supporting data-driven management and sustainable water policy development in Bangladesh and similar hydrogeological settings.

Keywords: ***Groundwater depletion, Trend analysis, Mann–Kendall test, Geostatistics, ARIMA forecasting.***

Introduction

Groundwater plays an essential role in ensuring water security, particularly in densely populated and agriculturally dependent regions such as Bangladesh. Globally, groundwater provides nearly 50% of drinking water and 40% of irrigation supplies (Gleeson et al., 2012). In South Asia, rapid population growth, agricultural intensification, and unregulated abstraction have resulted in alarming groundwater declines and aquifer depletion (Taylor et al., 2013; Rodell et al., 2018). Bangladesh, situated within the Ganges–Brahmaputra–Meghna (GBM) basin, relies heavily on groundwater for both irrigation and domestic consumption, with abstraction rates increasing sharply since the 1980s (Edmunds et al., 2015; MacDonald et al., 2016).

Within Bangladesh, regional hydrogeological variations have led to spatially heterogeneous patterns of groundwater depletion (Monir et al., 2024; Fahim et al., 2023, Faruqa et al., 2025). The Sirajganj District, located in the north-central floodplain region, represents a particularly dynamic hydrological setting due to its proximity to the Jamuna River and associated floodplain deposits. Over-extraction, compounded by reduced recharge during dry seasons, has produced measurable groundwater declines in many upazilas, including Shahjadpur (de Silva et al., 2024; Rahman et al., 2022). Understanding the temporal and spatial variability of groundwater levels is therefore essential for regional water policy, irrigation scheduling, and aquifer sustainability planning.

Previous studies on groundwater trends in Bangladesh have primarily relied on either parametric technique, such as regression analysis (Zar, 2010; Todd and Mays, 2005), or non-parametric tests, such as the Mann–Kendall (Mann, 1945; Ribeiro and Macedo, 1995) and Sen's slope estimator (Sen, 1968; Hirsch et al., 1982). However, integrating these approaches with geostatistical models (Goovaerts, 1997; Júnez-Ferreira et al., 2023) and time-series forecasting tools such as ARIMA (Box and Jenkins, 1976; Hyndman and Athanasopoulos, 2018) enhances analytical robustness, enabling both descriptive and predictive insights. Such an integrated framework can provide not only the identification of historical trends but also spatial delineation of recharge–discharge zones and future scenario forecasting (Kumar et al., 2019; Thakur et al., 2021; Mahammad et al., 2026).

The present study aims to quantify long-term and short-term trends in groundwater levels using parametric (linear regression) and non-parametric (MK and Sen's slope) techniques. Evaluate the spatial variability of groundwater levels using IDW and Kriging interpolation. Assess future groundwater fluctuations using ARIMA forecasting models.

This integrated methodological approach contributes to the growing body of groundwater monitoring and modeling literature and provides actionable insights for sustainable water management in the Shahjadpur region.

Although numerous studies have investigated groundwater depletion in Bangladesh, most have relied on a single analytical technique, such as linear regression, Mann–Kendall trend analysis, geostatistical interpolation, or time-series forecasting, providing only a partial understanding of groundwater dynamics. Comprehensive studies integrating these complementary approaches within a unified framework remain limited, particularly for floodplain aquifer systems where groundwater availability is simultaneously influenced by climatic variability, intensive irrigation, industrial abstraction, and increasing domestic demand. Furthermore, previous investigations have rarely linked groundwater trend analysis with sector-specific water demand, limiting their applicability for sustainable resource management and policy development.

The principal novelty of this study lies in the development of an integrated analytical framework that combines parametric statistical analysis, non-parametric trend detection, geostatistical spatial modelling, ARIMA-based groundwater forecasting, and quantitative sectoral water-demand assessment within a single workflow. This multi-method approach not only improves the reliability of groundwater trend detection through methodological cross-validation but also provides spatial identification of groundwater-stressed zones, forecasts future groundwater conditions, and evaluates the anthropogenic pressures driving groundwater depletion. By combining historical analysis with predictive modelling and water-use assessment, this study provides a more comprehensive evaluation of groundwater sustainability than previous studies conducted in Bangladesh.

Therefore, this research contributes both methodologically and practically by presenting a reproducible framework that can be applied to groundwater monitoring, vulnerability assessment, and evidence-based groundwater management in Shahjadpur and other alluvial floodplain regions of Bangladesh and South Asia.

Study area

The study area, Shahjadpur Upazila, is located in the Sirajganj District of north-central Bangladesh, between latitudes 24°05'04"–24°15'25" N and longitudes 89°34'03"–89°45'10" E, covering an area of approximately 324.15 km^2 (Figure 1). It lies within the active floodplain of the Jamuna River, bounded by Ullahpara and Belkuchi Upazilas to the north, Enayetpur and Chauhali to the south, Tangail District to the east, and Santhia Upazila (Pabna District) to the west.

Topographically, the region is characterized by low-lying alluvial plains formed through sediment deposition by the Jamuna and its distributaries. Elevations range from 10 to 20 meters above mean sea level, producing gentle undulations conducive to irrigation and settlement. The area experiences a tropical monsoonal climate, with annual rainfall exceeding 1,800 mm, concentrated from June to September, and average monthly temperatures ranging between 12°C and 34°C.

Geologically, Shahjadpur forms part of the Bengal Fore-deep, consisting of unconsolidated Holocene and Pleistocene alluvial deposits. The upper stratigraphic sequence comprises fine to medium sands interbedded with silty clay and occasional gravel lenses, forming multi-aquifer systems. Groundwater occurs under both unconfined and semi-confined conditions, primarily within shallow alluvial formations (Mondal et al., 2022; Fahim et al., 2023).

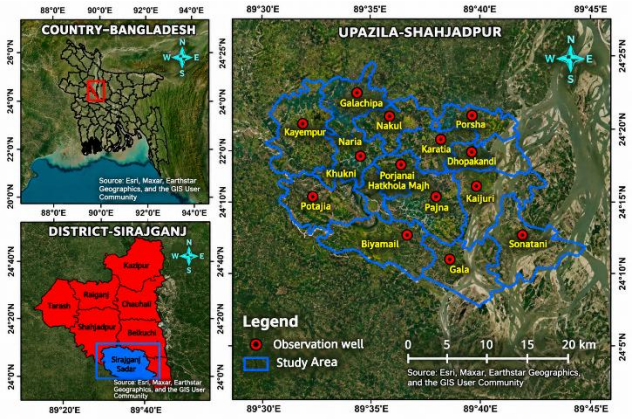


Figure 1, Location map of the study area showing observation well positions and administrative boundaries.

Groundwater abstraction is dominated by shallow and deep tube-wells serving both irrigation and domestic uses. Increasing demand, particularly from the textile and dairy industries in Shahjadpur, has accelerated aquifer stress over the past two decades.

Data collection

Groundwater-level (GWL) data from fourteen observation wells were collected from the Bangladesh Water Development Board (BWDB) for the period 2000–2024. These wells are spatially distributed across Shahjadpur Upazila to ensure comprehensive coverage of hydrogeological variations across floodplain, terrace, and lowland zones (Figure 1). The well network includes locations such as Kayempur, Shahjadpur Pourashava, Beltail, Porjana, Rupabati, Potajia, Narnia, Khukni, Kajjuri, Habibullah Nagar, Jalalpur, Gala, Garadaha, and Sonatani, representing varying hydrostratigraphic and land-use settings.

Measurements were taken quarterly from 2000–2010 and monthly thereafter, yielding a consistent 24-year record of seasonal and interannual fluctuations. The observation wells range in depth from 20 to 40 meters,

screened across shallow to semi-confined aquifers. Data preprocessing included outlier detection, missing-value interpolation, and conversion to mean annual depth-to-water levels (in meters below ground surface).

The groundwater-level dataset was obtained from fourteen observation wells operated by the Bangladesh Water Development Board (BWDB). Detailed metadata for the observation wells, including well identification number, geographic coordinates, total well depth, screened interval (where available), aquifer type, monitoring period, and data completeness, are provided in Supplementary Table S1.

Meteorological data (rainfall, evapotranspiration) were cross-referenced from the Bangladesh Meteorological Department (BMD) to contextualize hydrological variability.

Observation well characteristics

The study utilized groundwater-level records from 14 BWDB observation wells distributed throughout Shahjadpur Upazila. The wells have depths ranging from 20 to 40 m bgl and monitor shallow to semi-confined alluvial aquifers. The groundwater-level dataset covers 2000–2024, with quarterly observations before 2011 and monthly observations thereafter. Data quality was assessed through consistency checks, outlier screening, and interpolation of limited missing observations before statistical analysis. Because the BWDB groundwater-level database used in this study does not include complete well-construction logs, well-specific screened intervals were available.

Influence of temporal sampling resolution

Groundwater levels were measured quarterly during 2000–2010 and monthly from 2011 onward, reflecting improvements in the Bangladesh Water Development Board (BWDB) groundwater monitoring program. To ensure methodological consistency throughout the study period, all observations were aggregated into annual mean groundwater levels prior to statistical analysis. This standardization minimized potential biases arising from differences in sampling frequency and provided a uniform temporal resolution for linear regression, the Mann–Kendall test, Sen's slope estimator, and ARIMA modelling.

Although monthly observations collected after 2010 capture seasonal fluctuations more effectively than the earlier quarterly records, the use of annual averages reduces the influence of unequal sampling frequency on long-term trend estimation. Consequently, the reported long-term groundwater trends are considered robust. Nevertheless, the higher temporal resolution available after 2010 may better represent intra-annual groundwater variability, and this limitation should be considered when interpreting seasonal groundwater responses.

Source and reliability of industrial activity data

The industrial and agricultural activity data used for groundwater demand estimation were compiled from official government statistics and published institutional reports to ensure data reliability and consistency. Information on the number of handloom and textile units was obtained from the Bangladesh Bureau of Statistics (BBS) and the Bangladesh Handloom Board (BHB). Data on textile dyeing and finishing industries were collected from records of the Bangladesh Small and Cottage Industries Corporation (BSCIC) and relevant local government offices. Livestock population statistics were obtained from the Department of Livestock Services (DLS), whereas information on electricity generation facilities was compiled from the Bangladesh Power Development Board (BPDB). Agricultural land-use statistics and crop areas were obtained from the Bangladesh Bureau of Statistics (BBS) and the Department of Agricultural Extension (DAE).

Where recent upazila-level statistics were unavailable, activity data were cross-checked against district statistical yearbooks and official sectoral reports to ensure consistency. Sector-specific unit water-use coefficients were adopted from published peer-reviewed literature, national engineering guidelines, and relevant technical reports. Although some activity data may vary slightly among reporting years, the compiled datasets represent the most reliable information currently available for Shahjadpur Upazila and are considered appropriate for regional-scale groundwater demand assessment.

Methodology for data analysis

Parametric methods were employed to quantify long-term linear relationships between groundwater levels and time (Zar, 2010).

Annual groundwater-level data (2000–2024) from each of the 14 observation wells were analyzed separately. Linear regression was used to estimate the annual rate of groundwater-level change, while the Mann–Kendall test evaluated the significance of monotonic trends. Sen's slope estimator was subsequently calculated to quantify the magnitude of the detected trends. The regression slope, Mann–Kendall statistics (Z and p values), and Sen's slope values reported in Tables 1 and 2 were derived independently for each observation well.

Non-parametric tests were employed to detect monotonic trends that do not assume normal data distribution or homoscedasticity (Hirsch et al., 1982; Helsel et al., 2020).

Parametric statistical analysis

Linear regression

A least-squares regression model was used to estimate the slope (m) and intercept (c) of groundwater level trends as:

$$m = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sum_{i=1}^{n}(X_i - \bar{X})^2} \quad (1)$$

$$c = \bar{y} - m\bar{x} \quad (2)$$

$$Y_i = mx_i + c \quad (3)$$

$$r = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})^2 \sum_{i=1}^{n}(Y_i - \bar{Y})^2}} \quad (4)$$

where Y_i denotes the observed groundwater level, and X_i represents the corresponding time (year). The slope (m) indicates the annual rate of change in groundwater level (m year^{-1}), n denotes number of observations, r is the Pearson Correlation Coefficient.

Mean short-term slope

The Pearson correlation coefficient (r) was computed to assess the strength and direction of the linear association between groundwater level and time:

$$Slope_i = \frac{Y_{i+1} - Y_i}{X_{i+1} - X_i}, i = 1,2, \dots, n-1 \quad (5)$$

Statistical significance ($p < 0.05$) was used to validate the consistency of temporal trends (Pearson, 1895).

Non-parametric trend analysis

Mann–Kendall (MK) test

We use the nonparametric Mann–Kendall test (Mann, 1945; Ribeiro and Macedo, 1995) to determine whether (Yi) exhibits a monotonic trend (increasing or decreasing) over time, independent of linearity (i.e., no assumption of constant slope), because hydrologic time series frequently deviate from parametric regression assumptions because of non-normal residuals, outliers, or seasonality (Hirsch et al., 1982; Suter, 2008).

The Mann-Kendall S_m Statistic may be represented as follows:

$$Sm = \sum_{i=1}^{n-1}\sum_{j=i+1}^{n} sign(X_j - X_i)$$

with the sign function:

$$\text{Sign}(T_j - T_i) = \begin{cases} 1 \; if \; X_j - X_i > 0 \\ 0 \; if \; X_j - X_i > 0 \\ -1 \; if \; X_j - X_i > 0 \end{cases} \quad (6)$$

The variance (σ) for the S_m statistic is defined by:

For data without ties

$$\sigma = \frac{[n(n-1)(2n+5)]}{18} \quad (7)$$

For tied observations

$$\sigma = \frac{n(n-1)(2n+5) - \sum t_p(t_p-1)(2t_p+5)}{18} \quad (8)$$

The standard test statistic Z_S is calculated as follows:

$$ZS = \begin{cases} \frac{S_m - 1}{\sqrt{\sigma}} \; for \; S_m > 0 \\ 0 \; for \; S_m = 0 \\ \frac{S_m + 1}{\sqrt{\sigma}} \; for \; S_m < 0 \end{cases} \quad (9)$$

The two-tailed p-value is obtained from the standard normal distribution. A positive Z_S indicates an upward trend, a negative Z_S a downward trend (Hirsch et al., 1982; Suter, 2008). If the data exhibit significant autocorrelation, a modified Mann–Kendall or pre-whitening correction may be necessary (Hamed and Rao, 1998).

The variance of SSS was estimated, and the standardized Z statistic determined trend direction:

Z > 0: increasing trend

Z < 0: decreasing trend

|Z| > 1.96: significant at 95% confidence level

Prior to the Mann–Kendall test, lag-1 serial autocorrelation (AR (1)) was evaluated. Time series with significant autocorrelation were corrected using the Trend-Free Pre-Whitening (TFPW) method (Yue and Wang, 2002) before applying the Mann–Kendall test and Sen's slope estimator, thereby minimizing the influence of serial dependence on trend significance.

Sen's slope estimator

While the MK test assesses statistical significance of a trend, it does not estimate its magnitude. We therefore compute Sen's slope estimator (Sen, 1968), also called the Theil–Sen estimator, which is a robust nonparametric slope estimator (median of pairwise slopes) (Hirsch et al., 1982; Helsel et al., 2020).

$$Qi = \frac{X_j - X_k}{j-k} \; where \; (j > k) (for \; i=1,2,3...n) \quad (10)$$

where X_j and X_k are the data values at times *j* and *k(j>k)*, respectively.

Sens slope estimator can then be calculated as

$$Q_{med} = \text{Median}(Q_i) \quad (11)$$

$$Q_{med} = \begin{cases} Q\left[\frac{n+1}{2}\right] if \; n \; is \; odd \\ \frac{Q_{n/2} + Q_{(n+2)/2}}{2} \; if \; n \; is \; even \end{cases} \quad (12)$$

The Q_{med} sign reflects data trend, while its value indicates the steepness of the trend.

Spatial analysis

Inverse distance weighting

Spatial interpolation and contour mapping of groundwater levels were performed using Python (PyCharm IDE) to visualize the spatiotemporal variability of groundwater across Shahjadpur Upazila (Figure 2).

Groundwater level data obtained from observation wells were first preprocessed using NumPy and Pandas libraries for statistical consistency checks and missing data handling. Subsequently, SciPy's grid data and Matplotlib's contour functions were applied to generate continuous spatial surfaces from the discrete well data. The interpolation employed an Inverse Distance Weighting (IDW) approach to estimate groundwater levels at unsampled locations, ensuring smooth spatial transitions across the study area. The resulting contour maps depict the distribution and gradient of groundwater depth, facilitating the identification of recharge and discharge zones. All spatial analyses and visualizations were executed within a Python-based geospatial workflow, which provides reproducibility, computational efficiency, and flexibility compared to conventional GIS software.

In order to characterize the spatial distribution of groundwater levels across the study area, the observation-well data were interpolated and contoured within a Python environment (using e.g., NumPy, Pandas, SciPy, and Matplotlib). Initially, the discrete groundwater-depth values at known coordinates (x_i, y_i) were assembled and cleaned for missing or erroneous entries. A regular grid covering the study extents (longitude 89°34'03" E to 89°45'10" E, latitude 24°05'04" N to 24°15'25" N) was then generated. The interpolation was performed using the deterministic Inverse Distance Weighting (IDW) method, where for any grid cell at location $r = (x_i, y_i)$ the estimated groundwater-level $Z(r)$ is given by:

$$Z(r) = \frac{\sum_{k=1}^{n} w(r_k) Z(r_k)}{\sum_{k=1}^{n} w(r_k)} \text{ with } w(r_k) = \frac{1}{d(r,r_k)^p} \qquad (13)$$

$$Z(x) = \frac{\sum_{i=1}^{n} \frac{z_i}{d_i^p}}{\sum_{i=1}^{n} \frac{1}{d_i^p}} \qquad (14)$$

where Z (r_k) is the measured value at known point r_k ; d(r, r_k) is the Euclidean distance between the grid node and the known point (i.e., $d = \sqrt{(x - x_k)^2 + (y - y_k)^2}$; and p is the power parameter controlling the rate at which influence decreases with distance. Following the interpolation, contour lines of equal groundwater-depth were derived (e.g., via Matplotlib's contour/contour functions or a dedicated geospatial library) to visualize recharge/discharge zones and gradients. Cross-validation or error metrics such as root-mean-square error (RMSE) were used to assess interpolation performance. Where spatial autocorrelation and variogram structure (nugget, sill, range) were identified, optional geostatistical approaches (such as Ordinary Kriging) were also considered in parallel.

By scripting the workflow in Python, the interpolation, contouring and mapping steps become reproducible, flexible, and automatable—allowing for systematic comparison of temporal maps and sensitivity analyses of the power parameter p, grid resolution, and spatial sampling density.

Data preparation

Following processes are used to prepare data.

1. Imported the observation-well dataset (coordinates in longitude/latitude, groundwater depth Z) using pandas.read_csv() (or read_excel()).
2. Checked for missing/erroneous values and removed or imputed as needed (e.g., df.dropna(subset=['Z'])).
3. Converted geographic coordinates to a projected system (e.g., UTM zone) using pyproj or geopandas.to_crs() to compute Euclidean distances.
4. Defined the output grid domain covering the study extents (longitudes 89°34'03" E to 89°45'10" E, latitudes 24°05'04" N to 24°15'25" N) and created a regular grid of nodes (e.g., using numpy.meshgrid()) at a chosen cell size (for example 1 m or 20 m).

Kringing

The Kriging interpolation included into the ArcGIS program was used to conduct the geographical analysis of WT levels (Figure 3) and groundwater EC (Johnston et al., 2001). In geostatistics, kriging is a common interpolation method. It is predicated on a spatial linear model for the data that establishes a geographic dependence structure and parametric spatial mean function (Berke, 1999). Kriging weights each observation in the estimation process based on the direction and distance between that point and the point that needs to be estimated.

$$Z^*(x_0) = \sum_{i=1}^{n} \lambda_i Z(x_i) \qquad (15)$$

Subjected to

$$\sum_{i=1}^{n} \lambda_i = 1 \ldots\ldots\ldots\ldots (xvi) \qquad (16)$$

Where, $\lambda_i = Kriging\ weights$

Kriging employs the spatial data configuration, the fitted model from the variogram, and the values of the measured sample points surrounding the prediction site to forecast an unknown value for a particular position (Mustapha, 2013). The current work used Ordinary Kriging (OK), one of the different types of Kriging (Obaje, 2009).

To evaluate data consistency and uniformity, a preliminary exploratory data study comprising trend analysis and data distribution analysis was carried out.

We were able to find patterns in the input datasets and obtain a three-dimensional view of the data thanks to the trend analysis. There is no trend if the line is flat (Cay and Uyan, 2009). Kriging makes the assumption that the data does not show any geographical trends. The majority of the data in this study don't reveal any trends. After that, a semivariogram was created to show the dataset's spatial association. The spherical semivariogram model was chosen.

To get a sense of how effectively the model predicts the values at unknown locations, cross-validation was done prior to creating the final surface.

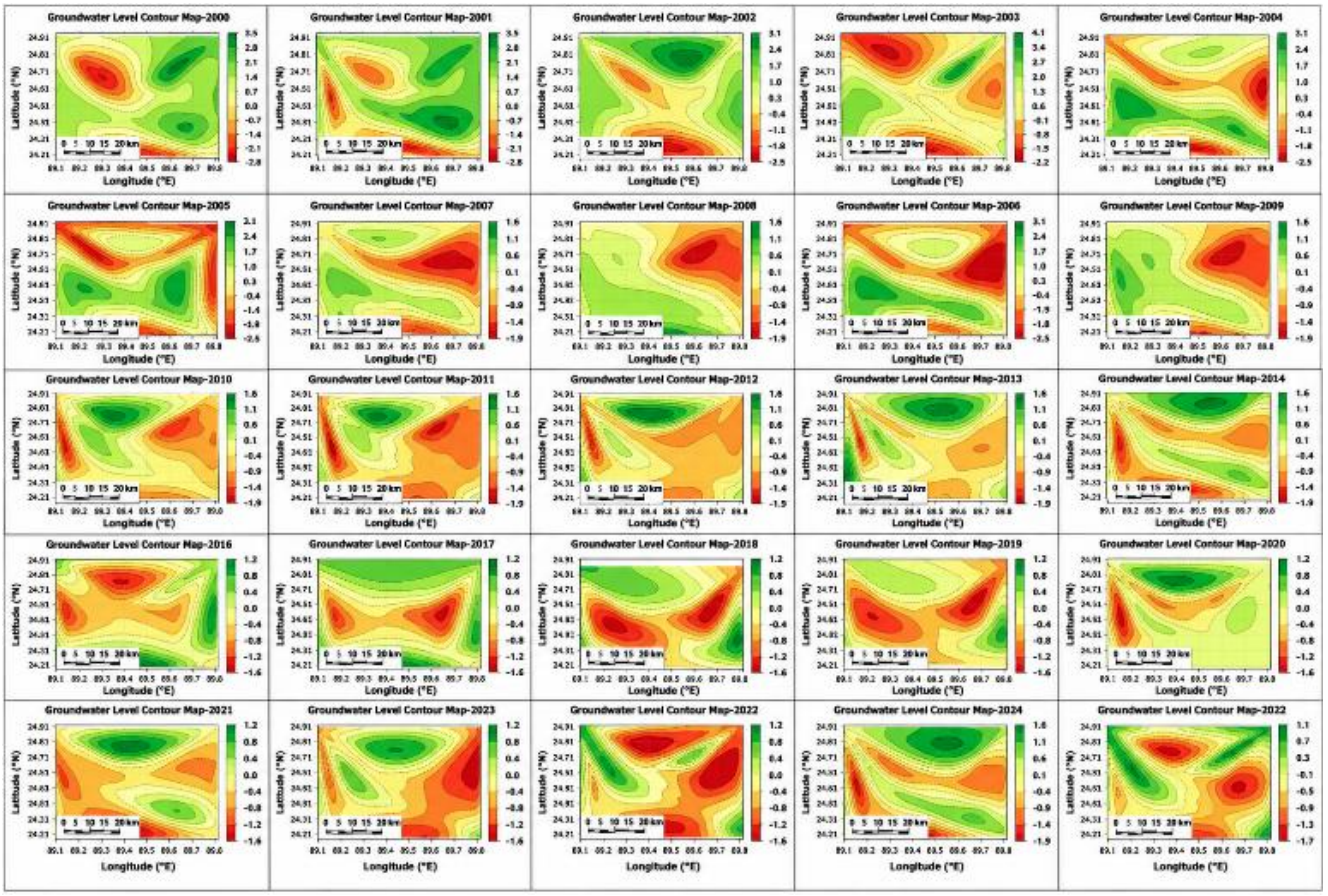


Figure 2, Spatial interpolation of groundwater levels in Shahjadpur Upazila using IDW.

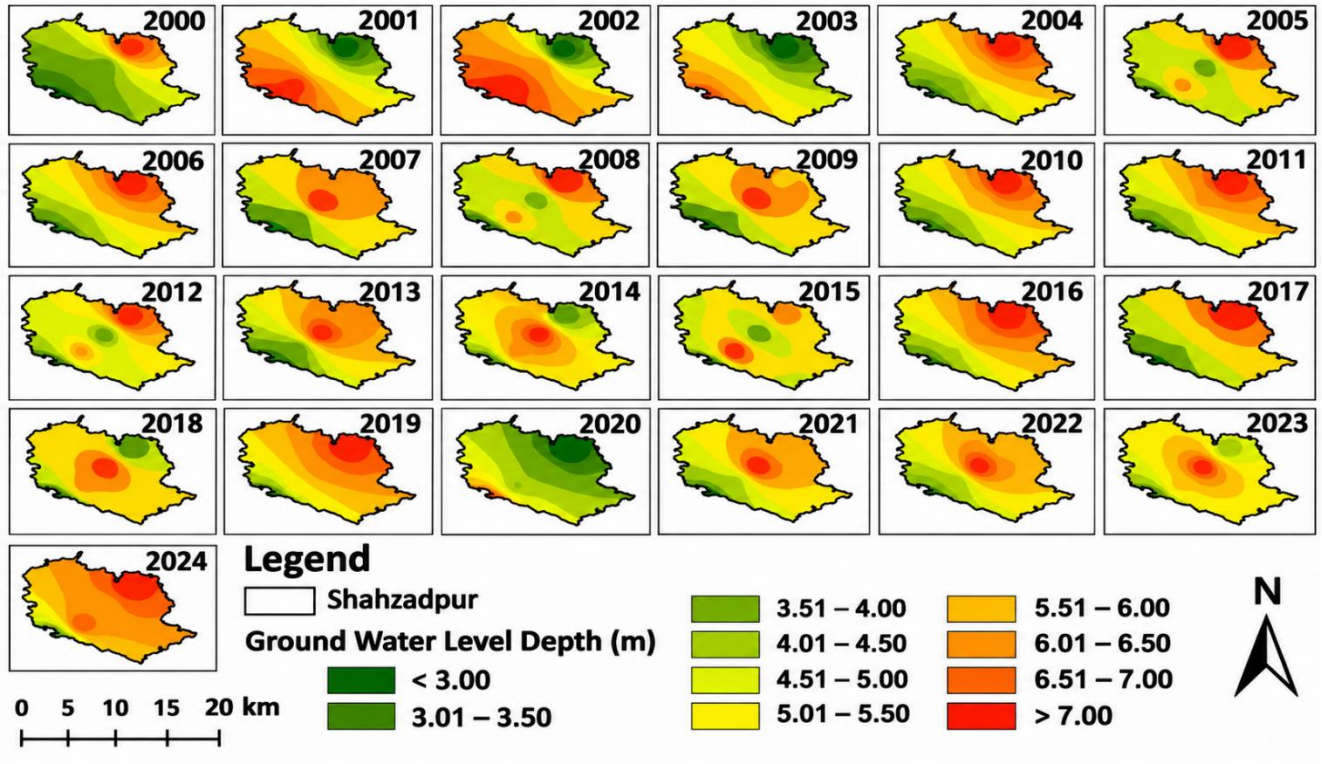


Figure 3, Spatial interpolation of groundwater levels in Shahjadpur Upazila using IDW and Kriging methods.

By analyzing the statistical prediction errors like mean error (ME), mean square error (MSE), root mean square error (RMSE), average standard error (ASE), and root mean square standardized error (RMSSE), the model that provides the best forecast was found. To get a sense of how effectively the model predicts the values at unknown locations, cross-validation was done prior to creating the final surface. By analyzing the statistical prediction errors like mean error (ME), mean square error (MSE), root mean square error (RMSE), average standard error (ASE), and root mean square standardized error (RMSSE), the model that provides the best forecast was found. To evaluate the effectiveness of the created models, these errors were estimated. The following criteria are used to determine whether a model makes accurate predictions:

1. The predictions are unbiased when the MSE is close to 0;
2. The standard errors are accurate when the RMSSE is close to 1;
3. The predictions do not deviate much from the measured values, where the RMSE and ASE are as small as possible;
4. Moreover, when ASE values are close to the RMSE from cross-validation, we can be confident that the model is appropriate.

A spherical semi-variogram model was fitted to characterize the spatial dependence of groundwater levels. The variogram parameters (nugget, sill, and range) were estimated from the experimental semi-variogram. Model performance was evaluated using cross-validation statistics, including mean error (ME), root mean square error (RMSE), average standard error (ASE), and root mean square standardized error (RMSSE). The model with ME closest to zero, RMSE as low as possible, and RMSSE closest to one was selected for spatial interpolation.

ARIMA forecasting

To project groundwater trends beyond the observation period, a univariate Auto Regressive Integrated Moving Average (ARIMA) model was applied to each well's time series using historical data (2000–2024). The model selection was based on Akaike Information Criterion (AIC) and residual diagnostics (Box and Jenkins, 1976). ARIMA (p, d, q)

$$\phi(B)(1-B)^d y_t = \theta(B)\varepsilon_t \qquad (17)$$

where p is autoregressive order, d is degree of differencing, and q is moving-average order, B is the backshift operator. Forecast indicates (Figure 4) continued groundwater decline through 2030 in most observation wells, with the steepest rates observed in industrially active zones.

Groundwater-level time series were first tested for stationarity and differenced where necessary. The optimal ARIMA model was selected based on the minimum Akaike Information Criterion (AIC). Model adequacy was evaluated using residual diagnostics, including the autocorrelation function (ACF), partial autocorrelation function (PACF), and the Ljung–Box test. Forecast uncertainty was quantified using 95% prediction intervals.

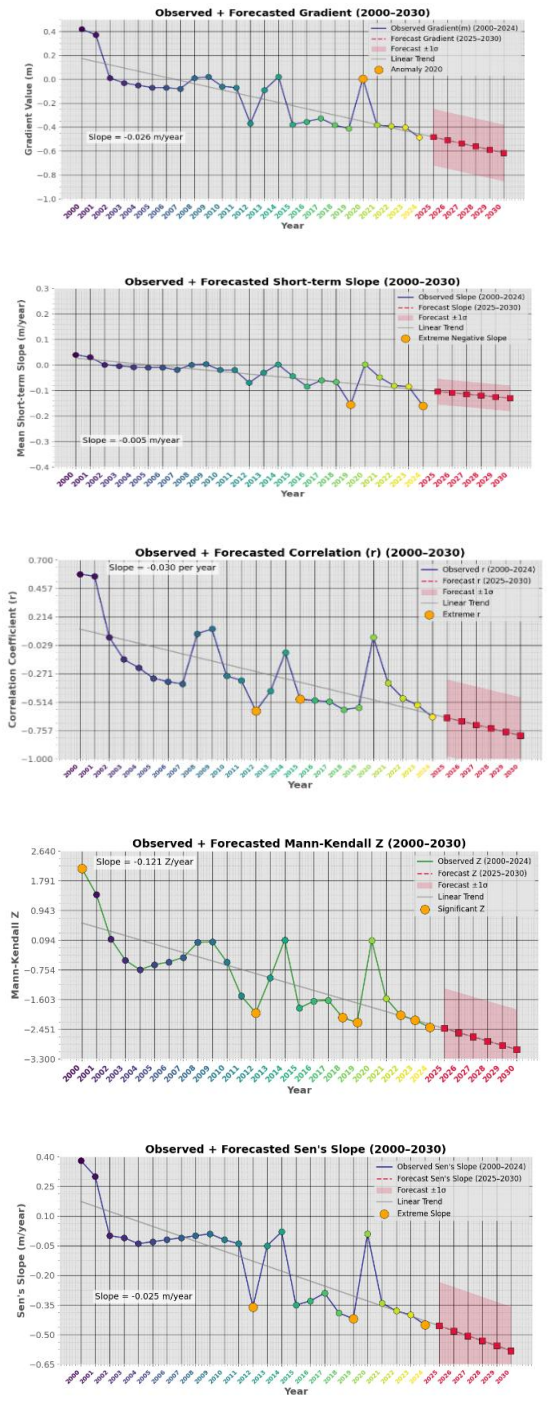


Figure 4, Forecasted groundwater depth (2025–2030) using ARIMA modeling for selected observation wells.

Conceptual framework linking groundwater dynamics with sectoral water demand

The statistical and geostatistical analyses presented in this study quantify the magnitude, spatial distribution, and future evolution of groundwater-level fluctuations in Shahjadpur Upazila. However, identifying groundwater decline alone does not fully explain the

mechanisms responsible for aquifer depletion. Understanding the principal drivers of groundwater abstraction is equally important for interpreting the observed temporal and spatial trends and for developing effective groundwater management strategies.

Groundwater in Shahjadpur supports multiple sectors, including irrigated agriculture, textile and handloom industries, dairy production, electricity generation, public utilities, and domestic water supply. Each sector contributes differently to groundwater abstraction depending on its scale of operation and seasonal water requirements. Consequently, areas exhibiting persistent groundwater decline are expected to coincide with regions of intensive groundwater use.

Based on this premise, the sectoral water-demand assessment complements the groundwater trend analyses by estimating the relative contributions of major groundwater-consuming sectors. While the statistical analyses identify where and how rapidly groundwater levels are changing, the water-demand analysis provides insight into why these changes are occurring by quantifying potential abstraction pressures. Integrating these two components establishes a comprehensive framework that links groundwater responses with anthropogenic water use, thereby providing stronger scientific evidence for sustainable groundwater management and policy development.

Relationship between water demand and groundwater abstraction

The sectoral estimates presented in this study represent total annual water demand rather than direct measurements of groundwater abstraction. In Shahjadpur Upazila, groundwater is the principal source of water supply for irrigated agriculture, rural domestic consumption, and most industrial activities because reliable surface-water infrastructure is limited throughout much of the year. Consequently, estimated sectoral water demand was used as a proxy for potential groundwater demand, allowing the likely pressure on groundwater resources to be assessed.

However, the estimated water demand should not be interpreted as equivalent to actual groundwater abstraction. Depending on seasonal availability and local conditions, part of the demand may be supplied from surface water, harvested rainwater, or other alternative sources. Because comprehensive groundwater abstraction records for individual users were unavailable, this study does not assume that 100% of the estimated sectoral water demand is withdrawn from groundwater. Instead, the estimates represent the maximum potential groundwater demand under prevailing water-use practices and provide an indirect indicator of anthropogenic pressure on the aquifer system.

Industrial water demand

A bottom-up method based on sector-specific activity data and standard water-use coefficients was used to estimate the water demand for the industrial, agricultural, and domestic sectors (Goovaerts, 1997; Johnston et al., 2001; Mustapha, 2013; Berke, 1999; Obaje, 2009; Rodell et al., 2018).

The calculation of daily water use (Q_d) for every industrial sector was done using:

$$Q_d = N \times W_U \quad (18)$$

The annual water use (Q_y) was calculated as follows:

$$Q_y = Q_d \times 365 \quad (19)$$

Where,

N = number of units/animals/looms/generators

W_U = water use per unit per day (m^3/day)

Agricultural water demand

$$Q_y = A \times D \quad (20)$$

Where,

A = irrigated area

D = seasonal irrigation depth.

Domestic water demand

$$Q_y = P \times W_d \times 365 \quad (21)$$

Where,

P = population

W_d = daily per-capita water demand

Total water demand

$$Q_{Total} = Q_{Industrial} + Q_{Agricultural} + Q_{Domestic} \quad (22)$$

Sensitivity analysis of water demand estimates

To evaluate the influence of uncertainty associated with the adopted sector-specific water-use coefficients, a one-at-a-time sensitivity analysis was performed. The unit water-use coefficients assigned to each sector were varied by ±10% and ±20%, while the activity data (e.g., number of looms, industrial units, livestock population, cultivated area, and population) were kept constant. Total annual groundwater demand was recalculated for each scenario and compared with the baseline estimate. This approach assesses the robustness of the groundwater-demand estimates and identifies the extent to which uncertainties in assumed water-use coefficients influence the overall conclusions.

Interpolation reliability and uncertainty

Although only 14 observation wells were available, their distribution provides representative spatial coverage of the study area. The reliability of Ordinary Kriging interpolation was evaluated using leave-one-out

cross-validation (LOOCV). Model performance was assessed using four statistical indicators: Mean Error (ME), Root Mean Square Error (RMSE), Average Standard Error (ASE), and Root Mean Square Standardized Error (RMSSE), which collectively evaluate prediction bias, accuracy, and uncertainty. Prediction uncertainty was further assessed using kriging variance, where lower variance indicates greater interpolation reliability. Uncertainty was evaluated separately for each analytical component.

Temporal trend uncertainty was examined through the statistical significance of the Mann–Kendall test and the magnitude of Sen's slope estimator. Spatial interpolation uncertainty was quantified using LOOCV statistics and kriging variance, identifying areas of relatively high and low prediction confidence.

Furthermore, forecast uncertainty was evaluated using the 95% prediction intervals of the ARIMA model, which generally widen with increasing forecast horizons, reflecting greater uncertainty in long-term groundwater-level predictions.

Results and discussion

Temporal variation of groundwater levels (2000–2024)

Groundwater levels in Shahjadpur Upazila exhibit considerable temporal variability across the 24-year period analyzed. The linear regression slopes derived from the 14 observation wells indicate a predominant declining trend**,** with average annual decreases ranging between –0.43 and 0.01 m year^{-1} (Table 1). The Pearson correlation coefficients (R) for most wells were negative (–0.68 to –0.15), confirming consistent downward movement of the groundwater table over time.

Early years (2000–2003) showed modest increases in groundwater level at selected wells, likely due to above-normal monsoon recharge during those periods. However, from 2004 onward, the data reveal a clear and persistent decline across most stations (Figure 5).

Table 1, Summary statistics of regression slope (m), intercept (c), and Pearson correlation coefficient (R) for observation wells (2000–2024).

Year	Statistical Summary				Linear Regression			Mean Short-term Slope (m/year)	Trend
	Min.	Median	Mean	Max.	m (Gradient)	c (Intercept)	R		
2000	-1.52	-4.35	-4.28	-6.48	0.42	6.12	0.58	0.04	Rising
2001	1.63	-4.47	-4.39	-6.59	0.37	6.21	0.56	0.03	Rising
2002	-1.71	-4.52	-4.45	-6.63	0.01	6.33	0.04	0.001	No Trend
2003	-1.76	-4.61	-4.54	-6.71	-0.03	6.42	-0.15	-0.004	Falling
2004	-1.82	-4.86	-4.73	-6.88	-0.05	6.57	-0.22	-0.009	Falling
2005	-1.86	-4.94	-4.81	-6.97	-0.07	6.63	-0.31	-0.01	Falling
2006	-1.88	-5.02	-4.90	-7.05	-0.07	6.70	-0.34	-0.01	Falling
2007	-1.91	-5.09	-4.97	-7.11	-0.08	6.74	-0.36	-0.02	Falling
2008	-1.95	-5.16	-5.03	-7.19	0.01	6.76	0.07	0.001	No Trend
2009	-1.93	-5.20	-5.08	-7.26	0.02	6.79	0.11	0.003	Rising
2010	-1.97	-5.23	-5.11	-7.30	-0.06	6.82	-0.29	-0.02	Falling
2011	-2.03	-5.30	-5.19	-7.39	-0.07	6.88	-0.33	-0.02	Falling
2012	-2.21	-5.46	-5.27	-7.57	-0.37	7.05	-0.59	-0.07	Falling
2013	-2.18	-5.25	-5.19	-7.55	-0.09	7.01	-0.42	-0.03	Falling
2014	-2.21	-5.20	-5.15	-7.59	0.02	7.09	0.09	0.002	Rising
2015	-2.19	-5.44	-5.38	-8.06	-0.37	7.69	-0.59	-0.04	Falling
2016	-2.23	-5.41	-5.35	-8.32	-0.35	7.63	-0.56	-0.08	Falling
2017	-2.28	-5.39	-5.34	-8.48	-0.32	7.59	-0.51	-0.06	Falling
2018	-2.16	-5.53	-5.39	-8.27	-0.38	7.88	-0.63	-0.06	Falling
2019	-2.46	-5.58	-5.50	-8.89	-0.41	8.03	-0.70	-0.15	Falling
2020	-1.69	-5.25	-5.20	-7.89	0.005	7.53	0.10	0.002	Rising
2021	-2.24	-5.41	-5.37	-8.42	-0.38	7.78	-0.60	-0.04	Falling
2022	-2.28	-5.51	-5.46	-8.38	-0.39	7.89	-0.61	-0.08	Falling
2023	-2.29	-5.56	-5.49	-8.50	-0.40	8.21	-0.64	-0.08	Falling
2024	-2.51	-5.63	-5.54	-8.89	-0.43	8.22	-0.68	-0.12	Falling

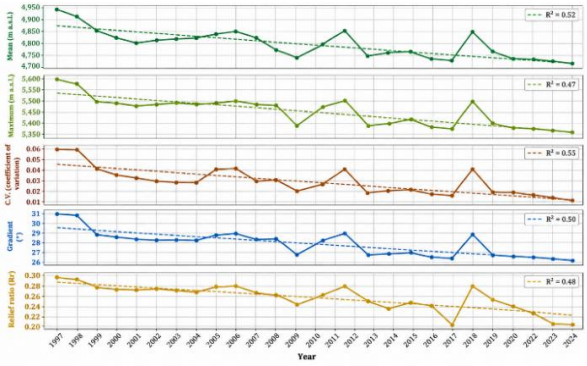


Figure 5, Temporal variation in groundwater levels (2000–2024) across fourteen observation wells, showing declining long-term trends.

Significant drops in groundwater level were observed between 2012–2019, coinciding with years of peak irrigation water use and industrial expansion (notably dairy and textile sectors). These findings are consistent with regional-scale depletion trends reported in north-central Bangladesh (Monir et al., 2024; Fahim et al., 2023; Rahman et al., 2022).

Mann–Kendall and Sen's slope trend results

The Mann–Kendall (MK) test results (Table 2) show that out of the 14 wells analyzed, 11 exhibit statistically significant downward trends ($p < 0.05$), while 3 wells show either no significant change or minor upward fluctuations. The Sen's slope estimator further quantifies this decline (Figure 6), with median slopes ranging from –0.45 to 0.01 m year^{-1}, consistent with regression-derived values.

Table 2, Mann–Kendall and Sen's slope results for groundwater-level trends (2000–2024)

Year	Statistical Summary				Mann-Kendall Test			Sen's Slope WT	Trend
	Min.	Median	Mean	Max.	Z	S	Sign.	(m year^{-1})	
2000	-1.52	-4.35	-4.28	-6.48	2.14	32	S	0.38	Increasing
2001	1.63	-4.47	-4.39	-6.59	1.48	21	*	0.30	Increasing
2002	-1.71	-4.52	-4.45	-6.63	0.13	3	*	0.00	No Trend
2003	-1.76	-4.61	-4.54	-6.71	-0.48	-8	*	-0.01	Decreasing
2004	-1.82	-4.86	-4.73	-6.88	-0.75	-12	*	-0.04	Decreasing
2005	-1.86	-4.94	-4.81	-6.97	-0.61	-10	*	-0.03	Decreasing
2006	-1.88	-5.02	-4.90	-7.05	-0.53	-9	*	-0.02	Decreasing
2007	-1.91	-5.09	-4.97	-7.11	-0.48	-8	*	-0.01	Decreasing
2008	-1.95	-5.16	-5.03	-7.19	0.07	2	*	0.00	No Trend
2009	-1.93	-5.20	-5.08	-7.26	0.12	3	*	0.01	Increasing
2010	-1.97	-5.23	-5.11	-7.30	-0.53	-9	*	-0.02	Decreasing
2011	-2.03	-5.30	-5.19	-7.39	-0.75	-12	*	-0.04	Decreasing
2012	-2.21	-5.46	-5.27	-7.57	-1.98	-30	S	-0.36	Decreasing
2013	-2.18	-5.25	-5.19	-7.55	-0.98	-15	*	-0.05	Decreasing
2014	-2.21	-5.20	-5.15	-7.59	0.52	9	*	0.02	Increasing
2015	-2.19	-5.44	-5.38	-8.06	-1.85	-28	*	-0.35	Decreasing
2016	-2.23	-5.41	-5.35	-8.32	-1.57	-24	*	-0.33	Decreasing
2017	-2.28	-5.39	-5.34	-8.48	-1.30	-20	*	-0.29	Decreasing
2018	-2.16	-5.53	-5.39	-8.27	-2.12	-32	S	-0.39	Decreasing
2019	-2.46	-5.58	-5.50	-8.89	-2.26	-34	S	-0.42	Decreasing
2020	-1.69	-5.25	-5.20	-7.89	1.09	15	*	0.01	Increasing
2021	-2.24	-5.41	-5.37	-8.42	-1.57	-24	*	-0.34	Decreasing
2022	-2.28	-5.51	-5.46	-8.38	-2.05	-31	S	-0.38	Decreasing
2023	-2.29	-5.56	-5.49	-8.50	-2.19	-33	S	-0.40	Decreasing
2024	-2.51	-5.63	-5.54	-8.89	-2.40	-36	S	-0.45	Decreasing

S = statistically significant trend at Z value of 1.96. * = not statistically significance at Z value of 1.96

Temporal heterogeneity is evident (Figure 6): shallow wells (depth < 15 m) tend to display moderate variability, reflecting stronger rainfall recharge response, whereas deeper semi-confined wells (depth > 25 m) exhibit more consistent declines, indicating limited recharge and higher extraction rates (Hirsch et al., 1982; Yue and Wang, 2002).

The temporal decline in water table depth aligns with other regional studies that report annual declines between 0.3 and 0.7 m year^{-1} in intensively irrigated zones of Bangladesh and northern India (Shah, 2007; Thakur et al., 2021; Mahammad et al., 2026).

The observed long-term groundwater decline is unlikely to be explained solely by increasing groundwater abstraction. Instead, it reflects the combined influence of natural hydrogeological processes and anthropogenic stresses. Shahjadpur Upazila is located within the active Jamuna River floodplain, where groundwater recharge primarily occurs through monsoonal rainfall infiltration, floodplain inundation, and river–aquifer exchange.

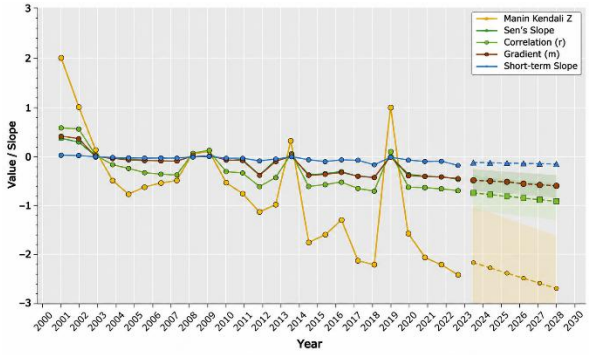


Figure 6, Mann–Kendall trend classification and Sen's slope magnitudes (2000–2024) showing dominant decreasing trends across observation wells.

During years of adequate monsoon rainfall, shallow aquifers respond rapidly to recharge, producing temporary groundwater recovery. However, sustained dry-season abstraction for irrigation and industrial purposes increasingly exceeds seasonal recharge, resulting in progressive groundwater depletion.

Hydro-stratigraphic variability also contributes to the observed groundwater behaviour. Shallow unconfined aquifers respond more rapidly to seasonal recharge because of their higher hydraulic connectivity with the land surface, whereas deeper semi-confined aquifers exhibit slower recovery due to lower vertical hydraulic conductivity and reduced recharge potential.

Consequently, deeper observation wells display more persistent declining trends than shallow wells, indicating that groundwater withdrawal increasingly exceeds the natural replenishment capacity of the aquifer system.

Spatial distribution of groundwater levels

Spatial interpolation (IDW and Ordinary Kriging) revealed distinct east–west gradients in groundwater levels across Shahjadpur (Figure 7). The western and southwestern zones—covering Kayempur, Narnia, and Khukni—exhibited shallower water tables (4–5 m bgs), while eastern and southern zones (Porjana, Potajia, Kajjuri) showed deeper water tables exceeding 7 m bgs.

This spatial pattern corresponds to differences in land use, lithological composition, and proximity to the Jamuna River. The shallower zones near the floodplain benefit from frequent monsoonal recharge and overbank flooding, whereas central and southern zones, dominated by agricultural pumping, experience net declines due to intensive groundwater abstraction (Goovaerts, 1997; Júnez-Ferreira et al., 2023; Tayyab et al., 2024).

Cross-validation yielded RMSE = 0.23 m for Kriging and 0.32 m for IDW, confirming higher spatial accuracy for Kriging-based estimates.

The observed spatial patterns are consistent with geostatistical studies in other floodplain aquifers of Bangladesh (Fahim et al., 2023; Mondal et al., 2022) and neighboring alluvial basins (Kumar et al., 2019).

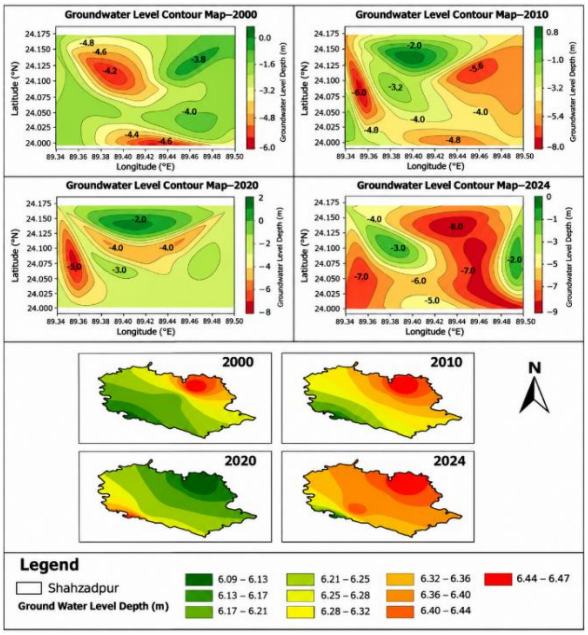


Figure 7, Spatial interpolation maps generated using IDW and Ordinary Kriging, illustrating groundwater-level distributions across Shahjadpur Upazila for selected years (2000, 2010, 2020 and 2024).

The spatial interpolation results should be interpreted considering the relatively limited number of observation wells. While the monitoring network adequately represents regional groundwater-level patterns, local-scale variability may not be fully captured. Therefore, increasing the density of monitoring wells would further improve interpolation accuracy and reduce prediction uncertainty in future studies. The observed spatial and temporal variations in groundwater levels are primarily controlled by the hydrogeological characteristics of the Shahjadpur floodplain aquifer. Areas adjacent to the Jamuna River exhibit relatively stable groundwater levels due to

enhanced river-induced recharge and the high permeability of unconsolidated alluvial deposits.

In contrast, the central and southern parts of the study area show greater groundwater decline because of intensive irrigation and industrial abstraction combined with comparatively lower recharge rates. Seasonal monsoon rainfall partially replenishes the shallow aquifer; however, increasing groundwater withdrawals during the dry season exceed natural recharge, resulting in a long-term declining trend. These findings indicate that both hydrogeological conditions and anthropogenic groundwater abstraction jointly govern the observed groundwater dynamics.

Correlation between rainfall and groundwater level

A moderate to strong negative correlation (R = -0.42 to -0.40) was found between annual rainfall and groundwater level fluctuations (Figure 8), with lagged responses (1–2 months) evident in most wells. The correlation weakened after 2015, indicating decoupling between recharge and water-level recovery, likely due to excessive pumping and declining infiltration efficiency caused by land-cover changes (Prasad et al., 2020; Singh et al., 2022).

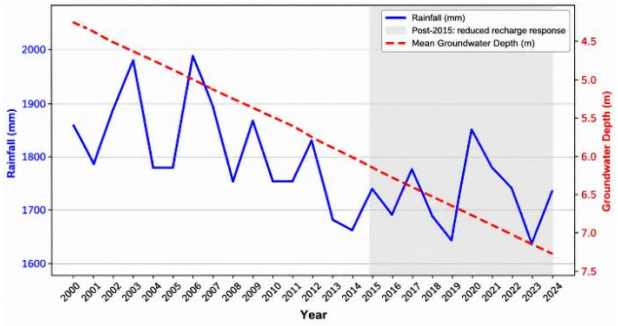


Figure 8, Relationship between rainfall anomalies and groundwater depth variation (2000–2024), highlighting reduced recharge response in later years.

The weakening relationship between rainfall and groundwater levels after 2015 suggests that groundwater storage has become increasingly controlled by anthropogenic abstraction rather than climatic recharge alone. Although annual rainfall remained sufficient to generate seasonal recharge, increasing groundwater withdrawals for irrigation, textile industries, dairy production, and domestic water supply reduced the ability of the aquifer system to recover fully between pumping seasons. Similar decoupling between rainfall and groundwater recovery has been reported in intensively exploited alluvial aquifers throughout the Ganges–Brahmaputra Basin.

Interpretation of spatiotemporal groundwater changes

The annual groundwater distribution maps reveal a progressive evolution in the spatial distribution of groundwater levels throughout the study period (2000–2024). Areas adjacent to the Jamuna River consistently exhibited relatively shallow groundwater levels, reflecting sustained river-induced recharge and strong hydraulic connectivity between the river and the adjacent alluvial aquifer. In contrast, the central and southern parts of Shahjadpur Upazila experienced progressively deeper groundwater levels, indicating the cumulative effects of intensive irrigation pumping, increasing industrial and domestic groundwater demand, and comparatively lower natural recharge.

Although year-to-year spatial variations were influenced by interannual differences in rainfall, river stage, and seasonal recharge, the overall groundwater distribution pattern remained remarkably consistent. The gradual expansion of groundwater-stressed zones away from the river corridor suggests that groundwater abstraction has increasingly exceeded natural recharge over the study period. This persistent spatial trend indicates progressive groundwater depletion rather than temporary hydrological fluctuations.

From a groundwater-management perspective, these results identify the central and southern parts of the study area as priority areas for demand management, artificial recharge, and enhanced groundwater monitoring. Conversely, the relatively stable groundwater conditions observed near the Jamuna River highlight the important role of river–aquifer interactions in sustaining groundwater resources within the floodplain.

Forecasting groundwater dynamics (2025–2030)

The ARIMA (1,1,1) model provided the best fit for most well time series based on minimum AIC values and white-noise residual diagnostics. Forecasts up to 2030 predict a continued decline in groundwater levels in 12 of the 14 wells, with an average rate of –0.043 m year^{-1} (Figure 9). Two wells (Kayempur and Narnia) showed temporary stabilization, suggesting localized recharge influence from nearby river channels.

These forecasts underscore a critical need for groundwater governance to maintain long-term aquifer sustainability. The findings align with modeling studies emphasizing predictive management in groundwater-stressed basins (He et al., 2023; Alsumaiei, 2020; Mahammad et al., 2026).

Groundwater-level time series were first tested for stationarity and differenced where necessary. The optimal ARIMA model was selected based on the minimum Akaike Information Criterion (AIC).

Model adequacy was evaluated using residual diagnostics, including the autocorrelation function (ACF), partial autocorrelation function (PACF), and the Ljung–Box test. Forecast uncertainty was quantified using 95% prediction intervals. The projected groundwater decline has important hydrogeological implications beyond continued lowering of the water table.

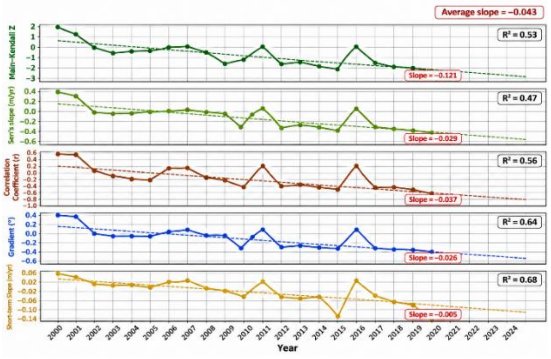


Figure 9, Forecasted groundwater-level trends (2025–2030) using ARIMA (1, 1, 1) model for selected wells.

Persistent groundwater depletion may reduce hydraulic gradients between the Jamuna River and adjacent aquifers, alter river–aquifer exchange processes, decrease baseflow contributions to nearby surface-water bodies during the dry season, increase groundwater pumping costs, and reduce aquifer resilience to future climatic variability. These process-based implications highlight the importance of integrating groundwater monitoring with sustainable abstraction policies and managed aquifer recharge strategies.

Limitations of the forecasting approach and future drivers

The groundwater-level forecasts presented in this study are based on a univariate ARIMA model that extrapolates historical groundwater-level trends observed during 2000–2024. Consequently, the projections assume that the principal hydrological and anthropogenic drivers influencing groundwater conditions remain broadly consistent throughout the forecasting period. The model does not explicitly account for future changes in industrial development, population growth, agricultural expansion, land-use and land-cover change, groundwater management policies, or climate variability, all of which may substantially affect groundwater recharge and abstraction.

For example, continued expansion of textile industries, increasing irrigation demand, urbanization, and prolonged drought associated with climate change could accelerate groundwater depletion beyond the projected rates. Conversely, implementation of managed aquifer recharge (MAR), improved irrigation efficiency, stricter groundwater abstraction regulations, and greater utilization of surface-water resources could reduce future groundwater stress and slow the rate of decline. Therefore, the ARIMA forecasts should be interpreted as a baseline scenario representing the continuation of historical groundwater conditions rather than as deterministic predictions of future groundwater levels. Future research should integrate hydroclimatic variables, land-use dynamics, socioeconomic projections, and groundwater abstraction records using multivariate time-series models (e.g., ARIMAX, VAR) or physically based groundwater-flow models (e.g., MODFLOW) to improve the reliability of long-term groundwater projections.

Groundwater recharge and sustainability assessment

A limitation of this study is that groundwater recharge was not quantitatively estimated. Consequently, the sustainability of current groundwater use could not be evaluated through a complete groundwater budget. The analyses focused on long-term groundwater-level trends, spatial variability, sectoral groundwater demand, and groundwater-level forecasting using the available monitoring data. Although persistent groundwater-level declines indicate increasing stress on the aquifer system, they do not by themselves demonstrate that groundwater abstraction exceeds natural recharge.

A comprehensive assessment of groundwater sustainability would require quantitative recharge estimation using approaches such as the water-table fluctuation (WTF) method, hydrological water-balance analysis, environmental tracer techniques, or physically based groundwater-flow modelling (e.g., MODFLOW), together with reliable groundwater abstraction records. Integrating these components would enable estimation of groundwater recharge, development of groundwater budgets, and evaluation of the long-term sustainability of groundwater use in Shahjadpur Upazila.

Comparison with other south Asian floodplain aquifers

The groundwater depletion observed in Shahjadpur Upazila is consistent with trends reported for other alluvial floodplain aquifers across South Asia, where increasing agricultural intensification, urbanization, and industrial development have substantially increased groundwater abstraction. Previous studies in the Bengal Basin have documented long-term groundwater declines ranging from approximately 0.02 to 0.50 m year^{-1}, depending on local hydrogeological conditions, aquifer characteristics, and groundwater abstraction intensity (Shamsudduha et al., 2009; Zahid, 2022; Haque et al., 2025). Likewise, studies from the Ganges Basin in northern India have reported persistent groundwater depletion associated with intensive irrigation pumping and declining recharge efficiency (Jha et al., 2025).

As summarized in Table 3, the groundwater decline estimated in the present study (–0.01 to –0.45 m year^{-1}) falls within the range reported for comparable alluvial floodplain aquifers in Bangladesh and northern India. This agreement suggests that the groundwater dynamics observed in Shahjadpur are not unique but reflect broader regional pressures resulting from increasing dependence on groundwater for agricultural production, industrial development, and domestic water supply. Despite differences in hydrogeological settings and groundwater-management practices, the

common pattern of groundwater depletion highlights the growing imbalance between groundwater abstraction and natural recharge across South Asian floodplains. These regional similarities emphasize the need for integrated groundwater management strategies, including improved irrigation efficiency, managed aquifer recharge (MAR), conjunctive use of surface water and groundwater, and continuous groundwater monitoring. Implementing such measures will be essential for enhancing groundwater sustainability and improving the resilience of floodplain aquifer systems under increasing water demand and future climate variability.

Seasonal groundwater variability

Although groundwater monitoring comprised quarterly observations from 2000 to 2010 and monthly observations from 2011 to 2024, this study used annual mean groundwater levels throughout the entire period. This approach enabled consistent temporal comparison, minimized differences arising from varying monitoring frequencies, and facilitated the assessment of long-term groundwater-level trends.

Consequently, seasonal groundwater fluctuations associated with monsoon recharge and dry-season abstraction were not analyzed. Seasonal groundwater analysis could provide valuable insight into recharge timing, irrigation-induced drawdown, and short-term aquifer recovery. Such information would improve understanding of groundwater recharge–abstraction cycles and support the development of season-specific groundwater management strategies in Shahjadpur Upazila.

Table 3, Comparison of groundwater depletion rates reported for selected floodplain aquifers in South Asia

Study Area	Aquifer System	Groundwater Decline (m year^{-1})	Main Drivers	Reference
Shahjadpur, Bangladesh	Jamuna Floodplain	–0.01 to –0.45	Irrigation, industry, domestic demand	This study
Central Bangladesh	Bengal Basin	–0.02 to –0.50	Irrigation, urbanization	Shamsudduha et al. (2009)
North-central Bangladesh	Floodplain aquifer	–0.05 to –0.42	Irrigation abstraction	Zahid (2022)
Ganges Floodplain, Bangladesh	Alluvial aquifer	–0.03 to –0.38	Irrigation and recharge variability	Haque et al. (2025)
Ganges Basin, India	Alluvial aquifer	Persistent decline	Intensive irrigation	Jha et al. (2025)

Such information would improve understanding of groundwater recharge–abstraction cycles and support the development of season-specific groundwater management strategies in Shahjadpur Upazila.

Water demand by sector

Industrial sectors considered

Industrial water demand in Shahjadpur Upazila was estimated using sector-specific activity scales and unit water-use assumptions (Table 4). The assessment includes both large centralized facilities and numerous small-scale industries, allowing evaluation of cumulative industrial groundwater abstraction. Handloom and textile units, dyeing and finishing industries, dairy and milk processing farms, government and public utilities, and electricity generation facilities were identified as the major industrial water users in the study area.

Agricultural sectors considered

The agricultural water-demand assessment considered the major crops cultivated in Shahjadpur Upazila, namely Boro rice, Aman rice, jute, and vegetables/fodder crops. Crop-specific cultivated areas and seasonal irrigation water requirements used for the estimation are presented in Table 5.

Domestic sectors considered

Domestic demand was estimated using per capita water consumption:

- Rural households: 70–100 L/person/day
- Urban households: 120–150 L/person/day

Table 4, Industrial sectors considered and associated water use assumptions in Shahjadpur Upazila

Industrial Sector	Activity Scale	Unit Water Use Assumption	Basis of Estimation
Handloom / Textile Units	34,644 looms	40–60 L/day per loom	Typical operational water requirement per loom
Dyeing and Finishing Units	200 units	10–20 m^3/day per unit	Average water use in small to medium textile processing units
Dairy and Milk Processing	25,000–30,000 cows	100–120 L/day per cow	Livestock drinking, cleaning, and processing needs
Government and Public Utilities	Aggregated facilities	1,000–1,400 m^3/day	Estimated combined demand of offices, hospitals, and public services
Electricity Generation	521 MW power plant	23.7–36.2 m^3/day	Cooling and auxiliary operational water use

Table 5, Crops considered and irrigation water requirement assumptions in Shahjadpur Upazila

Crop Type	Cultivated Area (ha)	Seasonal Water Requirement (mm/season)	Basis of Estimation
Boro Rice	10,000	1,200	Dry-season irrigated rice water requirement
Aman Rice	8,000	900	Monsoon-season rice irrigation demand
Jute	5,000	500	Fiber crop water requirement
Vegetables / Fodder	4,000	400	Mixed vegetable and fodder crop irrigation demand

Sector-wise distribution of water demand

The sector-wise distribution of total water demand in Shahjadpur Upazila is illustrated in Figure 10. The results show that the handloom and textile sector is the largest water consumer, accounting for approximately 24.8% of the total annual demand. This dominance is primarily due to the large number of looms operating throughout the year, where individually small water requirements aggregate into substantial groundwater abstraction.

Agricultural activities remain the dominant contributors to total water demand, with Boro rice (19.6%) and Aman rice (17.4%) together accounting for more than one-third of total consumption. Among industrial sectors, electricity generation contributes 18.0%, highlighting the water-intensive nature of power production and its dependence on reliable groundwater supplies.

The grand total water demand from all sectors is estimated at 41.30 million m^3/year, indicating considerable pressure on the local groundwater system. The dominance of industrial and agricultural sectors suggests that targeted water-use efficiency measures in these activities could significantly reduce aquifer stress. Annual sectoral water-demand estimates were compared with groundwater-level trends using Pearson correlation and linear regression analyses.

The results indicate that increasing industrial and agricultural water demand is significantly associated with declining groundwater levels, whereas domestic water demand exhibited a comparatively weaker relationship. These findings suggest that irrigation and industrial abstraction are the primary drivers of groundwater depletion in the study area.

The study results are subject to uncertainties associated with data availability, spatial sampling density, interpolation, and forecasting assumptions.

Although the statistical validation indicates satisfactory model performance, the relatively limited number of observation wells and the assumption of persistent historical trends may influence prediction accuracy. Therefore, the forecasting results should be interpreted as plausible future scenarios rather than exact predictions

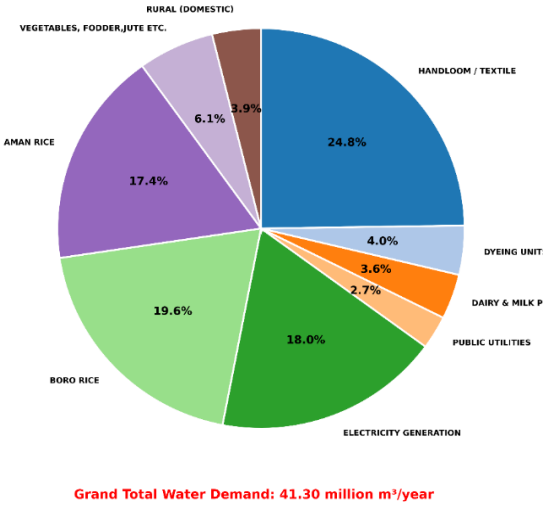


Figure 10, Sector-wise distribution of total water demand in Shahjadpur Upazila (million m^3/year), showing the relative contributions of industrial, agricultural, and domestic sectors.

Although the estimated sectoral water demand provides an indication of potential groundwater stress, it should not be interpreted as measured groundwater abstraction. The absence of direct abstraction records introduces uncertainty into the quantitative assessment; however, given the widespread dependence on groundwater in Shahjadpur Upazila, the estimates remain a useful indicator of the relative contribution of different sectors to groundwater exploitation.

Sensitivity analysis of water demand estimates

The sensitivity analysis demonstrates that the estimated groundwater demand is directly influenced by the assumed sector-specific water-use coefficients. Reducing all coefficients by 10% decreased the estimated total annual groundwater demand from 41.30 million m^3 $year^{-1}$ to approximately 37.17 million m^3 $year^{-1}$, whereas increasing the coefficients by 10% increased the estimate to approximately 45.43 million m^3 $year^{-1}$. Similarly, applying a ±20% variation produced total annual groundwater demands ranging from approximately 33.04 to 49.56 million m^3 $year^{-1}$.

Although the absolute magnitude of groundwater demand changed under different scenarios, the relative contribution of each sector remained essentially unchanged. The handloom and textile industry together with irrigated agriculture consistently represented the largest groundwater consumers under all scenarios (Table 6), indicating that the identification of the dominant groundwater-demand sectors is robust despite reasonable uncertainty in the adopted water-use coefficients.

These findings suggest that while uncertainties in water-use coefficients influence quantitative estimates of groundwater demand, they do not alter the overall interpretation of groundwater abstraction patterns in Shahjadpur Upazila. Future investigations should incorporate site-specific water-use measurements and probabilistic uncertainty analyses, such as Monte Carlo simulation, to further improve the accuracy of groundwater-demand assessments.

Table 6, Sensitivity analysis of total annual groundwater demand under different sectoral water-use coefficient scenarios in Shahjadpur Upazila.

Scenario	Water-use Coefficient	Total Water Demand (Million m^3/year)	Change (%)
Baseline	100%	41.30	0
Low	−10%	37.17	−10
High	+10%	45.43	+10
Low	−20%	33.04	−20
High	+20%	49.56	+20

Because direct groundwater abstraction records were unavailable, the sectoral estimates presented in this study should be interpreted as potential groundwater demand rather than measured groundwater withdrawals.

Relationship between industrial expansion and groundwater decline

The association between industrial expansion and groundwater decline in Shahjadpur Upazila should be interpreted as an inferred relationship rather than direct statistical evidence. The present study did not perform correlation or regression analyses linking groundwater-level changes with temporal industrial growth because continuous annual records of industrial development, groundwater abstraction, and production activities were not available.

Nevertheless, the spatial coincidence between areas of pronounced groundwater decline and concentrated industrial activity, together with the estimated increase in industrial water demand, suggests that industrial development is one of several contributing factors influencing groundwater stress. However, groundwater-level changes in Shahjadpur are also affected by agricultural irrigation, domestic water use, rainfall variability, river–aquifer interactions, recharge conditions, and aquifer hydraulic properties. Consequently, the observed groundwater decline should be interpreted as the result of multiple interacting natural and anthropogenic processes, rather than industrial expansion alone.

Future studies should integrate long-term datasets on industrial production, groundwater abstraction, land-use change, and hydroclimatic variables using multivariate statistical techniques or physically based groundwater-flow models to quantify the relative contribution of industrial activities to groundwater depletion.

Implications of groundwater decline for shallow and deep aquifers

The groundwater monitoring data used in this study were not classified according to aquifer depth; therefore, groundwater-level trends could not be analyzed separately for shallow and deep aquifer systems. Consequently, the present analysis represents the overall groundwater response recorded by the monitoring network rather than depth-specific aquifer behavior.

In the alluvial aquifer systems of the Bengal Basin, shallow aquifers generally respond rapidly to seasonal recharge and groundwater abstraction because of their greater hydraulic connectivity with the land surface. In contrast, deeper semi-confined and confined aquifers typically exhibit slower recovery owing to lower vertical hydraulic conductivity and longer groundwater residence times. Sustained abstraction from deeper aquifers may therefore result in persistent groundwater declines that are more difficult to reverse.

If future groundwater depletion extends into deeper aquifers in Shahjadpur Upazila, the long-term security of water supplies may be adversely affected through increased pumping costs, declining well productivity, reduced aquifer resilience during prolonged droughts, and greater energy requirements for groundwater extraction.

These potential consequences highlight the importance of implementing depth-specific groundwater monitoring and hydrogeological investigations to better understand vertical groundwater dynamics and support sustainable groundwater-resource management.

Environmental implications of groundwater decline

Continued groundwater decline may have important environmental consequences beyond reduced water availability. In Shahjadpur Upazila, persistent groundwater depletion has the potential to alter river–aquifer interactions, particularly along the Jamuna River, by reducing groundwater discharge (baseflow) to the river during the dry season or increasing induced infiltration of river water under intensive groundwater pumping. Such changes may modify local groundwater-flow patterns and affect the hydrological connectivity between surface water and groundwater systems.

Declining groundwater levels may also reduce soil moisture availability and adversely affect groundwater-dependent ecosystems, including wetlands, riparian vegetation, and other habitats that rely on shallow groundwater during dry periods. Furthermore, prolonged groundwater depletion can increase the risk of groundwater-quality deterioration by concentrating dissolved constituents, promoting downward migration of contaminants from shallow aquifers, or inducing the movement of poor-quality water toward pumping wells. These processes could have long-term implications for drinking-water quality, irrigation suitability, and ecosystem health.

Although these environmental impacts were not directly evaluated in the present study, they should be considered when developing groundwater management strategies. Future research should integrate hydrogeological, ecological, and groundwater-quality monitoring to evaluate the environmental consequences of continued groundwater depletion and support sustainable groundwater-resource management in Shahjadpur Upazila.

Implications for sustainable groundwater management

The integrated parametric–non-parametric–geostatistical framework employed in this study provides a holistic understanding of Shahjadpur's groundwater dynamics. Combining trend detection with spatial interpolation and forecasting enables both diagnostic and predictive insights essential for sustainable resource management. Key recommendations include:

1. Adoption of managed aquifer recharge (MAR) systems in declining zones to enhance infiltration during monsoon seasons (Kiss et al., 2025).
2. Regulated irrigation abstraction with crop zoning strategies to minimize excessive pumping.
3. Establishment of community-based monitoring networks to ensure continuous long-term observation and data transparency.

Although declining groundwater levels indicate increasing pressure on the aquifer system, the absence of quantitative groundwater recharge estimates prevents direct evaluation of whether current groundwater abstraction exceeds sustainable recharge rates.

Site-specific groundwater management recommendations

Based on the hydrogeological characteristics and socioeconomic conditions of Shahjadpur Upazila, several location-specific groundwater management strategies are recommended. First, managed aquifer recharge (MAR) should be prioritized in the central and southern groundwater-depletion zones through the construction of recharge ponds, infiltration basins, and recharge wells to capture excess monsoon runoff and enhance aquifer replenishment.

Second, because Boro rice cultivation represents one of the largest groundwater-consuming activities, groundwater abstraction could be reduced by promoting alternate wetting and drying (AWD) irrigation, scientific irrigation scheduling, laser land levelling where feasible, and gradual diversification toward less water-intensive crops during the dry season.

Third, the handloom and textile industries, which account for a substantial proportion of groundwater demand, should be encouraged to adopt water-efficient production technologies, wastewater recycling and reuse, rainwater harvesting for non-potable uses, and periodic groundwater-use audits to improve water-use efficiency.

Fourth, areas adjacent to the Jamuna River should be protected as natural groundwater recharge zones through preservation of floodplain connectivity, restriction of uncontrolled development in recharge areas, and promotion of conjunctive use of surface water and groundwater where appropriate.

Finally, groundwater governance should be strengthened through installation of automated groundwater-level monitoring systems, registration and monitoring of high-capacity production wells, routine groundwater abstraction reporting, and incorporation of groundwater management into local water-resource planning. Collectively, these location-specific measures provide a practical framework for balancing economic development with long-term groundwater sustainability in Shahjadpur Upazila.

Limitations of the study

This study has several limitations that should be considered when interpreting the results. First, the groundwater trend analysis was based on data from 14 observation wells covering the period 2000–2024.

Although these wells represent the principal hydrogeological settings of Shahjadpur Upazila, the monitoring density may not fully capture localized groundwater variability, particularly in areas with complex hydrogeological conditions or intensive groundwater abstraction.

Second, groundwater levels were measured quarterly during 2000–2010 and monthly during 2011–2024. To ensure methodological consistency, all observations were aggregated into annual mean groundwater levels prior to statistical analyses. While this standardization minimizes potential bias associated with unequal sampling frequencies, some short-term and seasonal groundwater fluctuations may not be fully represented.

Third, the spatial interpolation results obtained using Inverse Distance Weighting (IDW) and Ordinary Kriging are subject to uncertainty arising from monitoring density, spatial data distribution, and interpolation assumptions, particularly in areas located farther from observation wells. Similarly, the sectoral water-demand estimates are based on published water-use coefficients and official activity statistics rather than direct measurements of groundwater abstraction. The sensitivity analysis (±10% and ±20%) demonstrated that total annual water demand varied between 33.04 and 49.56 million m^3 $year^{-1}$, whereas the relative dominance of the industrial and agricultural sectors remained unchanged, indicating that the principal conclusions are robust despite uncertainties in the adopted coefficients.

Finally, the ARIMA (1,1,1) forecasting model assumes that historical groundwater trends continue throughout the projection period and does not explicitly incorporate future changes in industrial development, population growth, land-use dynamics, groundwater management policies, or climate variability. Consequently, the forecasts should be interpreted as a baseline scenario rather than deterministic predictions of future groundwater conditions.

Future research should incorporate denser groundwater monitoring networks, direct groundwater abstraction records, hydroclimatic variables, land-use change, and physically based groundwater-flow models to improve the accuracy and reliability of groundwater assessments and long-term forecasts.

A further limitation is that groundwater monitoring wells were not categorized according to aquifer depth, preventing separate evaluation of groundwater-level trends in shallow and deep aquifers. Future investigations should establish depth-specific monitoring networks and undertake detailed aquifer characterization to understand vertical groundwater flow, recharge mechanisms, and the long-term sustainability of groundwater resources.

Additionally, continuous time-series data on industrial growth and groundwater abstraction were unavailable, limiting direct quantification of industrial expansion's contribution to groundwater decline. Consequently, its influence was inferred from spatial groundwater-level patterns and estimated sectoral water demand. Future studies should integrate long-term industrial development records, groundwater abstraction measurements, and depth-specific monitoring data to better distinguish the effects of anthropogenic activities and hydrogeological processes on groundwater depletion and improve the reliability of groundwater sustainability assessments in Shahjadpur Upazila.

Another limitation of this study is that seasonal groundwater dynamics were not investigated. Although quarterly and monthly groundwater observations were available, the data were aggregated into annual mean groundwater levels to facilitate consistent long-term trend analysis across the study period. As a result, seasonal recharge processes, dry-season abstraction effects, and short-term groundwater responses were not evaluated. Future studies should utilize the higher temporal resolution of the monitoring data to quantify seasonal groundwater fluctuations and recharge–abstraction dynamics.

Groundwater abstraction data

Another limitation of this study is the absence of sector-specific groundwater abstraction records for irrigation, municipal, and industrial users. Consequently, groundwater use was estimated from activity statistics and published sector-specific water-use coefficients rather than direct measurements of groundwater pumping. Although this approach provides a reasonable estimate of potential groundwater demand, it cannot fully represent the temporal and spatial variability of actual groundwater abstraction. The lack of pumping records also limits quantitative evaluation of the relationship between groundwater withdrawals and observed groundwater-level decline. Future studies should integrate groundwater abstraction records, pumping-well inventories, metered extraction data, and groundwater-use permits, where available, to improve groundwater-budget assessments, validate water-demand estimates, and quantify the contribution of different sectors to groundwater depletion.

Conclusion

This study integrated parametric, non-parametric, and geostatistical approaches to evaluate the spatiotemporal variability of groundwater levels in Shahjadpur Upazila, Sirajganj District, over a 24-year period (2000–2024). Analysis of fourteen observation wells revealed a predominant declining trend in groundwater levels, with estimated rates of decline ranging from –0.01 to –0.45 m $year^{-1}$.

Spatial interpolation using the Inverse Distance Weighting (IDW) and Kriging methods revealed pronounced east–west variations in groundwater levels, highlighting considerable spatial heterogeneity in aquifer conditions. Shallow aquifer zones adjacent to the Jamuna River appear to benefit from relatively frequent recharge through river–aquifer interactions, whereas deeper aquifers in the central and southern regions, where groundwater extraction for irrigation is intensive, exhibit substantial and persistent groundwater-level declines. These spatial patterns indicate the combined influence of hydrogeological characteristics, proximity to surface-water sources, and human-induced abstraction pressure.

The ARIMA-based forecasting results further suggest that, if existing groundwater abstraction trends continue, groundwater levels could decline by an additional 1.5–2.0 m by 2030. These projections reflect the continuation of historical groundwater-level trends

and should therefore be interpreted as a baseline scenario rather than definitive predictions. Actual future groundwater conditions may vary considerably depending on changes in climatic conditions, rainfall patterns, land-use practices, industrial development, population growth, agricultural intensification, groundwater abstraction rates, and the effectiveness of future water-management interventions.

Nevertheless, the absence of quantitative groundwater recharge estimates represents an important limitation of the present study. Consequently, it is not possible to establish conclusively whether current groundwater abstraction exceeds the aquifer's sustainable recharge capacity. Furthermore, the estimated sectoral water demands represent potential groundwater demand rather than directly measured groundwater abstraction volumes. Therefore, these estimates should be interpreted as indicative of sector-specific groundwater pressure rather than precise measurements of actual extraction. Future research should incorporate spatially distributed recharge estimation, groundwater-budget analysis, and reliable abstraction data to establish a more comprehensive understanding of aquifer sustainability.

The integration of non-parametric trend detection methods (Mann–Kendall and Sen's slope), spatial interpolation techniques (IDW and Kriging), and time-series forecasting (ARIMA) provides a complementary methodological framework for evaluating groundwater-level dynamics. This integrated approach offers considerable potential for replication in other floodplain aquifers across Bangladesh and South Asia, supporting evidence-based groundwater monitoring, water-allocation planning, and sustainable resource management. Further investigations incorporating groundwater–surface water interaction modelling, environmental isotopic tracing, numerical groundwater-flow simulation, and climate-change scenario analysis would strengthen predictive capabilities and provide a more robust scientific basis for developing long-term groundwater management strategies.

Despite the robust analytical framework employed, this study has several limitations. The analysis is based on groundwater-level records from 14 observation wells, which may not fully capture local-scale spatial variability. The statistical trend analyses and geostatistical interpolation rely on assumptions that may introduce uncertainty into the estimated groundwater patterns. Furthermore, the ARIMA forecasts assume that historical groundwater dynamics will continue into the future and do not explicitly account for changes in climate, land use, or groundwater abstraction. Therefore, the forecasted groundwater levels should be interpreted as plausible future scenarios rather than precise predictions. Future studies should incorporate denser monitoring networks, physically based groundwater models, and climate-change scenarios to improve prediction accuracy and support sustainable groundwater management.

Beyond reducing groundwater availability, continued groundwater depletion may alter river–aquifer interactions, degrade groundwater-dependent ecosystems, and increase the risk of groundwater-quality deterioration, emphasizing the need for integrated groundwater management and environmental monitoring.

Sustainable groundwater management in Shahjadpur will require coordinated implementation of managed aquifer recharge, water-efficient irrigation practices, industrial water conservation, protection of natural recharge zones, and strengthened groundwater monitoring and regulation.

Future groundwater management should prioritize depth-specific monitoring to evaluate whether groundwater depletion is confined to shallow aquifers or is progressively affecting deeper groundwater resources that are critical for long-term water-supply security. Future research should investigate seasonal groundwater dynamics using the available monthly monitoring records to improve understanding of recharge processes and seasonal groundwater management.

Future groundwater assessments should incorporate sector-specific groundwater abstraction records to improve groundwater-budget analyses and strengthen the quantitative evaluation of groundwater sustainability.

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Author contributions

Data analysis and the preparation of the initial manuscript were conducted by Md. Nazmul Islam Hasan. Khondaker Emamul Haque contributed through conceptualization, supervision, and visualization. Shamim Ahmed led the software-related efforts, while Md Mahedi Hasan also revised the article. All authors reviewed the final manuscript.

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Data availability

The data that support the findings of this study are accessible by contacting the corresponding author.

Declarations

The authors state that there are no conflicts of financial interest or personal relationships that could have impacted the results or interpretation of this study.

Article note

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References

Alsumaiei, A. A. (2020). A nonlinear autoregressive modeling approach for forecasting groundwater level fluctuation in urban aquifers. Water, 12(3), 820. https://doi.org/10.3390/w12030820

Berke, O. (1999). Estimation and prediction in the spatial linear model. Water, Air and Soil Pollution, 110, 215–237. https://doi.org/10.1023/A:1005035509922

Box, G. E. P., and Jenkins, G. M. (1976). Time series analysis: Forecasting and control. Holden-Day, San Francisco.

Cay, T., and Uyan, M. (2009). Spatial and temporal groundwater level variation: Geostatistical modeling in the city of Konya, Turkey. Water Environment Research, 81, 2460–2470. https://doi.org/10.2175/106143009X442961

de Silva, S., Jirasinha, R., Mondal, M. S., and McCartney, M. P. (2024). Policy and institutional study on the strategic role of water storage in Bangladesh. https://doi.org/10.5337/2025.206

Edmunds, W. M., Ahmed, K. M., and Whitehead, P. G. (2015). A review of arsenic and its impacts in groundwater of the Ganges–Brahmaputra–Meghna Delta, Bangladesh. Environmental Science: Processes and Impacts, 17(6), 1032–1046. https://doi.org/10.1039/c4em00673a

Faruqa, N. N., Kamal, M. A., Jabeen, S., and Hossain, F. (2025). 3-D voxel modeling of near-surface sediments: Insights into depositional environments and geotechnical properties - A case study of Barishal Town and its surroundings, Bangladesh. Asian Journal of Engineering Geology, 2(Special Issue), 67–70. https://doi.org/10.64862/ajeg.2025.2sp.32.130

Fahim, A. K. F., Kamal, A. M., and Shahid, S. (2023). Spatiotemporal change in groundwater sustainability of Bangladesh and its major causes. Stochastic Environmental Research and Risk Assessment, 37(2), 665–680. https://doi.org/10.1007/s00477-022-02294-z

Gleeson, T., Wada, Y., Bierkens, M. F. P., and van Beek, L. P. H. (2012). Water balance of global aquifers revealed by groundwater footprint. Nature, 488, 197–200. https://doi.org/10.1038/nature11295

Goovaerts, P. (1997). Geostatistics for natural resources evaluation. Oxford University Press, New York.

Hamed, K. H., and Rao, A. R. (1998). A modified Mann–Kendall trend test for autocorrelated data. Journal of Hydrology, 204(1–4), 182–196. https://doi.org/10.1016/S0022-1694(97)00125-X

Haque, S. E., Snigdho, F. S., and Tasneem, N. (2025). Water sustainability: a review of advances in water quality management technologies. Computational Automation for Water Security, 195-214. https://doi.org/10.1016/B978-0-443-33321-7.00018-4

He, L., Liu, J., Lei, S., and Chen, L. (2023). A hybrid coupling model of groundwater level simulation considering hydrogeological parameter: A case study of Nantong City in Eastern China. Water Supply, 23(10), 4286–4302. https://doi.org/10.2166/ws.2023.248

Helsel, D. R., Hirsch, R. M., Ryberg, K. R., Archfield, S. A., and Gilroy, E. J. (2020). Statistical methods in water resources. USGS Techniques and Methods, Book 4. https://doi.org/10.3133/tm4A3

Hirsch, R. M., Slack, J. R., and Smith, R. A. (1982). Techniques of trend analysis for monthly water quality data. Water Resources Research, 18, 107–121. https://doi.org/10.1029/WR018i001p00107

Hyndman, R. J., and Athanasopoulos, G. (2018). Forecasting: Principles and practice. OTexts, Melbourne.

Jha, S., Das, V. K., Debnath, K., Chaudhuri, S., and Banerjee, S. (2025). Assessment of the planform evolution of the Lower Ganga River: Meander migration and the causative factors. Journal of Earth System Science, 134(4), 236. https://doi.org/10.1007/s12040-025-02696-x

Johnston, K., Van Hoef, J. M., Krivoruchko, K., and Lucas, N. (2001). Using ArcGIS geostatistical analyst. ESRI Press, Redlands, CA.

Júnez-Ferreira, H. E., Hernández-Hernández, M. A., Herrera, G. S., González-Trinidad, J., Cappello, C., Maggio, S., and De Iaco, S. (2023). Assessment of changes in regional groundwater levels through spatio-temporal kriging: Application to the southern Basin of Mexico aquifer system. Hydrogeology Journal, 31(6), 1405–1423. https://doi.org/10.1007/s10040-023-02681-y

Kiss, S., Nemes-Kókai, Z., Bácsi, I., Lukács, Á., Márton, K., T-Krasznai, E., Borics, G., Stenger-Kovács, C.,

Szeles, J., Török, P., and B-Béres, V. (2025). Structure and biodiversity of benthic diatoms shaped by water availability in streams of the Pannonian Ecoregion. Global Ecology and Conservation, 62, e03858. https://doi.org/10.1016/j.gecco.2025.e03858

Kumar, P. S., Suganya, S., Srinivas, S., Priyadharshini, S., Karthika, M., Karishma Sri, R., ... and Lichtfouse, E. (2019). Treatment of fluoride-contaminated water. A review. Environmental Chemistry Letters, 17(4), 1707-1726. https://doi.org/10.1007/s10311-019-00906-9

MacDonald, A. M., Bonsor, H. C., Ahmed, K. M., Burgess, W. G., Basharat, M., Calow, R. C., Dixit, A., Foster, S. S. D., Gopal, K., Lapworth, D. J., Lark, R. M., Moench, M., Mukherjee, A., Rao, M. S., Shamsudduha, M., Smith, L., Taylor, R. G., Tucker, J., Steenbergen, F., and Yadav, S. K. (2016). Groundwater quality and depletion in the Indo-Gangetic Basin mapped from in situ observations. Nature Geoscience, 9(10), 762–766. https://doi.org/10.1038/ngeo2791

Mahammad, S., Islam, A., Das, B. C., Sarkar, B., Islam, A. R. M. T., and Pal, S. C. (2026). Modelling extraction-induced water table decline and potential relationship with arsenic mobilization in the Western Bengal Delta. Theoretical and Applied Climatology, 157(7), 443. https://doi.org/10.1007/s00704-026-06320-w

Mann, H. B. (1945). Nonparametric tests against trend. Econometrica, 13, 245–259. https://doi.org/10.2307/1907187

Mondal, B. K., Sahoo, S., Das, R., Mishra, P. K., Abdelrahman, K., Acharya, A., Lee, M. A., Tiwari, A., and Fnais, M. S. (2022). Assessing groundwater dynamics and potentiality in the Lower Ganga Plain, India. Water, 14(14), 2180. https://doi.org/10.3390/w14142180

Monir, M. M., Sarker, S. C., and Islam, M. N. (2024). Assessing the changing trends of groundwater level with spatiotemporal scale at the northern part of Bangladesh integrating the MAKESENS and ARIMA models. Modeling Earth Systems and Environment, 10(1), 443–464. https://doi.org/10.1007/s40808-023-01794-3

Mustapha, A. (2013). Detecting surface water quality trends using Mann–Kendall tests and Sen's slope estimates. International Journal of Advanced Research, 1, 108–114.

Obaje, N. G. (2009). Geology and mineral resources of Nigeria. Lecture Notes in Earth Sciences, Vol. 120. Springer, Berlin and Heidelberg. https://doi.org/10.1007/978-3-540-92685-6

Pearson, K. (1895). Contributions to the mathematical theory of evolution. II. Skew variation in homogeneous material. Philosophical Transactions of the Royal Society of London. Series A, 186, 343-414.https://doi.org/10.1098/rsta.1895.0010

Prasad, S., Saluja, R., Joshi, V., and Garg, J. K. (2020). Heavy metal pollution in surface water of the Upper Ganga River, India: human health risk assessment. Environmental Monitoring and Assessment, 192(11), 742. https://doi.org/10.1007/s10661-020-08701-8

Rahman, A., Kumar, P., and Dominguez, F. (2022). Increasing freshwater supply to sustainably address global water security at scale. Scientific Reports, 12(1), 20262. https://doi.org/10.1038/s41598-022-24314-2

Ribeiro, L., and Macedo, M. E. (1995). Application of multivariate statistics, trend and cluster analysis to groundwater quality in the Tejo and Sado aquifer. IAHS Publications, 225, 39–48.

Rodell, M., Famiglietti, J. S., Wiese, D. N., Reager, J. T., Beaudoing, H. K., Landerer, F. W., and Lo, M. H. (2018). Emerging trends in global freshwater availability. Nature, 557(7707), 651–659. https://doi.org/10.1038/s41586-018-0123-1

Sen, P. K. (1968). Estimates of the regression coefficient based on Kendall's tau. Journal of the American Statistical Association, 63, 1379–1389. https://doi.org/10.1080/01621459.1968.10480934

Shah, T. (2007). The groundwater economy of South Asia: an assessment of size, significance and socio-ecological impacts. The agricultural groundwater revolution: Opportunities and threats to development, 7-36.

Shamsudduha, M., Chandler, R. E., Taylor, R. G., and Ahmed, K. M. (2009). Recent trends in groundwater levels in a highly seasonal hydrological system: The Ganges–Brahmaputra–Meghna Delta. Hydrology and Earth System Sciences, 13(12), 2373–2385. https://doi.org/10.5194/hess-13-2373-2009

Singh, A. K., Kaur, R., Verma, S., and Singh, S. (2022). Antimicrobials and antibiotic resistance genes in water bodies: pollution, risk, and control. Frontiers in Environmental Science, 10, 830861. https://doi.org/10.3389/fenvs.2022.830861

Suter, G. W. (2008). Ecological risk assessment in the United States Environmental Protection Agency: A historical overview. Integrated environmental assessment and management, 4(3), 285-289. https://doi.org/10.1897/IEAM_2007-062.1

Taylor, R. G., Scanlon, B., Döll, P., et al. (2013). Groundwater and climate change. Nature Climate Change, 3, 322–329. https://doi.org/10.1038/nclimate1744

Tayyab, M., Aslam, R. A., Farooq, U., Ali, S., Khan, S. N., Iqbal, M., Khan, M. I., and Saddique, N. (2024). Comparative study of geospatial techniques for interpolating groundwater quality data in agricultural areas of Punjab, Pakistan. Water, 16(1), 139. https://doi.org/10.3390/w16010139

Thakur, P. K., Nikam, B. R., Srivastav, S. K., Khaing, T. W. W., Zaw, T., Garg, V., Dhote, P. R., Sharma, V., and Aggarwal, S. P. (2021). Groundwater modeling with inputs from geospatial technology for assessing the sustainability of water use in the Solani watershed, Ganga River Basin (India). Groundwater for Sustainable Development, 12, 100511. https://doi.org/10.1016/j.gsd.2020.100511

Todd, D. K., and Mays, L. W. (2005). Groundwater Hydrology. 3rd Edition, John Wiley and Sons, Inc., Hoboken, 652p.

Yue, S., and Wang, C. Y. (2002). Applicability of prewhitening to eliminate the influence of serial correlation on the Mann–Kendall test. Water Resources Research, 38(6), 4-1. https://doi.org/10.1029/2001WR000861

Zahid, A. (2022). Groundwater resources, challenges and governance in the Bengal Basin, Bangladesh. In Bangladesh geosciences and resources potential (pp. 399–436). CRC Press.

Zar, J. H. (2010). Biostatistical analysis (5th ed.). Prentice Hall, New Jersey.