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Comparative Evaluation of Statistical and Machine Learning Models for Spatiotemporal Groundwater Level Forecasting in a Climate-Sensitive Coastal Aquifer

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Abstract

Coastal groundwater systems and deltaic systems portray a high level of spatiotemporal variability due to the seasonality in climate and human-induced stressors, and the assessment of the groundwater level (GWL) remains a consistent challenge. This paper gives a comparative data-driven modeling model to predict the level of groundwater variations with long-term records of the monitoring wells of Barishal, Bangladesh. The framework combines both a classical seasonal time-series model (SARIMA), deep learning (Long Short-Term Memory; LSTM) and ensemble machine learning (XGBoost and Random Forest) in order to model both linear and nonlinear groundwater dynamics. These methods were used in forecasting the changes in groundwater level (GWL) in susceptible wells in Barishal. RMSE, MAE, R², and Nash Sutcliffe Efficiency (NSE) were used as a measure of model performance. Findings show that LSTM and Random Forests models are better than traditional statistical models at modeling complex groundwater swings, especially in longer predictions. GIS-based spatial analysis also indicates how significant are regional heterogeneity in groundwater responses and the impact of climatic drivers in local groundwater variation. The results indicate that multi-model data-driven models can be useful in the evaluation of groundwater in hydro-climatically complex and data-constrained coastal areas that can be valuable information in the area of groundwater monitoring and management.

Keywords: Groundwater fluctuation, Barishal, Climate change, SARIMA, LSTM, XGBoost, Random Forest, Groundwater level, GIS mapping, Climatic fact

1. INTRODUCTION

Groundwater plays a significant role in the hydrological cycle, and it is also the major source of freshwaters in Bangladesh in terms of domestic, agricultural, and industrial applications. In the country, nearly 87 percent of the population uses groundwater as a source of drinking water (BBS, 2022), and more than 70 percent of the country relies on

groundwater sources of irrigation (WARPO, 2021). This widespread reliance has brought massive strain on the nationwide aquifers and this has been recorded to be particularly in the areas where the surface water is minimal or contaminated.

In Barishal District (low-lying floodplains and deltaic land) Boro rice is cultivated through groundwater use in the dry season. It is traditionally believed to

be a water-dense area because of the proximity to the Bay of Bengal and river channels, but the current pattern is disturbing because the levels of groundwater tables vary considerably. A study by the Institute of Water Modelling (IWM, 2021) showed that their groundwater level has been lowered by 2-3 meters in some upazilas in Barishal, especially in those with intensive irrigation and poor drainage systems.

Relational distribution in Barishal annual average precipitation is nearly 2,4002,800-mm, however, the trend has changed in natural recharge level over the past 30 years (BMD, 2020). This is being exacerbated by an increase in evapotranspiration which is caused by an increase in temperatures. The average temperature in Barishal increased by 0.7°C on average between the years 1980 and 2020, and the trend is expected to continue by another 1.5°C by the year 2050 (World Bank Climate Change Knowledge Portal, 2022).

The Bangladesh Water Development Board (BWDB, 2022) data showed that in some of the regions of Barishal, there is a continuous situation of decreasing pre-monsoon groundwater table, and its values obtained in the dry season were measured between 2.5 to 4.8 meters below the ground surface during the dry season.

In Bangladesh, urbanization has been contributing to the rapid depletion of groundwater, which requires the development of innovative measures of managing water demand to guarantee a sustainable long-term perspective (Arfanuzzaman & Atiq Rahman, 2017). Similar to several other parts of Bangladesh, the groundwater table of Barishal District has been varying throughout the years because of the

different factors. Top among them include the rising population and water demand in agriculture coupled with poor methods of water extraction and changes in climate. Rainfalls have become unpredictable and this part of the world has been experiencing extreme variations of both drought and rainfall leading to unnatural recharge of groundwater aquifers. Also, variations in temperature, alteration in soil moisture conditions and evapotranspiration rates further render the resources of groundwater rather unpredictable. Over abstraction of groundwater has caused a continuous dropping of the groundwater level, therefore, creating the fear of long-term water scarcity (Roy & Zahid, 2021). The anthropogenic processes (e.g., agricultural irrigation, construction, and urbanization) contribute to increasing the rate at which the amount of groundwater is diminished (Gholami et al., 2023).

Several global and local reports support the rise of a crisis of groundwater fluctuation caused by climatic variations as well as irrational human activities. In the given global review study, Azad et al. (2025) considered various countries, including Malaysia, Iran, India, Turkey, China, and the USA, and showed that such deep learning models as ANN, SVM, and LSTM always outperformed classical ARIMA models in predicting the groundwater level.

In the case of study by Elmotawakkil et al. (2024), the Rabat-Kénitra region in Morocco was analyzed with the GRACE and MODIS satellite data in combination with Gradient Boosting Regression that demonstrated a better performance to reveal the areas of vulnerability compared with conventional methods. In parallel, Gonzalez and Arsanjani (2021) used Random Forest and predicted

modest seasonal changes in groundwater in Denmark even acknowledging the limitations of the models caused by the lack of anthropogenic factors.

By use of models based on CNN, Wunsch et al. (2022) has reported a nationwide decrease in groundwaters in Germany based on RCP climate predictions mainly under RCP8.5. Panahi et al. (2023) have determined that Mashhad aquifer in Iran could experience the loss of more than 6 meters of water by 2064 during the dry seasons in particular; RBF Neural Networks reported the most accurate findings.

Rashid et al. (2021) noted that the level of groundwater around Joypurhat in Bangladesh remained constant with the data projecting a consistent decrease until 2050. Similarly, Tabassum et al. (2024) also observed a declining water level in Mymensingh Sadar, especially in dry months. These findings show a large degree of susceptibility and active planning should be embraced, in particular to low-lying and climate vulnerable Districts such as Barishal.

In climatic terms Bamal et al. (2024) pointed out temperature, rainfalls and evapotranspiration as some of the important variables that influence the groundwater recharge and the discharge process. The same estimate emphasized by Ghazi et al. (2021) and Panahi et al. (2023) on the case studies of Iran demonstrated that under hotter and drier projections of the future (e.g., RCP8.5), the levels of groundwater decrease. On the same line, the Apaydin et al. (2010) revealed that shallow aquifers in semi-arid Turkey are highly sensitive to seasonal changes in the climate. Wunsch et al. (2022) wrote that by discounting these human factors, they were underestimating the projections of

groundwater. Salem et al. (2018) also linked the decrease in groundwater level in northwest Bangladesh with irrigation expenses and climatic-stress crops.

Monir et al. (2023) and Islam et al. (2023) revealed that the most common sources of stress in Bangladesh are over-extraction and increasing evapotranspiration, as well as poorly controlled irrigation. The mathematical modeling that the Islam applied indicated that no less than 84.6 percent of the total depletion may be due to the over-pumping alone indicating the extent of decline as epitomized by man.

These results suggest that climate-sensitive parameters and the human stressors are required to be modeled holistically in order to make predictive modeling of groundwater stress and reduce stress in the regions that are highly vulnerable to climatic conditions including Barishal.

2. Materials and Methodology

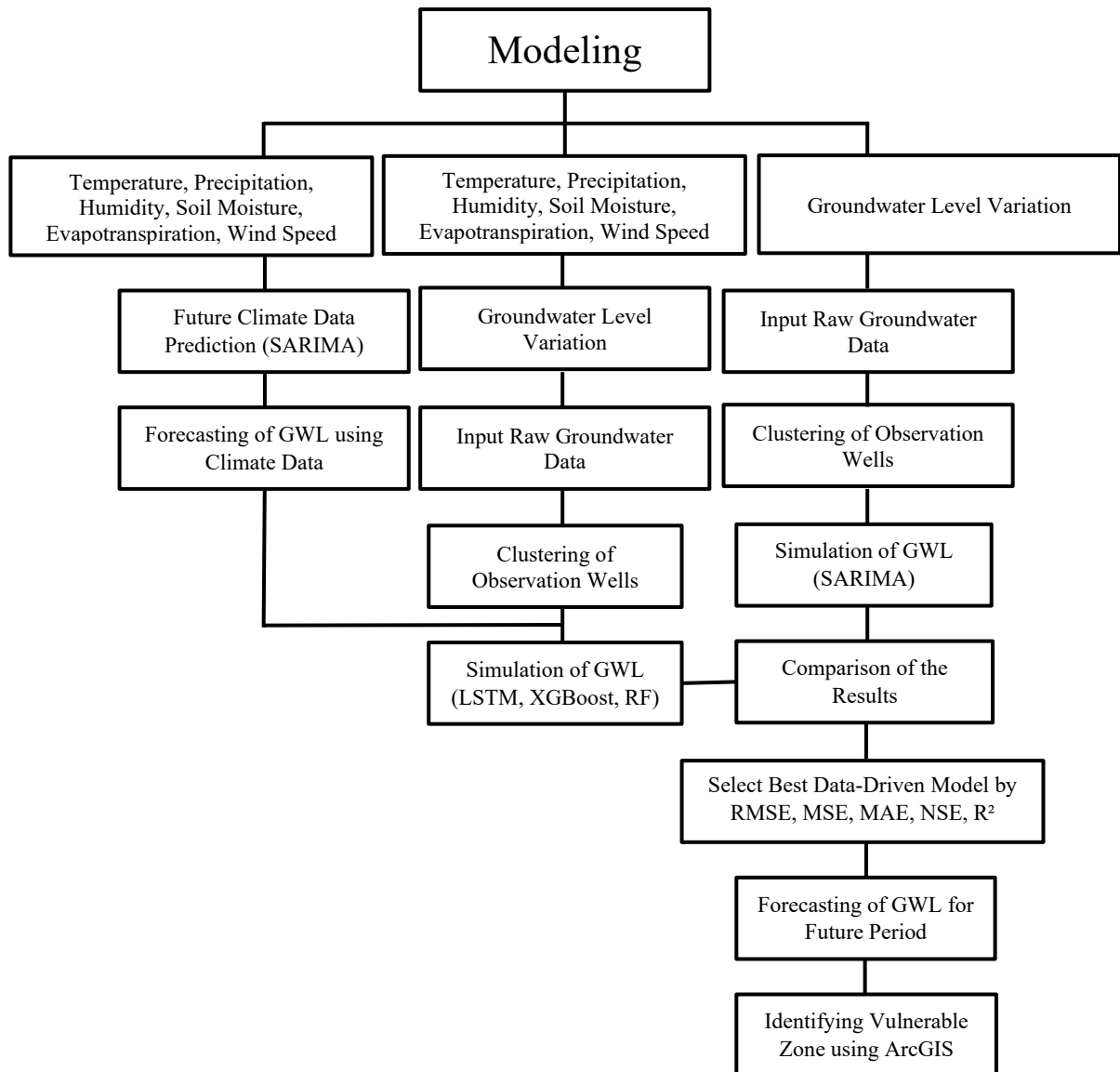
2.1 Study Area

Barishal district that forms the study area is located within the southern coastal strip of Bangladesh with the study area lying between the latitude 22°37'N and 22°45'N and longitude 90°16'E and 90°32'E coordinates (ICLEI South Asia, 2016). The district comprises ten upazilas Barishal Sadar, Babuganj, Banaripara, Bakerganj, Gournadi, Hizla, Mehendiganj, Muladi, Wazirpur, and Agailjhara. All the upazilas have special hydro-climatic and geophysical characteristics and thus the area is very suitable in terms of spatial quantification of groundwater changes under climatic variability.

This area has complex environmental pressures such as sea-level rise, tidal surges, salt-water intrusion and changing rainfall patterns as indicated by Rahman, et.al. (2019). Haque et al. (2021) pointed to the fact that the reliance on groundwater during the dry season experienced in Barishal exacerbates the pressure on resources, and this condition

requires deploying climate resilient management of groundwater. Additionally, Islam et al. (2022) categorized the geographic location of Barishal within the coastal delta plain as vital toward modelling the associated behavior of aquifer under climate-based environmental pressure within other lowland coastal zones.

2.2 Overview of the Modeling Framework



2.3 Hydrogeological and Hydro-Climatic Context of the Study Area

Barishal district is found in south-central coastal floodplain area in Bangladesh, the geomorphology of which is deltaic, seasonal rainfall, and shallow alluvial aquifer environment. The region is defined by low lying flat terrain, large river-floodplain regimes, and unconsolidated sedimentary deposits that combine to provide spatial variability of recharge, storage, and fluctuation of ground water.

The monsoonal hydro-climatic regime determines the ground water levels in the area and seasonal recharge is mostly experienced during the wet monsoon months where relatively higher recharge and decreasing ground water levels are normally experienced during the dry season. Consequently, groundwater systems in Barishal show apparent seasonal fluctuations in relation to rainfall, evapotranspiration and soil moisture.

Besides climatic forcing, the study area also experiences other anthropogenic pressures that may affect ground water variations, such as ground water abstraction to the domestic, agricultural, and irrigation uses, though the magnitude of these effects might be in dissimilar geographic locations within the district. Moreover, the hydrogeological reaction of the aquifer system can be uneven in the locality because of the changes in the sediment composition, surface-water interaction, recharge potential, and shallow subsurface conditions.

Considering such hydro-climatic and hydrogeological features, Barishal offers an appropriate context to investigate the spatiotemporal dynamics of groundwater levels and to assess the relevance of numerical forecasting models on a climate-sensitive coastal aquifer.

2.4 Data Acquisition

To evaluate and geographically distribute the change in groundwater level in Barishal district, the study used primary data sources to determine the groundwater level change in some credible government sources. Primary data of groundwater level was available in the Hydrology Department of the Bangladesh Water Development Board (BWDB). BWDB runs a wide groundwater observation network through 1,250 groundwater observation boreholes across the country (Moshfika et al., 2022). In the present study, 12 gauging locations in the district of Barishal were used to determine the groundwater level changes with space and time over the period January 1996 to March 2025.

In order to integrate the climatic controls in the forecasting models, hydro-climatic variables such as precipitation, maximum temperature, minimum temperature, relative humidity, wind speed, evapotranspiration, and soil moisture were assembled from multiple sources. Monthly total rainfall data were obtained from five rainfall gauging stations within Barishal district, as provided by BWDB. Climatic conditions such as the maximum and minimum temperature, relative humidity, and speed of the wind were gathered using the Climate Information Management System (CIMS) set up under the Bangladesh Agricultural Research Council (BARC), and the data

was gathered and verified by the Bangladesh Meteorological Department (BMD). Moreover, the evapotranspiration and soil moisture were received through the National Agricultural Drought Watch -Bangladesh platform to capture more regional hydro-climatic processes that affect groundwater behavior.

Since the hydro-climatic data were available at a larger scale of the district, as opposed to the single location of the well, a district-based shared climate dataset was utilized to develop the model. That is, the identical week-based hydro-climatic time series was given to all the observation wells of Barishal district. The small number of available well-specific climate observations justified this assumption, as did the relatively small size of the study area in terms of region. In cases where the variables initially had a monthly resolution (mostly minimum and maximum temperature), the monthly values were then transformed to weekly inputs, by giving the same monthly value to all the matching weeks in the same month so that the predictor variables would have the same temporal consistency.

Before model development, the datasets were pre-temporally aligned and continued. The interpolation methods were used to fill missing data in groundwater and climatic time series and the records could be constructed continuously to show all variables during the study. The resulting integrated dataset was subsequently broken down into training and testing subsets (80:20 temporal split) with about 80 percent of the data (1996-2020) being utilized in model training and calibration and the other 20 percent (2020-2025) remaining untouched as out-of-sample testing and

performance data. This time slicing was in place to maintain the time series structure of the time series and to evaluate the ability of the model to forecast under unobservable future conditions.

The resultant data set covers almost 30 years, which is long enough to record seasonal trends, long-term fluctuations and shifting groundwater reactions in the face of hydro-climatic effects in the Barishal district.

2.5 Statistical and Machine Learning Modeling Approaches

In the present paper, we utilize a multi-layered and comprehensive model so that we can forecast changes in groundwater level (GWL) in the Barishal district correctly. In this method, time series forecasting, spatial clustering, and machine learning simulation are incorporated to generate a sound overview of the response of groundwater to climatic variations and seasonal conditions.

2.6 Forecasting Climatic Drivers Using SARIMA

In predicting groundwater elevation, a modeling process known as a time series is used to solve the problem of data uncertainty and variability effectively (Mirzavand & Ghazavi, 2015). The Seasonal AutoRegressive Integrated Moving Average (SARIMA) model is useful in the prediction of the climatic inputs necessary in the analysis of the groundwater patterns. The parameters that are to be forecasted are: Maximum and Minimum Temperatures, Rainfall (Precipitation), Relative Humidity, Evapotranspiration, Soil Moisture, Wind Speed.

The SARIMA model was used as a baseline time-series forecasting approach to predict groundwater level based on its historical temporal and seasonal patterns. As the groundwater levels tend to exhibit seasonal recurrent changes which are related to rainfall and recharge situations, SARIMA was used to investigate the extent to which a traditional seasonal model can explain the observed groundwater level data series. It is a single parameter represented as,

$$\text{SARIMA}(p,d,q)(P,D,Q)_s$$

Where:

- p: Order of the non-seasonal autoregressive (AR) term.
- d: Degree of non-seasonal differencing.
- q: Order of the non-seasonal moving average (MA) term.
- P: Order of the seasonal autoregressive (SAR) term.
- D: Degree of seasonal differencing.
- Q: Order of the seasonal moving average (SMA) term.
- s: Length of the seasonal cycle

2.7 Data-Driven GWL Simulation Models

Long Short-Term Memory (LSTM)

Use of deep learning methods, especially LSTM network, is a highly sound tool to use when it comes to filling in the gap of missing groundwater level data with high accuracy despite having incomplete data records (Vu et al., 2020). Long-term temporal dependencies between the past groundwater measurements and the hydro-climatic variables were learnt using the LSTM model to predict the groundwater levels. In the research,

LSTM was trained with groundwater level alongside climatic conditions including rainfall, maximum temperature, minimum temperature, relative humidity, wind speed, evapotranspiration, soil moisture, which enabled the model to reflect delayed and nonlinear responses of groundwater.

XGBoost (Extreme Gradient Boosting)

The XGBoost model was employed to forecast the groundwater levels through learning the connections between the changes in the groundwater and the chosen hydro-climatic variables. XGBoost was also added because it has a good predictive power, computational efficiency, and the fact that it can enhance its performance with the help of gradient-boosted decision trees.

Random Forest (RF)

The other type of ensemble technique is Random Forest which builds a number of decision trees which are based on random subsets of the training data as well as features. The average of the total trees is mostly taken as the final prediction. It is also good at minimizing variance and overfitting. The algorithms have a great potential in prediction of groundwater level through capturing non-linear and complex relationships among hydro-climatic data and effective processing of large datasets (Kombo et al., 2020). The important hyperparameters are: Number of trees, max depth of each tree, min samples per leaf.

2.8 Model Validation and Forecasting Framework

To ensure a consistent and realistic assessment of forecasting performance, all models were evaluated using a temporal hold-out validation approach. The complete time-series dataset was

divided into training and testing periods following an 80:20 chronological split, where data from January 1996 to December 2020 were used for model training and calibration, and data from January 2021 to March 2025 were used for out-of-sample testing. This time-based separation was adopted to preserve the sequential structure of the groundwater and hydro-climatic series and to simulate practical forecasting under unseen future conditions.

For each observation well, the models were trained using historical groundwater levels together with the selected hydro-climatic predictors, and their predictive performance was assessed on the reserved testing period. The forecasting period therefore corresponds to the same January 2021 to March 2025 interval used for model validation. This framework allowed direct comparison of the statistical and machine learning models under a common forecasting setup.

Although advanced uncertainty quantification methods were not explicitly implemented in this study, model uncertainty was indirectly examined through comparative performance across multiple models and testing over an independent hold-out period. It should be noted that prediction uncertainty may still arise from data interpolation, temporal aggregation of climatic variables, and the use of district-scale shared climate inputs, which may not fully represent local well-specific conditions.

2.9 Model Evaluation Using Performance Metrics

The performance of every model is considered based on the following statistical measures:

- Root Mean Square Error (RMSE): It is highly sensitive to big errors; it puts so much weight to the extreme deviations.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$$

- y_i = Actual value
- $\hat{y}_i$ = Predicted value
- n = Number of observations

The less the value of RMSE the better the model fits the data. Mean Absolute Error (MAE): It is an average representation of the number of errors of prediction.

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|$$

- y_i = Actual value
- $\hat{y}_i$ = Predicted value

When MAE is lower, it means that the model has minor errors on average that will increase its predictive accuracy. Mean Squared Error (MSE): Confers greater penalties on a larger error as compared to smaller errors unlike MAE.

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|$$

- y_i = Actual value
- $\hat{y}_i$ = Predicted value

The less the mean square error the better the fits of the data and the model. A reduced MSE implies that the model is not committing larger errors as a whole,

but it is more hypersensitive towards bigger errors, which are punished more than smaller ones.

- Nash-Sutcliffe Efficiency (NSE): It is a measure of the model's predictive skill.

$$NSE = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2}$$

- y_i = Actual value
- $\hat{y}_i$ = Predicted value
- n = Number of observations
- $\bar{y}$ = Mean of observed values

A closer value to 1 implies that the performance of the model is good since this means the predictions made by the model get near the observed results. Negative numbers show that the model is inferior to the mean.

- Coefficient of Determination (R^2): Resembles the estimate of variability of the observed values that the model accounts.

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2}$$

- y_i = Actual value
- $\hat{y}_i$ = Predicted value
- n = Number of observations
- $\bar{y}$ = Mean of observed values

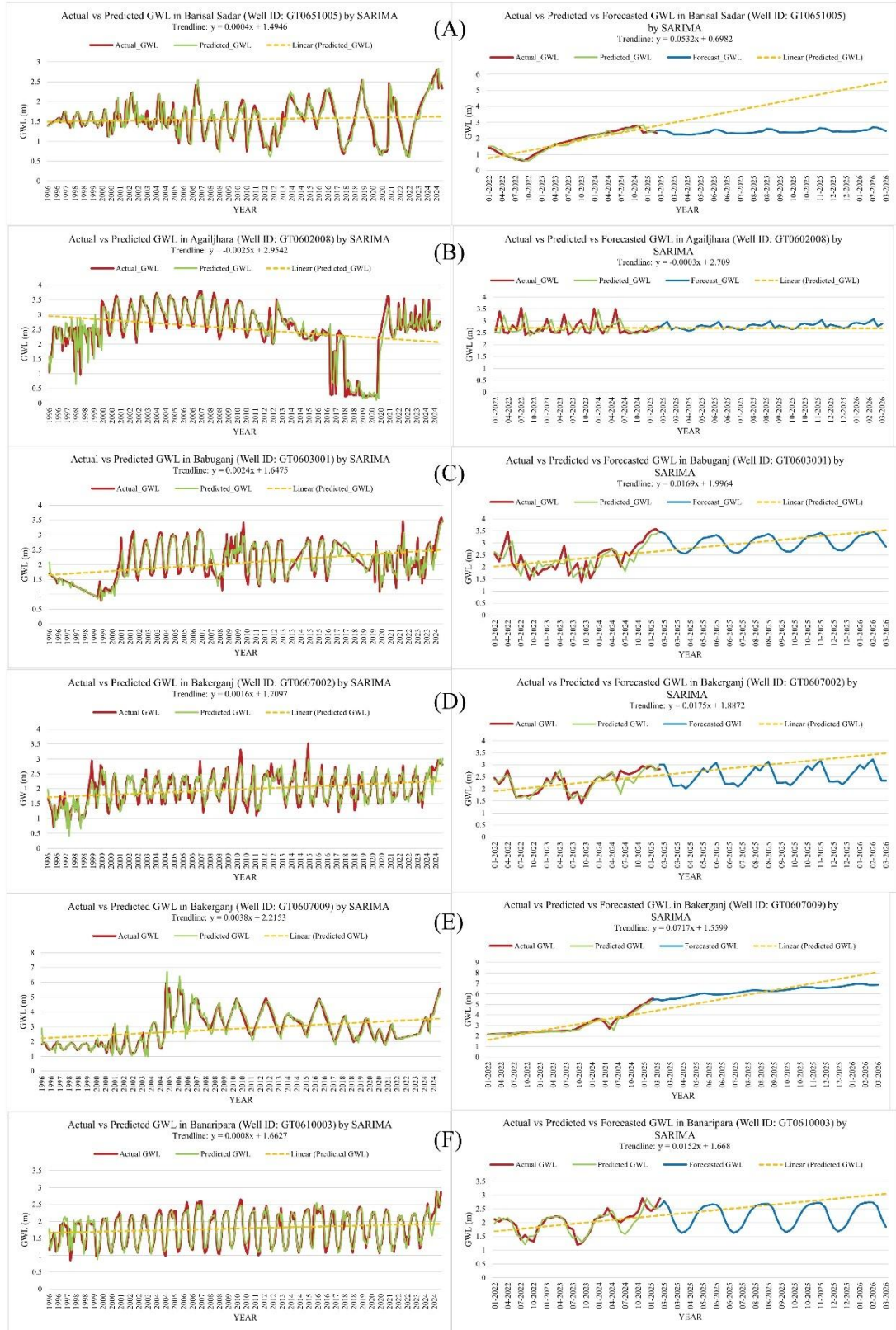
A larger value indicates more fits of the model and data with a value of R^2 being the fraction of the variance measured in the dependent variable opposing the predictable variance in the independent variables.

3. Results and Discussion

The forecasting outcomes of the Four predictive models were applied to the forecasting results of groundwater level (GWL) in Barishal district, and they included SARIMA, LSTM, XGBoost, and Random Forest. They were used on the historical groundwater data of 12 observation wells to determine their capacity to capture temporal variability and used in future groundwater predictions under hydro-climatic variability.

In this section a comparative analysis of model performance is provided alongside with the spatiotemporal behavior of groundwater levels in the study area. These results are explained according to the forecasting accuracy and regional groundwater responsiveness, with special references to those areas where the fluctuation of groundwater is relatively more pronounced.

3.1 SARIMA Model Results



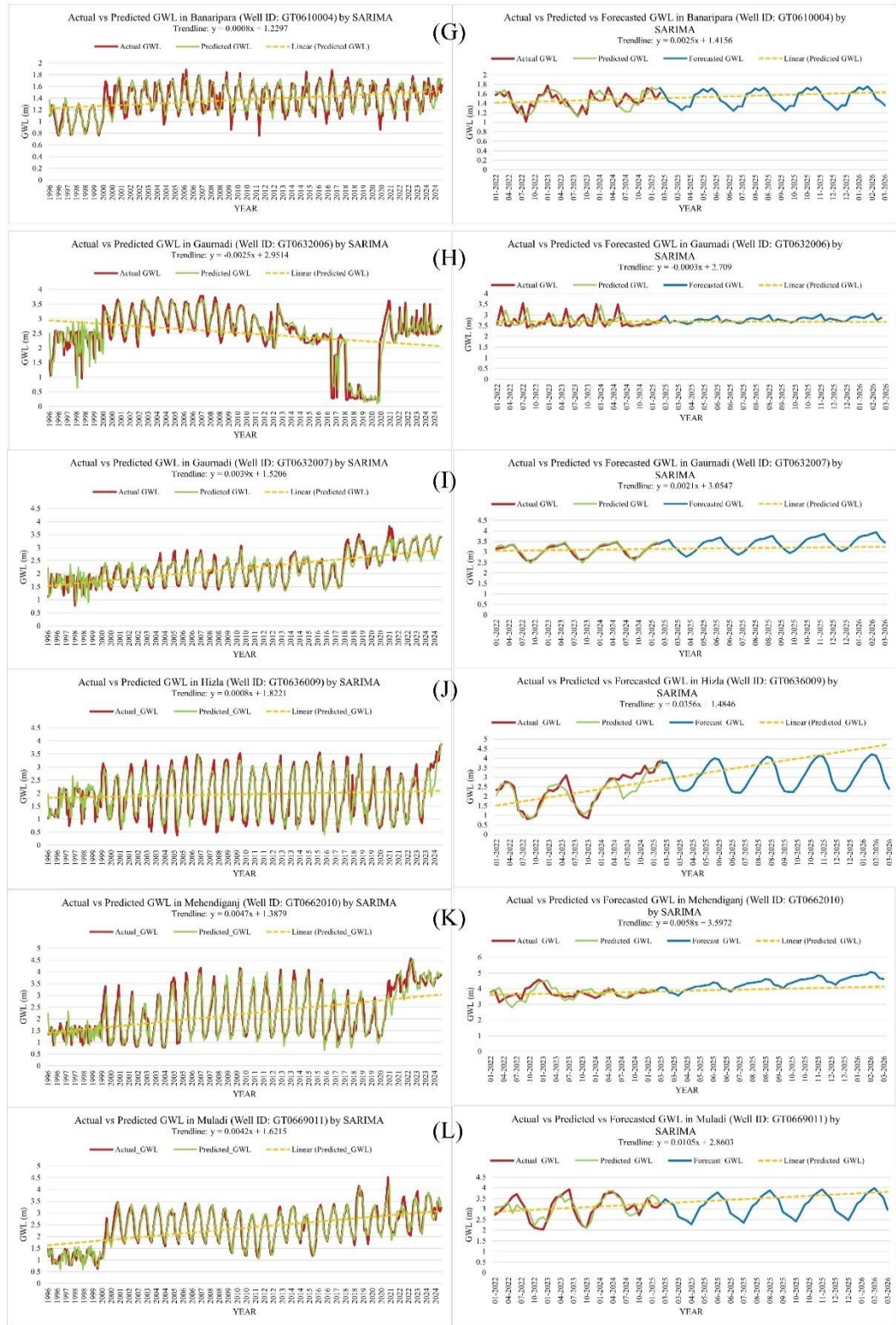
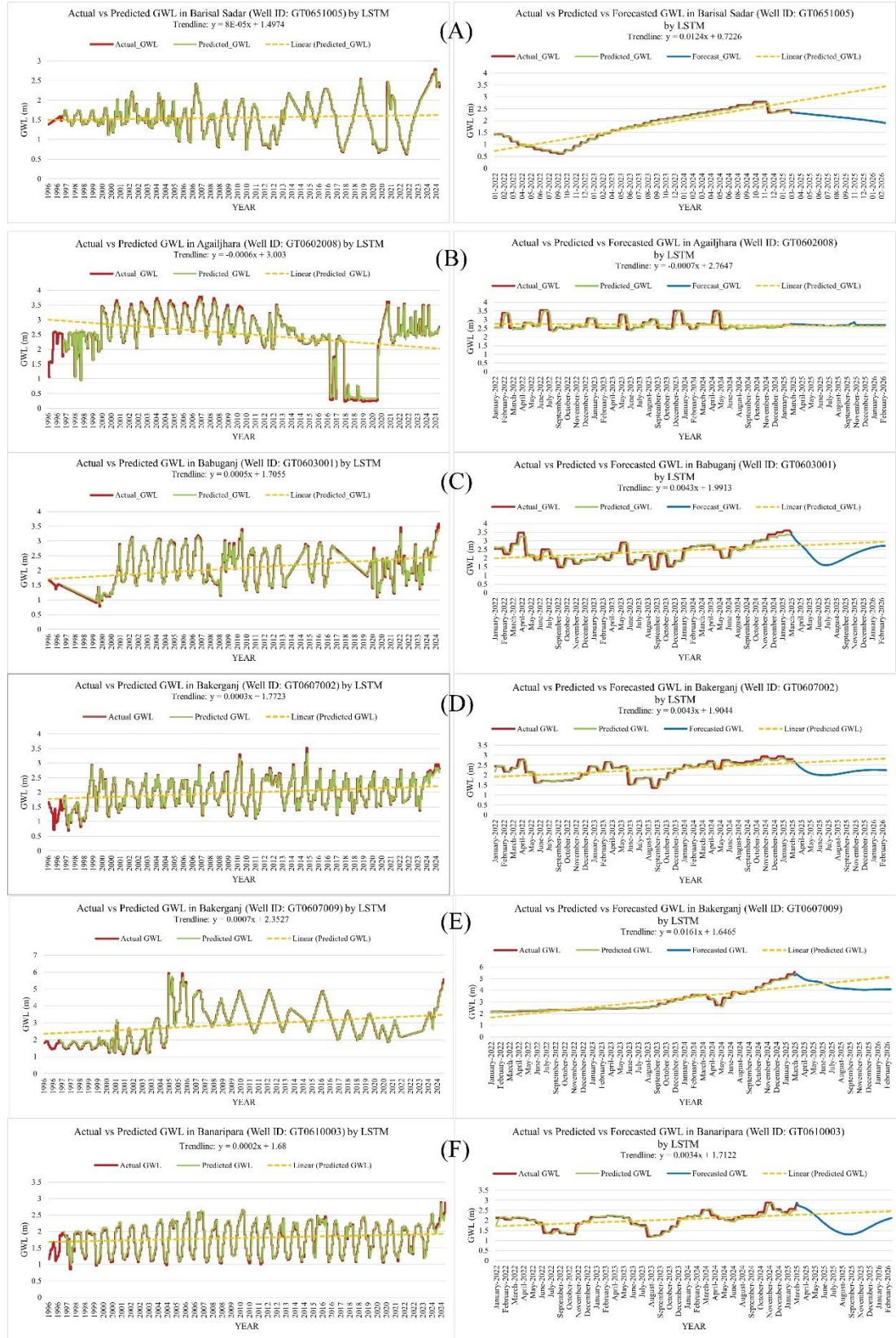


Figure 1: Actual vs Predicted GWL and Actual vs Predicted vs Forecasted GWL in Barishal by SARIMA model

3.2 LSTM Model Results



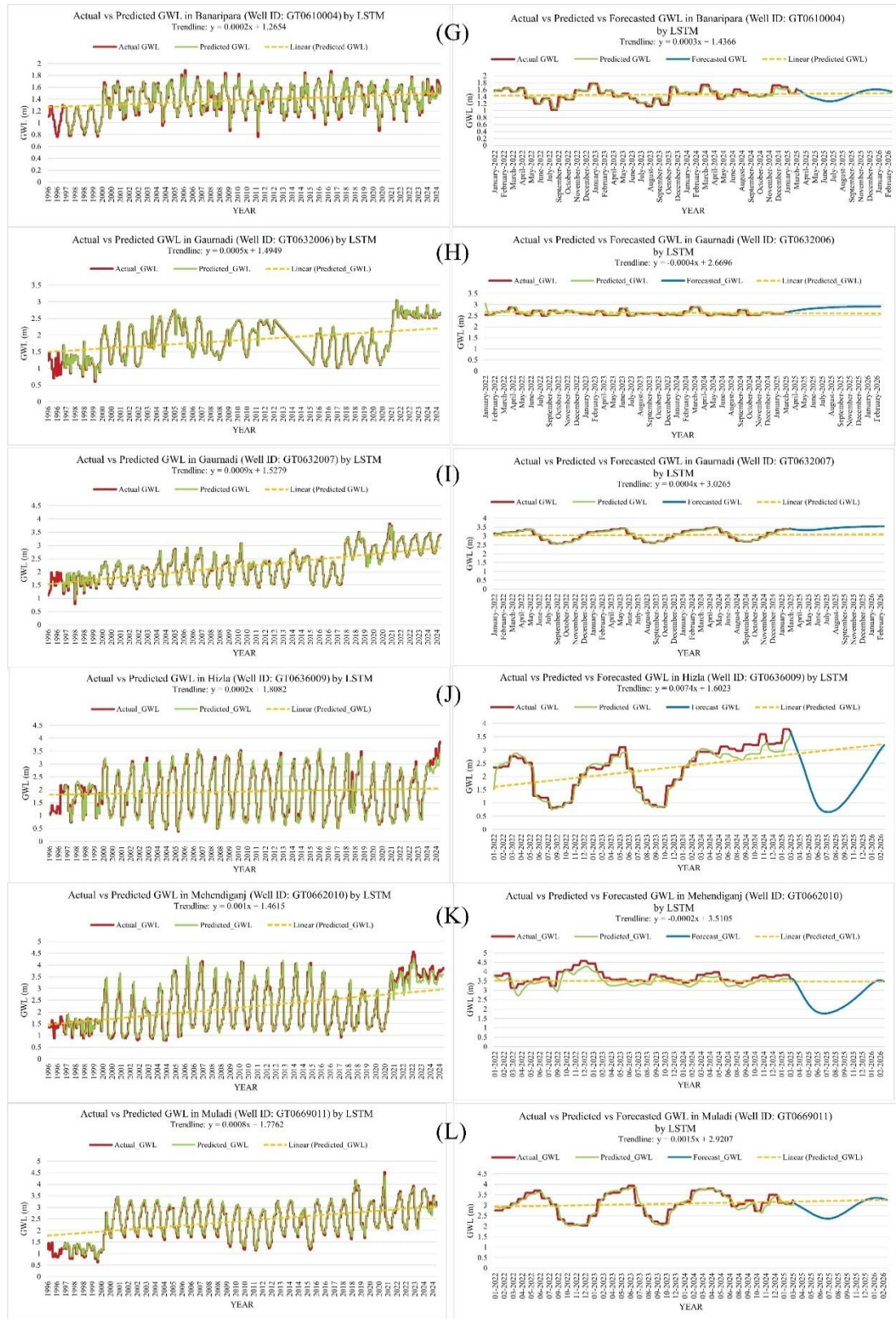
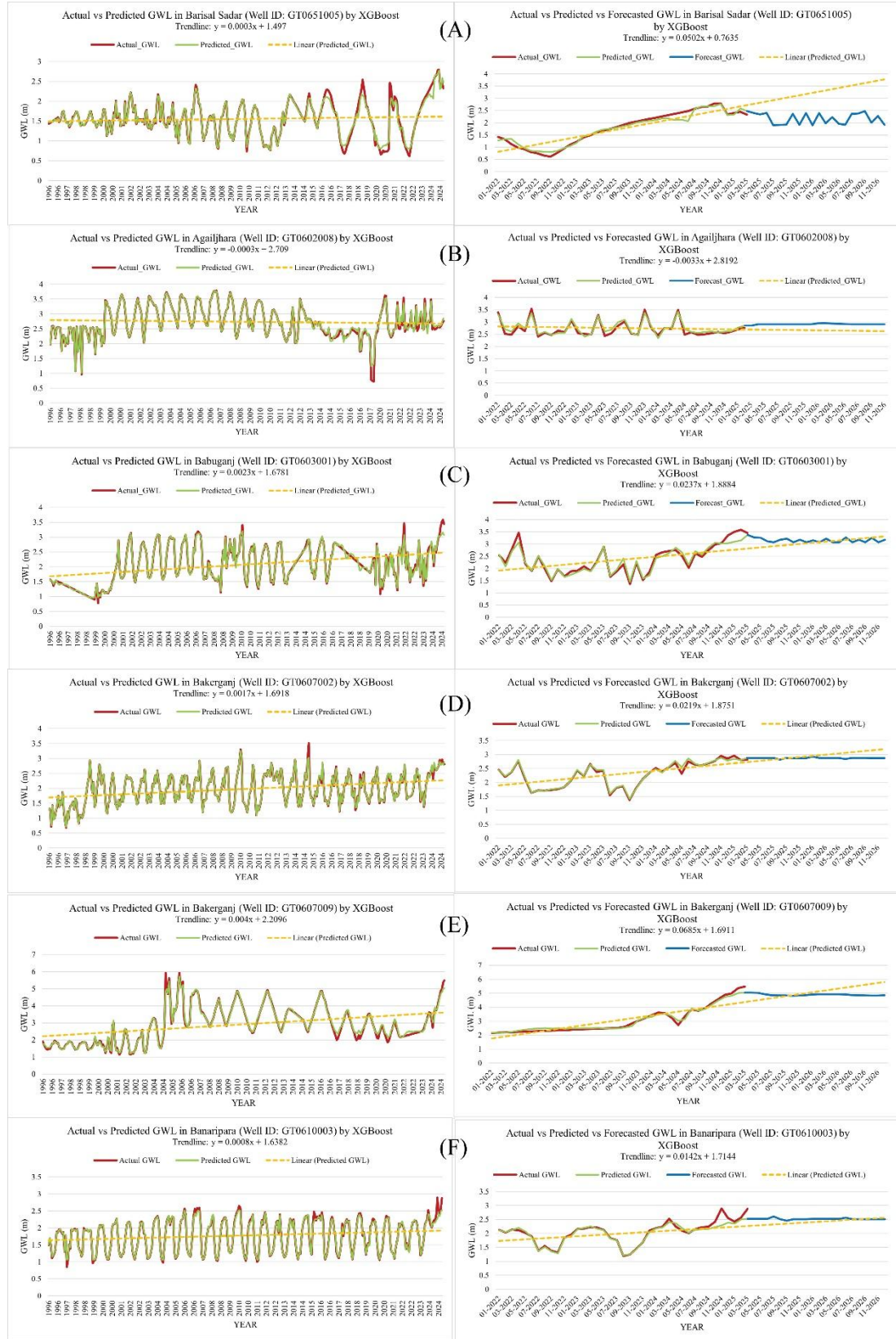


Figure 2: Actual vs Predicted GWL and Actual vs Predicted vs Forecasted GWL in Barishal by LSTM model

3.3 XGBoost Model Results



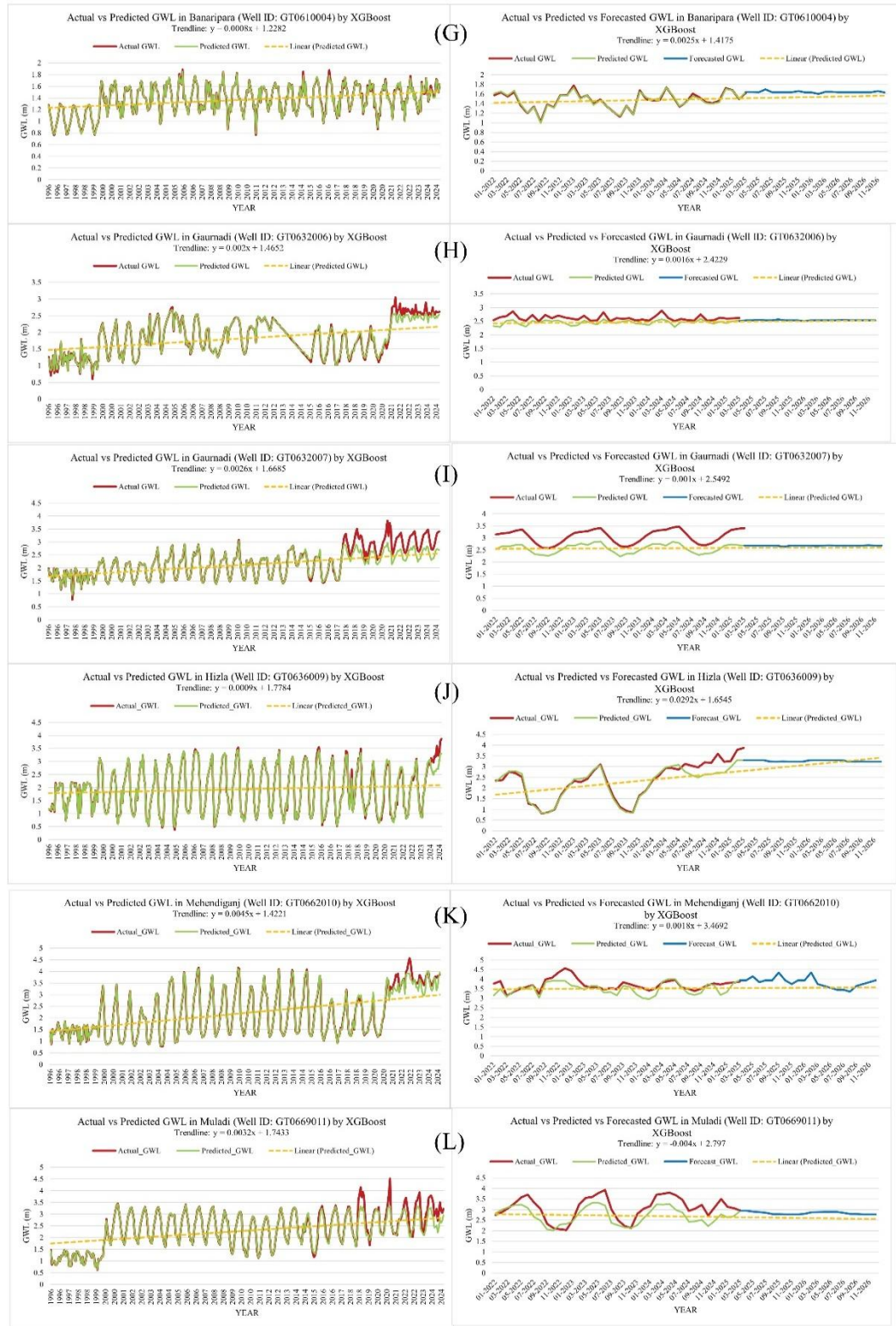
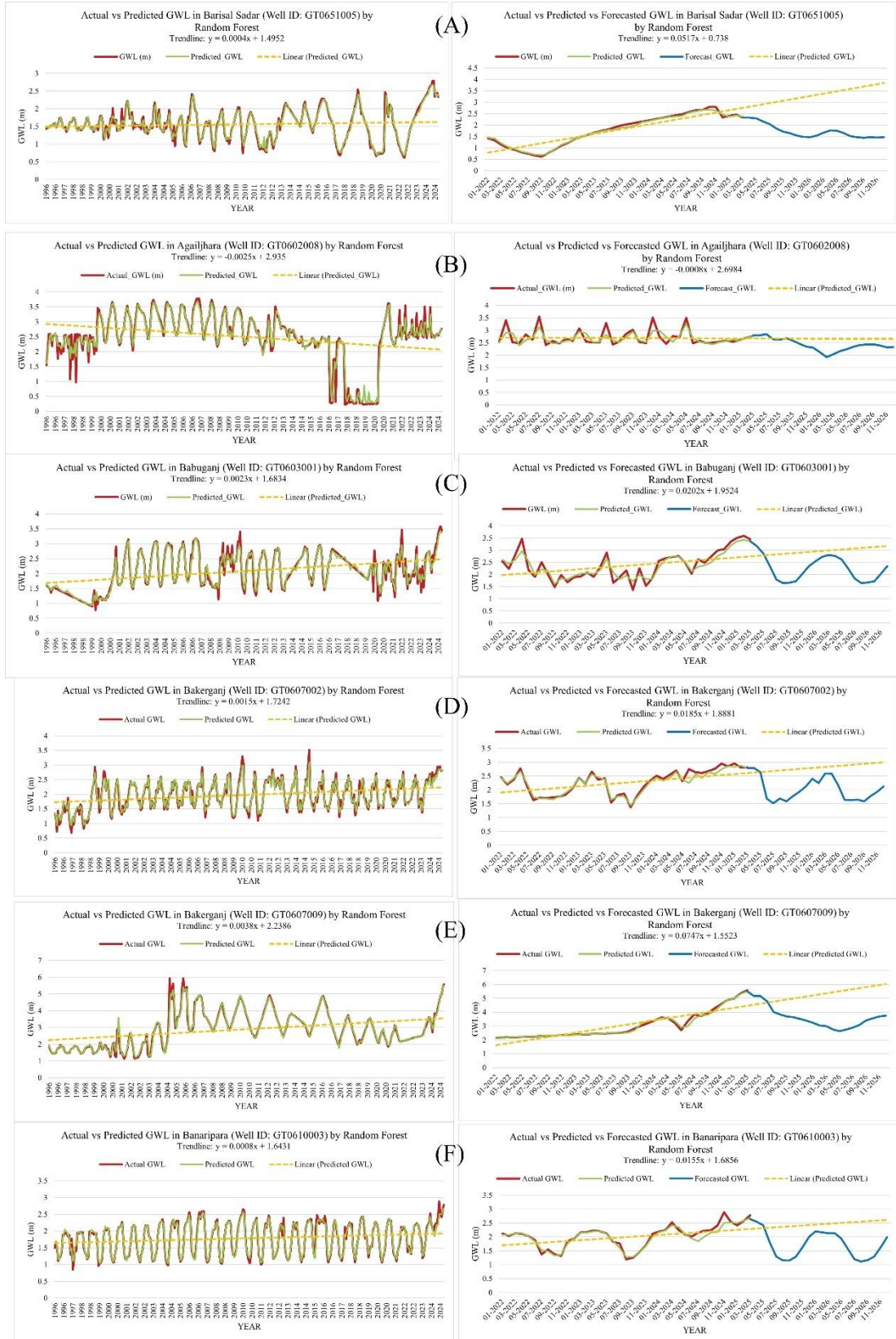


Figure 3: Actual vs Predicted GWL and Actual vs Predicted vs Forecasted GWL in Barishal by XGBoost model

3.4 Random Forest Model Results



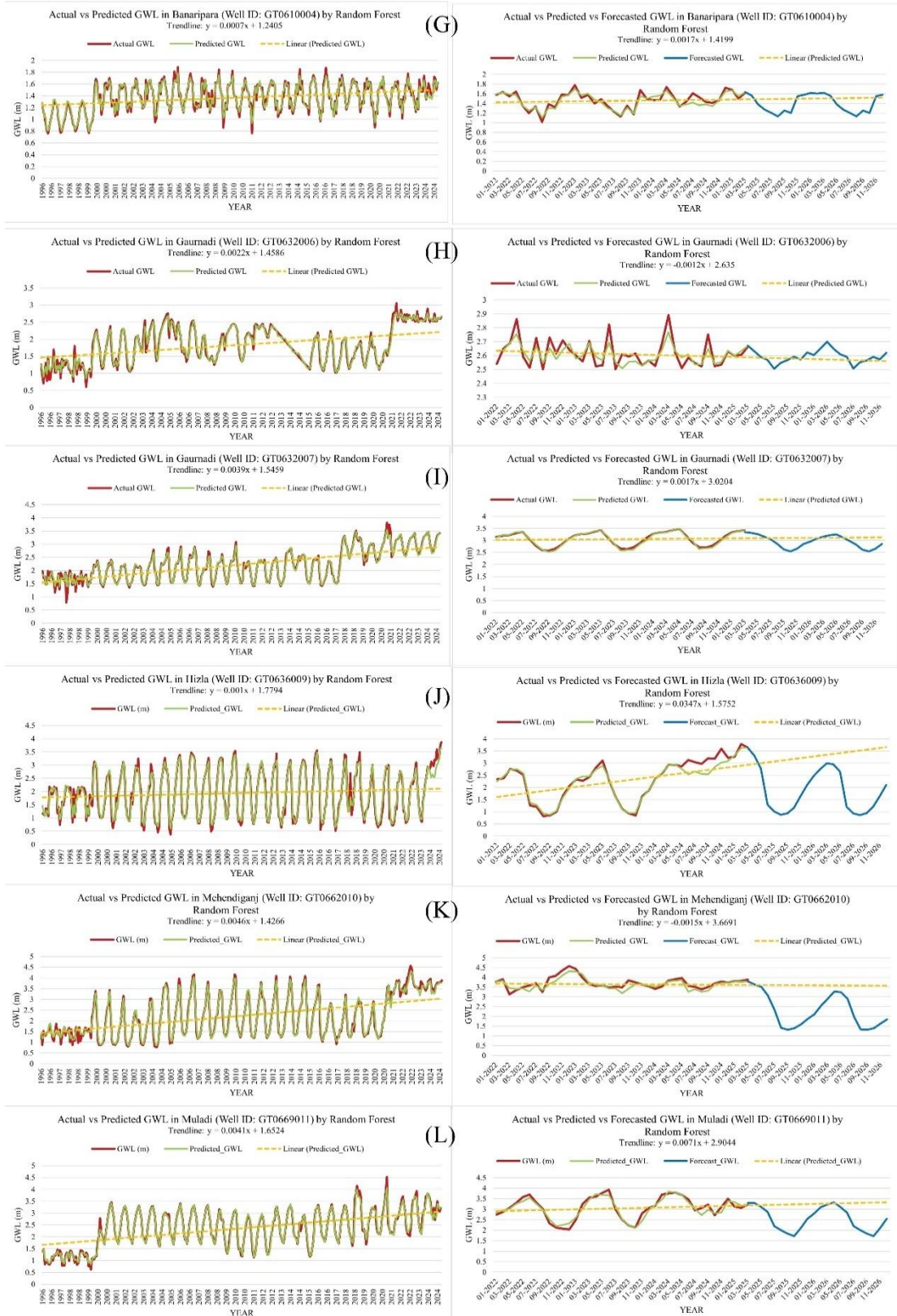


Figure 4: Actual vs Predicted GWL and Actual vs Predicted vs Forecasted GWL in Barishal by Random Forest model

Historical groundwater level data were adopted to train the models from 1996 to 2025 with a wide range of climatic variables of temperature, precipitation, humidity, wind speed, soil moisture, and evapotranspiration being adopted. The outcome of every model was compared on the basis of how well they predicted the real groundwater, and a series of measuring performances were applied to determine the effectiveness and accuracy of the model in reflecting the actual trend in the data.

Findings of this research would shed light on spatiotemporal change in the groundwater level (GWL) in the region of Barisal with emphasis on the reported decrease in groundwater level on account of different environmental and human induced pressurizing factors. The study assesses the accuracy and forecasting capacity of different machine learning and time series techniques: SARIMA, LSTM, XGBoost and Random Forest for this purpose. The obtained observations of various wells at different locations in the region were compared to determine the degree to which these models predict improvement of levels in the groundwater with time elapsed. The results and their visual comparison (of the actual and predicted GWL trends) as well as the discussion of the model's performance in providing insight and predictive information about groundwater trends, and particularly, the declining trends attributable to the influences of climate change and anthropogenic withdrawn are presented in this section.

Conclusively, both SARIMA and LSTM models could offer the most desirable results concerning the long-term prediction given the fact that SARIMA offered a fairer forecast with respect to the whole period. Although useful to

work with, XGBoost and Random Forest models have more difficulties with predictions over a longer period of time.

3.5 Comparative Performance of Models

There were four different models used to compare the accuracy of various forecasting methods of groundwater level (GWL) in the Barishal district in Bangladesh namely; SARIMA (A classical statistical model) and a combination of three machine learning algorithms i.e.: LSTM, XGBoost, and random forest. To determine the performance of each model, five common evaluation criteria were used which include Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Root Mean Square Error (MSE), Coefficient of Determination (R^2), and Nash-Sutcliffe Efficiency (NSE).

In the presented analysis, the visual inspection of model evaluation bar charts derived for each well is used along with focusing on the relative performance of each model.

Random Forest, LSTM and XGBoost were successful and they provided accuracy and consistency, these models happened to be the most accurate as far as prediction is concerned, and hence strong instruments in the management of groundwater. A combination of these models can offer good basis to predict the fluctuation of groundwater in Barishal district in the conditions of climate change. Moreover, the GIS mapping was introduced to trace the groundwater tendencies and define the weak points and it contributed to the spatial concept of the problem.

Table 1: Model Evaluation Metrics

Well Name and ID		RMSE	MAE	MSE	R ²	NSE
Barishal Sadar (Well ID: GT0651005)	SARIMA	0.2095	0.14	0.0439	0.7797	0.7797
	LSTM	0.1025	0.0432	0.0105	0.949	0.949
	XG Boost	0.1016	0.0462	0.0103	0.9486	0.9486
	Random Forest	0.1024	0.0625	0.0105	0.9478	0.9478
Agailjhara (Well ID: GT0602008)	SARIMA	0.3368	0.1991	0.1134	0.8695	0.8695
	LSTM	0.1609	0.0707	0.0259	0.9708	0.9708
	XG Boost	0.6401	0.2393	0.4097	0.5324	0.5324
	Random Forest	0.1692	0.0914	0.0286	0.9673	0.9673
Babuganj (Well ID: GT0603001)	SARIMA	0.3206	0.2353	0.1028	0.6335	0.6335
	LSTM	0.1782	0.0978	0.0318	0.8848	0.8848
	XG Boost	0.1143	0.0726	0.0131	0.9532	0.9532
	Random Forest	0.1429	0.1561	0.0356	0.8412	0.8412
Bakerganj (Well ID: GT0607002)	SARIMA	0.3801	0.2495	0.1445	0.8442	0.8442
	LSTM	0.1877	0.0937	0.0352	0.9633	0.9633
	XG Boost	0.1041	0.0661	0.0108	0.9884	0.9884
	Random Forest	0.1933	0.0991	0.0374	0.96	0.96
Bakerganj (Well ID: GT0607009)	SARIMA	0.2598	0.1974	0.0675	0.6382	0.6382
	LSTM	0.1578	0.0823	0.0249	0.8698	0.8698
	XG Boost	0.0466	0.0237	0.0022	0.9885	0.9885
	Random Forest	0.1093	0.0782	0.012	0.9364	0.9364
Banaripara (Well ID: GT0610003)	SARIMA	0.1937	0.1386	0.0375	0.6435	0.6435
	LSTM	0.0972	0.056	0.0068	0.8068	0.8068
	XG Boost	0.0337	0.022	0.0011	0.9848	0.9848
	Random Forest	0.0714	0.0495	0.0051	0.949	0.949
Banaripara (Well ID: GT0610004)	SARIMA	0.1971	0.1469	0.0389	0.8154	0.8154
	LSTM	0.131	0.073	0.0172	0.9193	0.9193
	XG Boost	0.0941	0.0409	0.0089	0.9577	0.9577
	Random Forest	0.0882	0.1455	0.0424	0.7315	0.7315
Gournadi (Well ID: GT0632006)	SARIMA	0.2092	0.155	0.0438	0.7521	0.7521
	LSTM	0.1101	0.0588	0.0121	0.9311	0.9311
	XG Boost	0.0704	0.0447	0.005	0.972	0.972
	Random Forest	0.096	0.067	0.0092	0.9479	0.9479
Gournadi (Well ID: GT0632007)	SARIMA	0.2396	0.159	0.0574	0.8432	0.8432
	LSTM	0.1346	0.0776	0.0181	0.9485	0.9485
	XG Boost	0.143	0.0722	0.0204	0.9434	0.9434
	Random Forest	0.1037	0.0667	0.0108	0.9702	0.9702
Hizla (Well ID: GT0636009)	SARIMA	0.3536	0.2539	0.1252	0.8191	0.8191
	LSTM	0.2481	0.1626	0.0616	0.9139	0.9139
	XG Boost	0.1114	0.0602	0.0124	0.9822	0.9822
	Random Forest	0.1461	0.0995	0.0213	0.9694	0.9694
	SARIMA	0.3421	0.2405	0.117	0.816	0.816

Mehendiganj (Well ID: GT0662010)	LSTM	0.2213	0.1133	0.049	0.9255	0.9255
	XG Boost	0.1399	0.0698	0.0196	0.9694	0.9694
	Random Forest	0.125	0.0839	0.0156	0.9756	0.9756
Muladi (Well ID: GT0669011)	SARIMA	0.27	0.1735	0.0729	0.8298	0.8298
	LSTM	0.1845	0.1065	0.0341	0.921	0.921
	XG Boost	0.2013	0.0915	0.0405	0.9059	0.9059
	Random Forest	0.1344	0.0785	0.0181	0.9581	0.9581

3.6 GIS-Based Vulnerability Mapping

The Barishal district is experiencing an overall downward trend in the groundwater levels, with the rate of depletion increasing over the years, between the years 1996 and 2025. In Hizla, Mehendiganj, Babuganj, and Bakerganj, there is a gradual transition from the safe/moderate zones to the severe depletion (red), and the regions that have been in the moderate risk are now entering the moderate risk (yellow). The tendency has shown an increase in groundwater stress, especially in the western and southern regions, which is going to get worse.

According to the vulnerability mapping based on the GIS, it is true that depletion of groundwater is still a significant problem even throughout the Barishal district. Areas in which the groundwater table has gone below 10 feet have turned out to be the most susceptible regions indicating severe water shortage. Such red zones are accumulated in the western and northern sides of the district specifically in areas like Hizla, Mehendiganj, Bakerganj, Gaurnadi and Muladi which have already noticed huge depletion of the groundwater level.

The groundwater table has already surpassed the 10 feet mark in these areas

(3.05 meters) and these areas can be considered to be the most vulnerable. Groundwater management in these areas is thus an urgent need. This depletion is expected to continue further in the future projections i.e., in 2026 and this aspect is expected to increase likelihood of water shortage, particularly on agricultural and domestic basis.

On the contrary, regions such as Barishal Sadar (Kotwali) and Agailjhara that are facing depletion at this moment still lie in moderate risk areas and are relatively better in the management of water resources. Nevertheless, these regions also experience the tendency of becoming weak and will have to switch to being sustainable in water management processes so that they could not trespass into the high-risk bracket.

The exposed zones that have been chosen within 2026 prediction depict that some immediate measures are required like better water conservation, harvest of rainwater and less extractions of groundwater. Unless this is done, chances are high that Barishal will be experiencing a water crisis in the near future and therefore it is imperative that steps be taken to ensure that the groundwater supply of Barishal is preserved so that the future generations will not have to grapple with water shortages in the area.

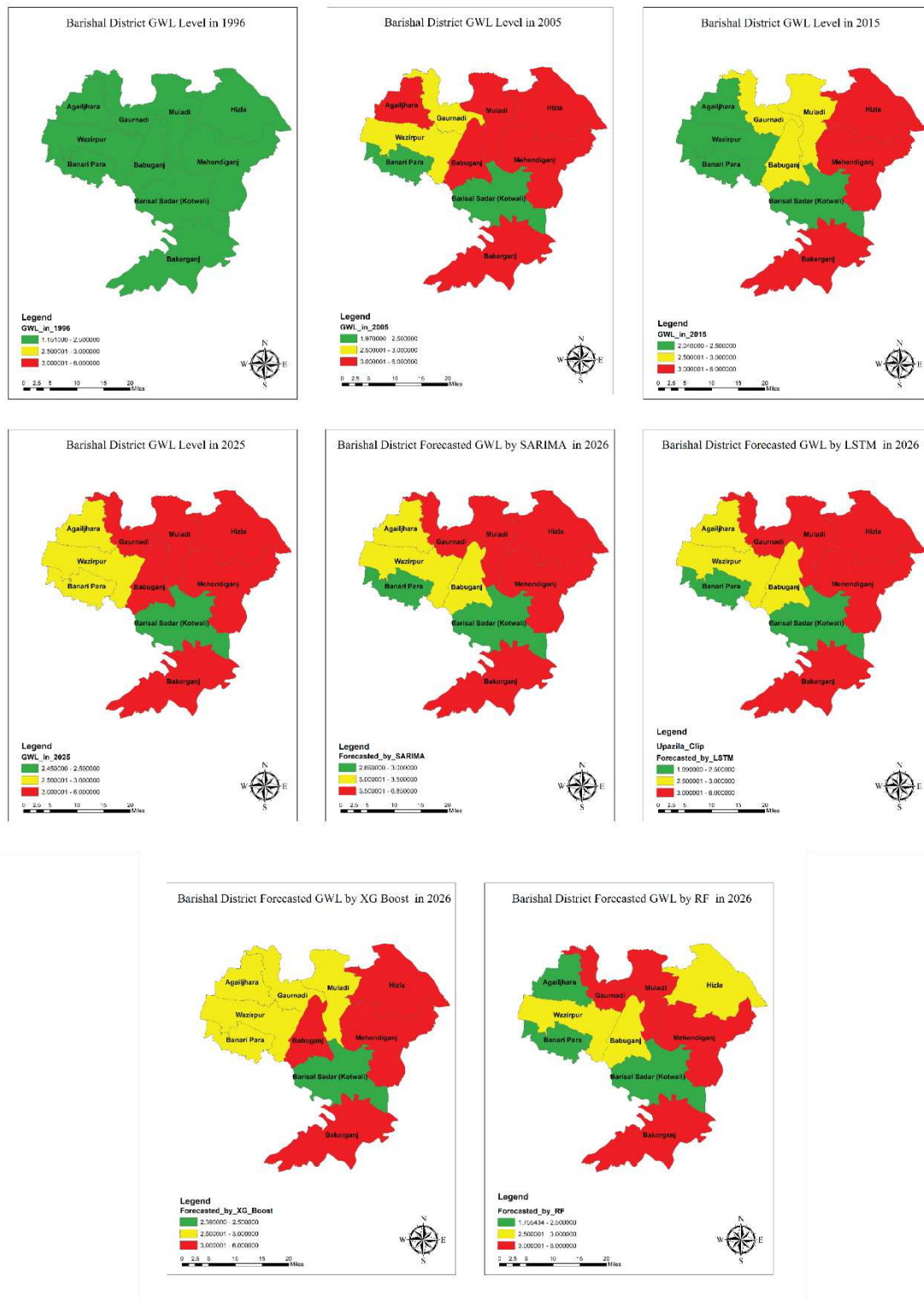


Figure 101: Groundwater Level Map (1996-2025) and Forecasted Groundwater Level Map (2026) for Barishal District

3.7 Model Limitations

- **Data Quality and Availability:**
The groundwater level data are collected in 12 wells in Barishal that cannot surely reflect the variety of hydrogeological conditions in the area. Missing data or erroneous data in the data of the past may affect the predictions of the models particularly where there is a low amount of data.
- **Overfitting and Model Complexity:**
The complexity of LSTM and the Random Forest model was a problem since they overfit. As a deep learning model, LSTM will need significant dataset to enable optimum training. Random Forest models, containing large number of decision trees, would be computationally costly and they would be at risk of overfitting, without proper configuration
- **Seasonality and Climatic variation:**
The models, particularly SARIMA models, are susceptible to seasonality but likely to underestimate abrupt climatic variations, i.e., remarkable weather occurrences or climatic changes in the long run (ex: droughts).
- **Model Interpretability:**
LSTM and Random Forest can provide powerful capabilities when it comes to making a prediction, but they can be referred to as black-box models because it is not very straightforward to understand how certain input variables affect the output.
- **Computational Resources:**
The models that need to be used, LSTM especially, demand a lot of resources in terms of training and predictive purposes. On the same note, Random Forest, compared to LSTM, is computationally less

demanding, nevertheless, it remains a resource intensive approach when dealing with large amounts of data.

- **Geospatial and Temporal Limitation:**

The prediction capacity of the models in other geographical or weather conditions outside Barishal is questionable, and more work needs to be done in terms of testing and calibration of the models to allow extensive use.

3.8 Key Findings

- **Decline in groundwater Level:**
The trend observation shows a considerable reduction, and it is being caused by such factors as an intensified water withdrawal and climate change. Not only SARIMA but also LSTM models closely correspond with observed data, and it is confirmed that GWL decreased.
- **Model Performance:**
LSTM and Random Forest models performed better than others, and LSTM was very adequate in predicting short-term variations and Random Forest robust in terms of overall predictions.
- **Vulnerable Areas:**
Analysis showed the following areas in Barishal as the areas where groundwater depletion is particularly dangerous: Muladi, Mehendiganj, Gaurnadi, Bakerganj, and Hizla. These were the regions that recorded the most notable declines in groundwater levels.
- **Effects of Climatic Change:**
Unchecked increase in temperature and fluctuation in precipitation has caused irregularity in recharge cycle,

which is a reason of observed decline in groundwater level.

➤ **Prediction Accuracy and Model Comparison:**

The assessment of performances (RMSE, MAE, R^2), vindicated the supremacy of the models in dealing with the issue of long-term and short-term projections of water levels on the ground.

➤ **Management Recommendations:**

It is recommended that the vulnerable areas which are at risk of groundwater depletion drainage be considered first before other areas toward mitigating the risk of groundwater depletion (Muladi, Mehendiganj, Gaurnadi, Bakerganj, Hizla). The future recommended research should be the optimization of LSTM and Random Forest to monitor real-time observation and advance groundwater prediction accuracy in the future planning of the resources.

4. Conclusions and Recommendations

4.1 Current Groundwater Status in Barishal District

The current analysis shows that the groundwater level (GWL) behavior in Barishal district is pronounced by the obvious spatial and temporal variability, rather than a regional pattern. According to the groundwater records that were observed between 1996 and 2025 and the corresponding spatial analysis, there are various sections of the district that show relatively high groundwater dynamics as compared to others. Specifically, the variability in groundwater levels at Muladi, Mehendiganj, Gaurnadi, Bakerganj, and Hizla was always higher, which implies that these areas are more

susceptible to seasonal and long-term groundwater stress.

These measured variations in these regions are presumably linked to the joint actions of hydro-climatic heterogeneity, seasonal recharge states and local groundwater demand strains, even though the contribution of each influence might be spatially distributed. Hydro-climatic environment of Barishal, especially its reliance on monsoon rainfall, evapotranspiration climate, and shallow alluvial aquifer response seems to be rather crucial in the development of the temporal behavior of groundwater throughout the district.

Conversely, in other regions like Barishal Sadar and Banaripara, the groundwater was relatively more stable with the fluctuation being less pronounced and the seasonal variation being smoother. This implies that the ground water reaction of Barishal is not subordinated to a district-wide process, but per local hydrogeological and environmental circumstances. The overall state of groundwater in the district can thus be deemed heterogeneous where certain upazilas seem more susceptible to fluctuations and may be more susceptible than others.

In a practical sense, the current pattern of groundwater indicates the significance of place-based monitoring and evaluation, particularly in the zones that are more volatile. The findings also show that using of generalized district-scale groundwater interpretation only can be inadequate in capturing the critical local variations that are significant in sustainable groundwater planning.

4.2 Future Groundwater Status in Barishal District

The results of the forecasting indicate that the future water situation of groundwater in the Barishal district will probably be spatially unbalanced with certain regions still reporting a relatively higher water variability as compared to others. The generally similar pattern across the applied forecasting models, such as SARIMA, LSTM, Random Forest, and XGBoost, was that they identified the most vulnerable areas to the instability in the future.

Out of the predicted areas, Muladi, Mehendiganj, Hizla and Bakerganj showed repetitive behavior of being the areas that are more vulnerable during the period of forecast, which suggests that the areas still have a tendency towards greater groundwater variability. Such findings indicate that the groundwater systems in these regions of the district might be more vulnerable to variations in hydro-climatic conditions and local stress factors in case the current trends are maintained. Conversely, locations with relatively low predicted variability like Barishal Sadar demonstrated relatively more stable groundwater behavior in the near future.

Though the perceived extent of the projected fluctuation was varying in the models, an over-all forecasting trend justifies an inference that the state of groundwater stress in Barishal is likely to be concentrated in certain localities as opposed to being uniformly distributed in the district. Among the experimented methods, the LSTM and the Random Forest showed a relatively greater ability to capture the long-term behavior of groundwater, and the models with the possibility to learn nonlinear and delayed reactions can be more reasonable to use in the context of regional groundwater

prediction in climate-sensitive regions like Barishal.

The proactive results of the research in the future point out that specific groundwater management and the enhancement of observation systems in the more liable areas of the district are needed. It should be prioritized to focus on enhancing continuous monitoring, increasing well-specific hydro-climatic data, and introduction of other hydrogeological information to aid in more credible forecasting and planning of groundwater. Simultaneously, the results of the forecast should be viewed with a grain of salt because the current modeling system is based on district-scale common climate inputs, interpolated records, and temporally adjusted datasets, which do not necessarily encode local-scale variability in all well sites.

By and large, both the current and future analyses indicate that groundwater fluctuation in Barishal district is a local and changing phenomenon, which is determined by both the climatic variability and the spatial variations of the response of the groundwater system. The combined application of time-series forecasting, machine learning, and GIS-based spatial interpretation in this study offers a viable framework in the identification of groundwater-sensitive areas and the future groundwater planning in Bangladesh coastal and climate-prone areas.

4.3 Future Scope of Study

➤ Inclusion of Wider Climatic and Anthropogenic Factors:

The models applied in the paper were primarily based on historical records regarding groundwater levels, but in future applications it would be

recommended that additional parameters of the form of changes in land use, demand on crop water, irrigation depth, soil moisture analytics, and socio-economic factors be included as well.

➤ **Long Term Temporal and Spatial Forecasting:**

The existing models of forecasting have been trained on currently available data until 2025. It is possible that future research would be able to increase its time scale to several decades and possibly have utility in planning and policy formulation given a long-term prospect of climate change.

➤ **High-Resolution Remote Sensing and GIS:**

Satellite-based data together with geographic analysis systems may help in improving the prediction in the spatial context, and also introduce more precise mapping of vulnerable areas.

➤ **Model Hybridization and Real-Time Simulation:**

Although the results of LSTM and Random Forest in the current study were good, it is possible to consider future work based on a hybrid version of the model, when machines and physical hydrological models or ensembles of models are combined.

➤ **Policy and Management Scenarios:**

Simulations Future studies are possible to test various policy scenarios of groundwater extraction, recharge, and conservation based on the developed models.

➤ **Community-Centered Groundwater Monitoring and Decision Support Systems:**

Participatory decision support tools and the development of mobile based

groundwater monitoring systems that include the local communities may be developed to bridge the gap between science and practice.

The potential of future research is to further develop our knowledge of the groundwater dynamics and dynamics in response to the shifting climatic and anthropogenic changes, and in achieving more effective, data-driven

and all-inclusive groundwater management practices in Barishal and such areas.

5. Declarations

5.1 Funding

The authors received no specific funding for this research.

5.2 Competing Interests

The authors declare that they have no competing interests.

5.3 Data Availability

The datasets used in this study were obtained from government and institutional sources, including the Bangladesh Water Development Board (BWDB), the Climate Information Management System (CIMS) under the Bangladesh Agricultural Research Council (BARC), and the National Agricultural Drought Watch – Bangladesh platform. The processed data supporting the findings of this study are available from the corresponding author upon reasonable request.

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