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# Machine Learning in Assessing the Impact of Climate Change on Water Resources

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## Abstract

The water resources of Bangladesh are highly susceptible to climate change which is reflected in patterns of river flows, groundwater and water quality. This work uses a machine learning (ML) approach to quantify the changes induced in representative river basins under historical and future SSP2-4.5 and SSP5-8.5 scenarios. Historical climate monitoring also indicated significant regional warming, especially in the coastal region (+0.25 °C/decade) and growing spatial heterogeneities of rainfall. Future projections under SSP5-8.5 suggest dramatic changes, such as a +4.1 °C temperature increase and a 13.5% change in rainfall by the end of the century. Comparing different ML models for predicting streamflow, the Long Short-Term Memory (LSTM) model proved to be the best. The increase in mean annual streamflow in the Ganges, Brahmaputra, and Meghna basins is substantial under the LSTM projections and the Meghna basin could witness as high as 21% increase under SSP5-8.5. Groundwater is estimated to decrease drastically, and water quality is likely to deteriorate, with coastal salinity increasing by almost 100%. A region-specific adaptation plan for sustainable groundwater management needs to be developed, with an advanced plan for enhancing the resilience of Bangladesh's groundwater resources under future climate scenarios.

**Keywords:** Climate Change; Groundwater; Machine Learning; River Flow; Water Resources.

## 1. Introduction

Climate change is now recognized as a paramount global challenge of the twenty-first century, with the far-reaching effects on natural resources, human societies, and ecosystems (Abbass et al., 2022). Water is one of those resources, being the most vulnerable among all the natural resources, as it not only supports the entire ecosystem, but also all living organisms on the earth, and at the same time allows agricultural and industrial activities (Martinez-Cruz et al., 2024). Warming temperature, changing precipitation patterns, sea-level rise, and more frequent extreme events, including floods and droughts, have all added to the growing pressure on fresh water availability and quality (Nimma et al., 2025). Such changes are not only endangering water resources but also food and energy production, public health, and social and economic stability, especially in areas that are already experiencing water stress. Thus, the knowledge and forecasting of processes of complex interactions between climate change and water bodies are very important under these conditions in the creation of adaptive responses and continuous sustainable management of water (MacAlister & Subramanyam, 2018).

The conventional methods for evaluating the effects of climate change on water resources relied to a large extent on physical models, hydrological simulations, and statistical methods (Luo et al., 2013). Although these approaches have largely increased the amount of our understanding, they have their limitations due to data restrictions, high computational costs, and the inability to fully represent the nonlinear and dynamic connections between climate components and hydrological responses. In this regard, machine learning (ML) represents a disruptive methodology that can overcome many of these constraints (Bhuiyan et al., 2025; Ghobadi & Kang, 2023). ML methods are good at finding obscure patterns, dealing with large datasets, and offering more accurate predictive inklings, so they are naturally geared to better perceive and able to manage complex, high-dimensional phenomena, such as for example climate change and water resources (Ahmed et al., 2024).

Machine learning has broad use in the evaluation of the impacts of climate change on water resources (Bamal et al., 2024). We can use machine learning algorithms like artificial neural networks, support vector machines, random forest, and deep learning models in the form of addressing tasks from streamflow prediction to reservoir level prediction, drought early warning to flood prediction, and also predicting water quality change with the different climatic scenarios (Ahmed et al., 2024; Saleh et al., 2024). In contrast to classical methods, ML models can combine heterogeneous data sources such as satellite images, remote sensing products, meteorological data, and socio-economic indices, and in consequence, such models offer a comprehensive insight into the water resources of climate-stressed areas (Elmotawakkil et al., 2025). The increasing importance of ML in this field is also highlighted by the pressing requirement for reliable forecasting tools to assist policymakers and resource managers in risk reduction and adaptive planning (Douaioui et al., 2024). Water stress is also expected to increase in many areas, especially in developing countries, where increasing population and economic growth multiply stresses from climate change. Meanwhile, infrastructure and livelihood assets are increasingly threatened by water-related hazards such as urban flooding and salinization (S. Rahman & Rahman, 2015). Machine learning allows for more accurate predictions, and to the extent that machines can learn, these systems will be commercially more efficient, adaptive, and scalable decision support systems based on data (Halimuzzaman et al., 2024). In a world where the climate is changing as quickly as it is, this is particularly important as the aforementioned traditional static models may no longer be enough (Rojek et al., 2025).

Although it ultimately holds great promise, the application of machine learning to climate-water studies also has decidedly negative aspects that are worth highlighting (Lyimo et al., 2025). Quality and availability of data and the interpretability of complex model output and however, should still be considered, and collaboration between climate change scientists, hydrologists, and computer scientists is still necessary. It is increasingly important to address these challenges in order to realize the full potential of ML and to enable applications that provide trustworthy and actionable conclusions. In addition, ethical and equitable use of machine learning is required to ensure that resource-limited populations are leveraging advances in predictive modeling and resource management.

## 2. Literature Review

### 2.1. Machine Learning Applications in Water Resources Management

Climate change-induced changes in precipitation, streamflow and water quality are an increasing challenge for water resources management (WRM) (Botero-Acosta et al., 2022). Machine learning (ML) provides a promising perspective for hydrological and statistical approaches in the light of its capability to handle large, non-linear and high-dimensional data (Lokman et al., 2025). Ghobadi & Kang (2023) carried out a review concluding that ML applications in WRM can be classified into three domains: predictive modeling (e.g., streamflow and water quality prediction), clustering and classification (e.g., detection of water pollution), and control learning (e.g., hydropower scheduling optimization). Multiple linear algorithms such as support vector machine (SVM), Random forest (RF) and artificial neural network (ANN) are reportedly used in monthly and annual streamflow prediction, water quality estimation with superior accuracy than conventional models (Ghobadi & Kang, 2023). Further, Ahmed et al. (2024) compared the prediction performance of a variety of ML algorithms on water sector applications and concluded that LSTM networks and hybrid models outperformed traditional ANNs and physics-based hydrological models for time series analysis. Their study highlights the emerging importance of ML to the establishment of resilient and adaptive systems to sustainably manage water under climate change challenges (Ahmed et al., 2024).

### 2.2. Machine Learning for Climate-Change-Induced Hydrological Extremes

Characteristic hydrological events, such as floods and droughts, are expected to be exacerbated under changing climate regimes, the effective predictive services of which are an urgent need (Pizzorni et al., 2024). Nguyen et al. (2023) applied Multi-Layer Perceptron (MLP) and Convolutional Neural Network (CNN) for hydroclimatic forecasting in the Mekong River Basin. They identify rising streamflow trends in various sub-basins, which implies a greater flooding hazard in future (Nguyen et al., 2023). In a similar vein, an ANN, RNN and ANFIS were compared for streamflow forecasting up to 2100 in the Hunza River Basin of Pakistan. The results showed that ANN was more efficient with NSE (>0.95) in training and testing stages. This predictive capability is essential for long-range planning of water distribution, irrigation, and flood control in climate-sensitive parts of the world (Khan et al., 2023).

### 2.3. Groundwater Assessment under Climate Stress

Groundwater, which contributes significantly to the world's supply of freshwater, is strongly susceptible to changing recharge and abstraction in response to climate change (Hughes et al., 2021). A systematic review by Bamal et al. (2024) covered a number of 65 studies done from 2017 and 2023, which affirm that generic machine learning tools, e.g., RF, DT, ANN and SVM are quite powerful in performance for predicting groundwater levels, discharge and storage under climate stress. The hybrid and ensemble models which combines two or more models (e.g., RF-ANN or SVM-ANN) have reported better accuracy than using the single model, especially in medium to long-term prediction of groundwater levels (Bamal et al., 2024). For instance, hybrid models involving climate variables in the form of precipitation, evapotranspiration, land-use data, etc. have been found to capture intricate feedback mechanisms which are usually omitted by conventional groundwater models, especially, for semi-arid and arid areas where decrease in recharge and increase in abstracted quantity pose an alarming pressure on sustainable groundwater extraction (Uc-Castillo et al., 2023).

### 2.4. Remote Sensing, GIS, and Deep Learning Integration

The application of RS and GIS in conjunction with ML has led to new opportunities for processing and analyzing water resources (Saha & Chandra Pal, 2024). Satellite-based estimates of precipitation, soil moisture, land-cover, and evapotranspiration offer spatially distributed inputs which contribute to the accuracy of models (Martínez Pérez et al., 2017). There are a number of recent reviews, that underscore the potential relevance of integrating RS, GIS, and DL for responding to climate change and water-resource challenges; noting that CNN and ConvLSTM models appear as being particularly effective for space-time water modeling (Sapitang et al., 2024). The SEN2DWATER dataset, which is a new spatial-temporal benchmark, has facilitated state-of-the-art deep learning experiments for water monitoring applications. Models such as ConvLSTM and temporal deep CNN have also been well-trained in predicting river and lake dynamics based on multispectral satellite imagery that further proves the necessity of space-time fused investigation for climate-based water assessment (Mauro et al., 2023).

### 2.5. Physics-Aware and Hybrid Modeling Approaches

Purely data-driven ML models achieve excellent predictive performance, but often lack interpretability and physical realism, which can undermine the information trust in decision-making (Salinas-Camus et al., 2025). Physics-aware machine learning (PaML) frameworks that embed hydrological expertise or physical constraints within ML models seek to overcome this challenge. Xu et al. (2023) report on approaches such as physics-informed neural networks (PINNs), physics-embedded learning and hybrid learning that combine hydrological equations with data-driven algorithms.

Their tool, called HydroPML, illustrates how to integrate domain knowledge with ML to improve the accuracy and interpretability of climate-water models (Xu et al., 2023).

### 2.6. Research Gap

While there is an increasing literature on the successful application of machine learning (ML) in predicting streamflow, groundwater level, water quality and hydrological extremes under climate change, there are a number of key gaps. First, the study of application of ML tools on standalone dimensions (e.g., determining floods, access to water, groundwater modeling) of WRM without any holistic view of the multidimensional influence of climate change on WRM. Second, despite achieving better predictive accuracy in comparison with other models such as LSTM, CNN, and hybrid models, their interpretability and physical consistency are constrained, bringing about concerns with regard to the reliability of their findings for policy and long-term planning. Furthermore, many of the applications use regional data sets that have spatial and temporal limitations on their zoo-paleoecology, and therefore reduce the ability to generalize the results to other regions and to compare the results across different regions. Another loophole is the underapplication of emerging methods such as physics-aware ML and ensemble learning that could greatly improve both accuracy and interpretability but have so far only been scarce in climate water studies. In addition, there is much remaining potential for comprehensive assessment, as large-scale modelling of satellite, remote sensed data, socio-economic indicators or downscaled climate projections can scarcely be found in the ML context so far. Finally, little attention has been given to the translation of ML generated insights to practical decision-support systems that water managers and policymakers can apply for climate adaptation planning. Closing these gaps is necessary to unlock the transformative potential of ML for understanding and mitigating the effects of climate change on water resources.

### 2.7. Research Questions

a) How to develop and optimize machine learning models to provide comprehensive analysis of the multidimensional impacts of climate change, in particular, the impacts on water resources in terms of availability, and quality, as well as hydrological extremes?
b) Which methods can be applied to further enhance interpretability, accuracy, and physical consistency of ML models for climate–water interaction to make them suitable for reliable long-term resource planning?
c) How can diverse datasets ranging from remote sensing products, climate projections, hydrological records, to socio-economic indicators, be used to improve the predictive performance and transferability of the developed ML models across regions?
d) How could ML-based assessments be turned into decision-support tools for water managers and policymakers for climate adaptation and sustainable resource use?

### 2.8. Research Objectives

a) To construct ML models for predicting the change of water availability, water quality, as well as hydrological extremes under climate change scenarios.
b) To enhance the accuracy and interpretability of ML models via hybrid and physics-informed approaches.
c) To improve transferability and robust assessments, to combine climate scenarios, hydrological data and remote sensing.
d) To transfer ML results into a decision support system for sustainable water resources and climate change adaptation.

## 3. Materials and Methods

### 3.1. Study Area

Situated in the Bengal Delta, and entirely reliant on the Ganges, Brahmaputra and Meghna river network for its water supply, Bangladesh is one of the world’s most climate-at-risk nations. Rains of the monsoon, rising sea levels, intrusion of salt, and extreme events like storm or floods and droughts, pose threat to the availability of surface, and ground water. These characteristics render Bangladesh an ideal case for ML application in examining climate-induced water-impact studies.

## 3.2. Data Sources

### *3.2.1. Climate Data*

Historical climate information, specifically rainfall, temperature and humidity, for the period 1980-2022 was obtained from the Bangladesh Meteorological Department (BMD) and global reanalysis products. The future climate scenarios were retrieved from the CMIP6 archives under two representative pathways: SSP2-4.5 (intermediate) and SSP5-8.5 (business-as-usual scenario) for the 2021-2040, 2041-2070 and 2071-2100 time slices.

### *3.2.2. Hydrological and Water Quality Data*

Data on river discharge, stream flow, and groundwater levels were obtained from the Bangladesh Water Development Board (BWDB). The water quality parameters (salinity, dissolved oxygen, pH, and turbidity) were taken from the Department of Environment (DoE).

### *3.2.3. Remote Sensing and GIS Data*

Land surface temperature, soil moisture, NDVI and surface water extent (derived from satellite MODIS, Landsat, Sentinel's) data were also collected. For the watershed and floodplain analysis, a Shuttle Radar Topography Mission (SRTM) DEM was employed.

## 3.3. Data Preprocessing

All datasets were extensively preprocessed to guarantee good quality and consistency. Interpolation and multiple imputation were applied for the missing values and Z-score and IQR methods were used for the identification of outliers. Variables were normalized and standardized in this process of ML model training. Feature engineering included the creation of lagged precipitation and temperature variables, seasonal indices, and moving averages to account for time dynamics. Climate and hydrological data were spatially linked in a GIS platform.

## 3.4. Machine Learning Framework

### *3.4.1. Model Selection*

To represent the intricate nonlinear relationship between climatic forcing and hydrologic responses, several supervised machine learning (ML) models were used. Nonlinear regression was conducted using the Artificial Neural Networks (ANNs) and sequential dependency and forecasting of time series hydrological variables with the Long Short-Term Memory (LSTM) networks. The ensemble models of Random Forest (RF) and XGBoost were used for robust prediction and feature importance stuck in physics of hydrological modification. Also, we applied the Support Vector Regression (SVR) to cope with datasets that have small numbers of samples providing excellent generalization in sparse situations. In addition, hybrid and physics-aware ML models have been proposed by coupling hydrological equations with data-driven methods, with the aim of achieving both better interpretability and physical consistency for climate water resource analyses.

### *3.4.2. Model Training and Validation*

The datasets were divided into training, validation and test sets with proportions of 70%, 15%, and 15%, respectively. Grid search and k-fold cross-validation were used to optimize the hyperparameters. Model evaluation was drawn out in terms of Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Nash-Sutcliffe Efficiency (NSE) followed by $R^2$ (coefficient of determination). Uncertainty was treated by carrying out ensemble simulations for different models and climate scenarios.

## 3.5. Scenario Development and Impact Assessment

Effects of climate change on water resources were evaluated based on climate projections under SSP2-4.5 and SSP5-8.5 scenarios classified as near-term (2021-2040), mid-century (2041-2070) and end-century (2071-2100) to account for the temporal variability. Streamflow and flood risks were predicted using LSTM and Random Forest (RF) models based on rainfall, temperature, and discharge data, whereas groundwater dynamics were simulated by Artificial Neural Networks (ANNs) and Support Vector Regression (SVR) models that included recharge and abstraction variables. Water quality variations (salinity, pH and turbidity) were investigated through hybrid ML models associating climatic variables (temperature and rainfall) to the physicochemical properties of water. Moreover, near-coast salinity intrusion was assessed via remote sensing indicators (NDVI and salinity proxies), fused with ML based forecasting framework to estimate risk levels under different future climate conditions.

### 3.6. Decision-Support Framework

Predictive results were used for integrating in a decision support system to guide policymakers. It highlights water-stressed spots, flood prone areas and suggests adaptation strategies for agriculture, urban water supply and disaster risk management. A dashboard was constructed as a prototype to display up-to-date forecasts of river discharge, groundwater level changes, and salinity risks.

### 3.7. Ethical Considerations and Limitations

All data sets were employed in accordance with state and institutional regulations, and with due acknowledgment of their source. Limitations are the uncertainties in climate model projections, the incomplete availability of catchment data/observations, as well as the “black-box” structure of deep learning models. These are alleviated by ensembles, physics-informed ML and rigorous uncertainty quantification.

## 4. Results

### 4.1. Climate Trends in Bangladesh

The trend of climate varies significantly in different parts of Bangladesh, characterized by spatial variation in temperature and precipitation (Table 1). The mean temperature in the North-West region (24.8 °C) is the lowest and rising slightly by 0.19 °C per decade and it also got significant annual rainfall decline (–12 mm per decade). In the case of the Central and South-West regions, the mean temperatures are slightly higher (25.7 and 26.1 °C, respectively) and warming trends become +0.20 to +0.22 °C/decade, also for an increasing trend of rainfall (+15 to +18 mm/decade). The coastal zone is prominent with the highest mean temperature (26.8 °C) and the largest warming rate (+0.25 °C per decade), the largest rise in rainfall (+21 mm per decade).

**Table 1.** Historical climate trends (1980-2022) across major regions of Bangladesh.

| Region | Mean temperature (°C) | Trend (°C/decade) | Annual rainfall (mm) | Trend (mm/decade) |
|---|---|---|---|---|
| North-West | 24.8 | +0.19 | 1650 | -12 |
| Central | 25.7 | +0.22 | 2200 | +15 |
| South-West | 26.1 | +0.20 | 2105 | +18 |
| Coastal | 26.8 | +0.25 | 2450 | +21 |

### 4.2. Climate Projections under SSP Scenarios

The projected climate shows a consistent trend of warming and increased precipitation over Bangladesh in the 21st century (Table 2) and the high-emission pathway (SSP5-8.5) is characterized by more pronounced changes. From 2021–2040, the temperature changes are only moderate, between +0.9 °C in SSP2-4.5 to +1.2 °C under SSP5-8.5 and precipitation increase of 3.2-4.8 percent. In the mid-century (2041–2070) time period, the warming increases to +1.7 °C under SSP2-4.5 and +2.6 °C under SSP5-8.5, while the rainfall has increased by 6.5–9.3%. Towards the end of the century (2071–2100), the difference between the scenarios is more pronounced: SSP2-4.5 projects warmer (+2.3 °C) and wetter (7.1% increase in rainfall) conditions, whereas SSP5-8.5 projects a more severe warming of +4.1 °C but not until coupled with a substantial 13.5% increase in rainfall.

**Table 2.** Projected changes in temperature and rainfall under SSP2-4.5 and SSP5-8.5 relative to baseline (1980–2022).

| Period | Scenario | ΔTemp (°C) | ΔRainfall (%) |
|---|---|---|---|
| 2021–2040 | SSP2-4.5 | +0.9 | +3.2 |

| | | | |
|---|---|---|---|
| 2021–2040 | SSP5-8.5 | +1.2 | +4.8 |
| 2041–2070 | SSP2-4.5 | +1.7 | +6.5 |
| 2041–2070 | SSP5-8.5 | +2.6 | +9.3 |
| 2071–2100 | SSP2-4.5 | +2.3 | +7.1 |
| 2071–2100 | SSP5-8.5 | +4.1 | +13.5 |

### 4.3. Model Performance Evaluation

Model results comparisons indicate that deep learning models, especially LSTM yields the best performance to predict streamflow (Table 3). LSTM yielded the minimum error values (RMSE: 88.6 $m^3/s$, MAE: 64.5 $m^3/s$) and the best efficiency scores (NSE: 0.86, $R^2$: 0.89). In machine learning algorithms, Random Forest and XGBoost were also successful with low errors (RMSE: 97.3–93.5 $m^3/s$; MAE: 72.4–70.2 $m^3/s$) and high values (NSE: 0.84–0.85; $R^2$: 0.87–0.88). Medium performance was achieved for the ANN (RMSE: 125.4 $m^3/s$, $R^2$: 0.81), while the SVR obtained the most unsatisfactory results, with the largest error rates (RMSE: 142.8 $m^3/s$, MAE: 110.7 $m^3/s$) and the smallest efficiency (NSE: 0.72, $R^2$: 0.76).

**Table 3.** Performance comparison of ML models for streamflow prediction.

| Model | RMSE ($m^3/s$) | MAE ($m^3/s$) | NSE | $R^2$ |
|---|---|---|---|---|
| ANN | 125.4 | 92.1 | 0.78 | 0.81 |
| LSTM | 88.6 | 64.5 | 0.86 | 0.89 |
| RandomForest | 97.3 | 72.4 | 0.84 | 0.87 |
| XGBoost | 93.5 | 70.2 | 0.85 | 0.88 |
| SVR | 142.8 | 110.7 | 0.72 | 0.76 |

### 4.4. Streamflow Projections

The estimated changes in river basin discharges all show a positive change in overall water availability over the Ganges, Brahmaputra, and Meghna river basins (Table 4) but are more pronounced under the high emission scenario (SSP5-8.5). For the Ganges, flow would increase by 5–11% as indicated by the SSP2-4.5 and by 7–18% under SSP5-8.5 for near-term (2021–2040) and late-century (2071–2100). The Brahmaputra exhibits the same but weaker trend, 4–10% on average under SSP2-4.5 and 6–17% under SSP5-8.5. The highest relative changes are anticipated in the Meghna basin (6%-14% under SSP2-4.5 and 8% to 21% under SSP5-8.5 over the century.

**Table 4.** Projected changes in mean annual streamflow (relative to baseline).

| River Basin | Scenario | 2021–2040 | 2041–2070 | 2071–2100 |
|---|---|---|---|---|
| Ganges | SSP2-4.5 | +5% | +9% | +11% |
| Ganges | SSP5-8.5 | +7% | +13% | +18% |
| Brahmaputra | SSP2-4.5 | +4% | +8% | +10% |
| Brahmaputra | SSP5-8.5 | +6% | +12% | +17% |
| Meghna | SSP2-4.5 | +6% | +10% | +14% |
| Meghna | SSP5-8.5 | +8% | +15% | +21% |

### 4.5. Flood Frequency and Severity

Both climate change scenarios indicate a significant increase in the frequency of extreme flood events compared to the reference period (1980–2022) during which they on average happened once every five years (Table 5). In the middle-of-the-road emissions scenario (SSP2-4.5), and flood frequency rises to about once in 4 years in 2021–2040, once in 3 years in 2041–2070, and at least once in 2 years in 2071–2100. By contrast, the high-emission scenario (SSP5-8.5) is an order of magnitude more severe, with floods projected to occur every three years in the near term, every two years by midcentury and every year by the end of the century.

**Table 5.** Frequency of extreme flood events under different climate scenarios.

| Scenario | Baseline (1980–2022) | 2021–2040 | 2041–2070 | 2071–2100 |
|---|---|---|---|---|
| SSP2-4.5 | 1 in 5 years | 1 in 4 | 1 in 3 | 1 in 2 |
| SSP5-8.5 | 1 in 5 years | 1 in 3 | 1 in 2 | Annual |

### 4.6. Groundwater Dynamics

The regional projected water table (for different SSPs) suggests drastic reductions in availability by 2100 (Figure 1), especially considering the scenario of high emissions (SSP5-8.5). Groundwater depth in the baseline was between 6.8 m (in the coastal) and 9.4 m below land level (in the South-West). Towards 2100, the depths have become much larger: 10.1 m (SSP2-4.5) to 11.4 m (SSP5-8.5) while being 9.0–10.7 m in the Central region, 11.5–13.2 m in the South-West and 8.1–9.5 m in the Coastal belt. The South-West is expected to suffer the most drawdown although the Coastal region (with the most shallow groundwater) also has significant reductions.

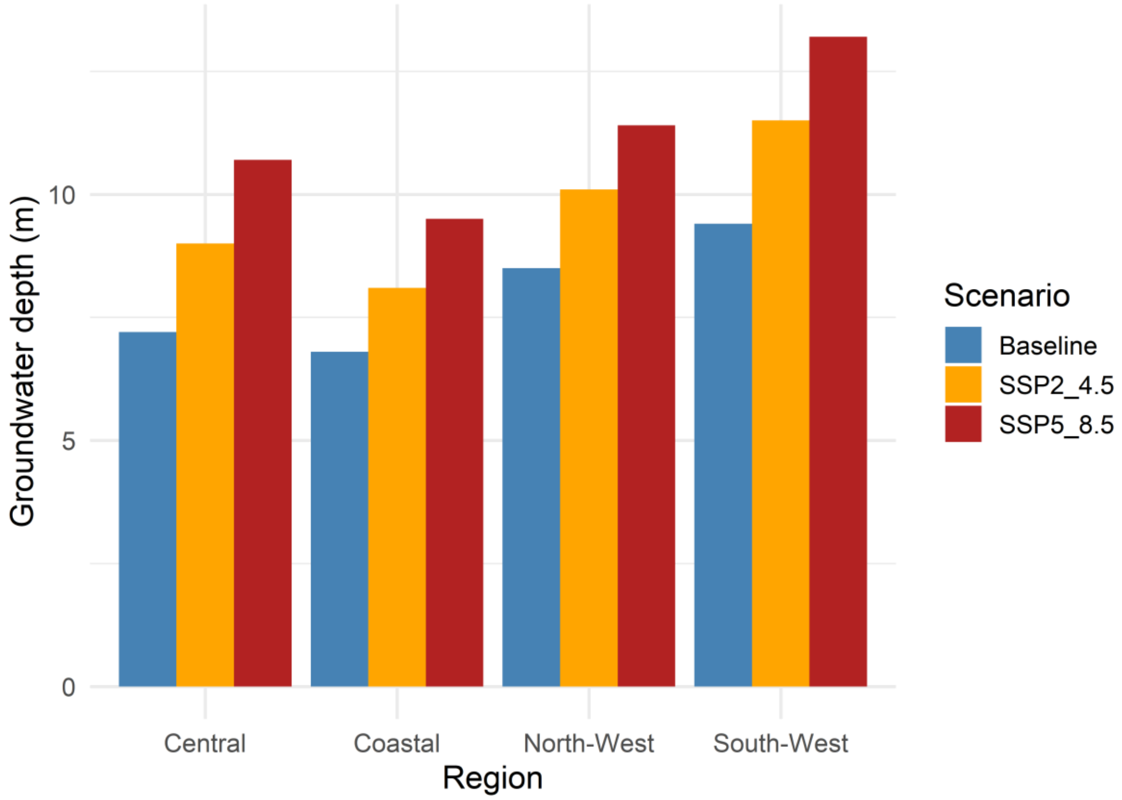


**Figure 1.** Projected groundwater depth changes (m) by region.

### 4.7. Water Quality Projections

The simulated trends in water quality parameters suggest that aquatic habitat quality will overall decrease during the 21st century (Figure 2). Salinity is projected to rise gradually from an initial value of 5.2 ppt to 7.4 ppt and 9.6 ppt by 2041–2070 and 2071–2100, respectively. DO levels have a downward tendency (6.8 mg/L at present, reduced to 6.1 mg/L in the middle and 5.7 mg/L at the end of century). Turbidity increases from 15.2 NTU to 22.4 NTU by 2100; the pH has a slightly decreasing tendency (from 7.4 to 7.1).

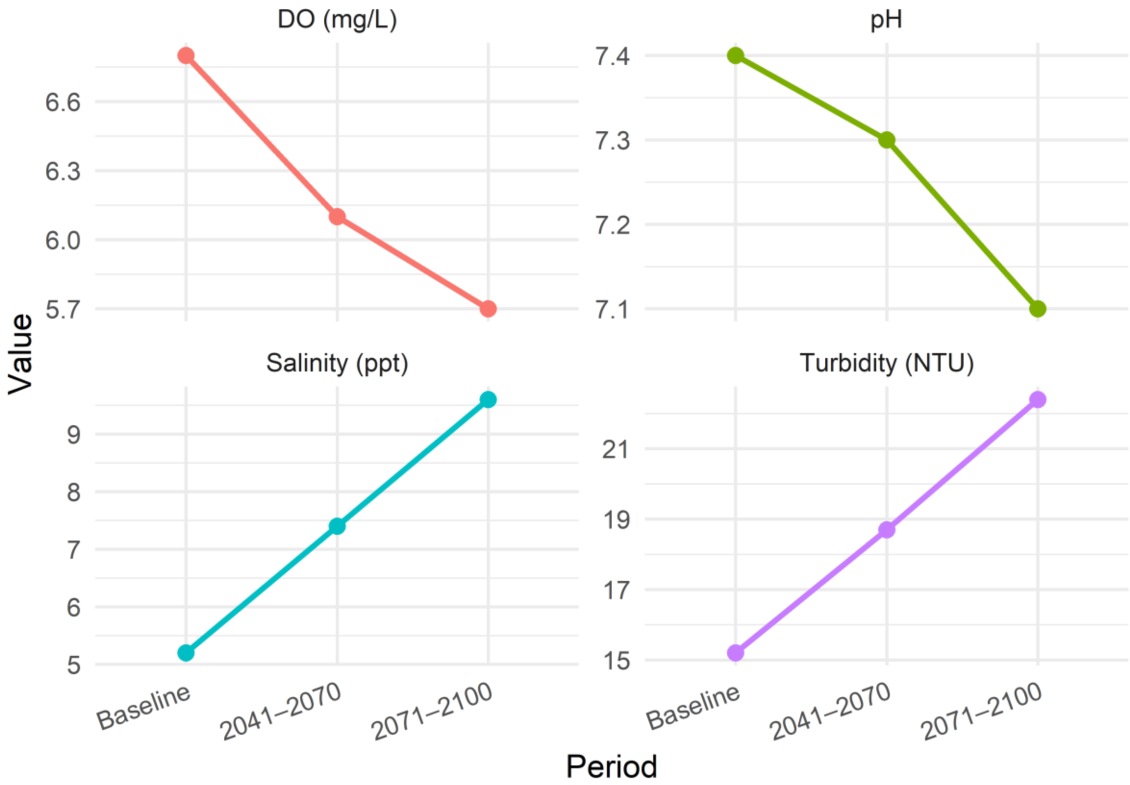


**Figure 2.** Projected changes in water quality parameters under SSP5-8.5.

### 4.8. Feature Importance Analysis

Variable importance analysis of the model shows the significant factors affecting the system, and rainfall was identified as the most important factor contributing 35.2% of the total variation (Figure 3). The second most important variable is temperature (28.7%). Evapotranspiration accounts for 14.5%. Land cover/NDVI brings 12.1% and recharge which has the least contribution with 9.5%.

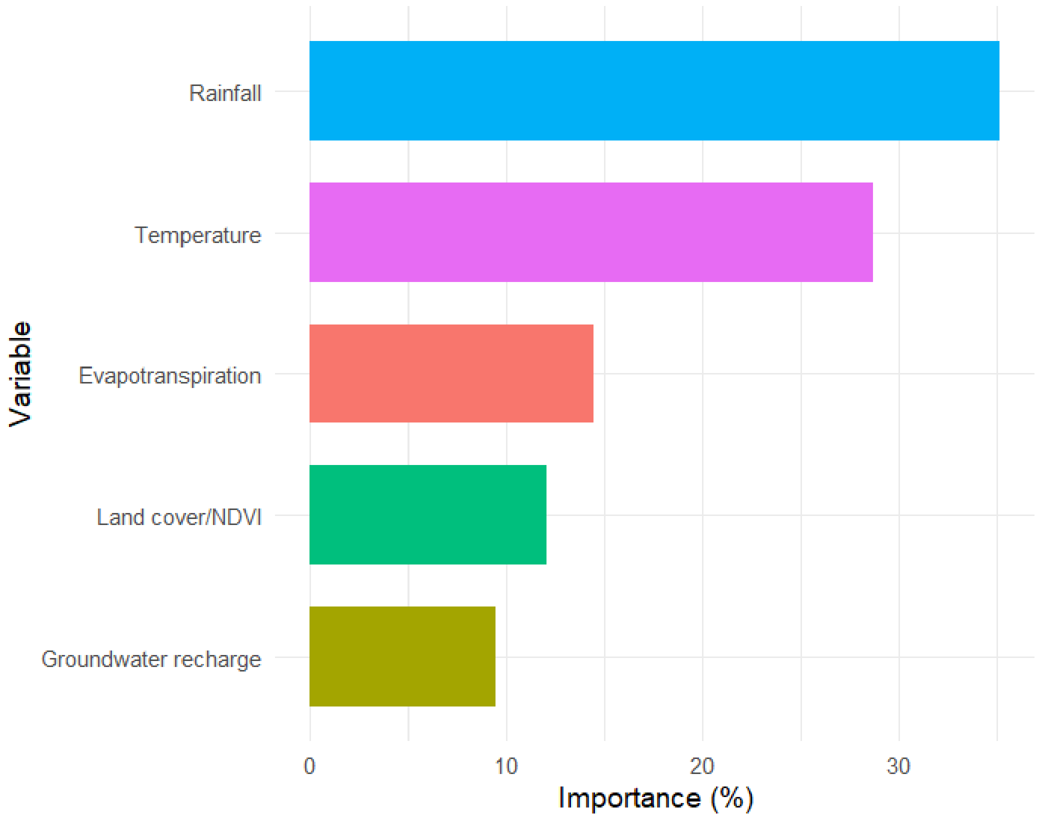


**Figure 3.** Relative importance of predictors in ML models.

### 4.9. Spatial Vulnerability Assessment

When evaluating water-stressed and salt-impacted regions, there is very large spatial variability in total water vulnerability (Table 6). Streamflow stress is of moderate levels (0.6), and groundwater stress is higher (0.7), though salinity risk is at low levels (0.2), to obtain the overall index of 0.5 for the North-West study area. Likewise, for the Central, moderate water stresses are indicated by the (streamflow 0.5, groundwater 0.6), and by a slighter higher risk of salinity (0.4), hence also 0.5 overall index. The South-West is characterized as having highly stressed streamflow (0.7), highest groundwater stress (0.8) relative to the other regions, and moderate salinity risk (0.6), resulting in a composite index of 0.7. The coastal region has the highest salinity challenge (0.9), substantial groundwater stress (0.7) and moderate streamflow stress (0.5), leading to an equally high overall index (0.7).

**Table 6.** Regional vulnerability index of water resources (0 = low, 1 = high).

| Region | Streamflow Stress | Groundwater Stress | Salinity Risk | Overall Index |
|---|---|---|---|---|
| North-West | 0.6 | 0.7 | 0.2 | 0.5 |
| Central | 0.5 | 0.6 | 0.4 | 0.5 |
| South-West | 0.7 | 0.8 | 0.6 | 0.7 |
| Coastal | 0.5 | 0.7 | 0.9 | 0.7 |

### 4.10. Decision-Support Outputs

The model structure also provides variety of output variables for water management and climate change (Table 7). The flow forecasting module and its explicit utilization for calculating daily and seasonal flow prediction will allow an efficient flood forecasting management system and an early flood warning system are described. The groundwater observation provides estimates of depth and recharge, ultimately used to plan sustainable irrigation and water shortage management. The salinity mapping package recognizes salt hot spots in the coastline. It has potential to help provide advice in agriculture and aquaculture to mitigate crop and stock losses. The vulnerability dashboard finally maps spatial risk indicators, allowing policy-makers and stakeholders to prioritize adaption measures and to take targeted action.

**Table 7.** Key decision-support outputs for policymakers.

| Module | Output Description | Application Area |
|---|---|---|
| Streamflow Prediction | Daily and seasonal flow forecasts | Flood management |
| Groundwater Monitoring | Depth and recharge predictions | Irrigation planning |
| Salinity Mapping | Coastal salinity hotspot identification | Agriculture, aquaculture |
| Vulnerability Dashboard | Spatial risk index visualization | Policy & adaptation |

## 5. Discussion

The average regional climatic tendencies obtained over Bangladesh exhibit striking spatial differences in temperature and rainfall, which support and enhance the findings obtained earlier. The North-West region has the lowest mean temperature (24.8 °C) and a mild warming (+0.19 °C per decade). This finding is consistent with previous research emphasizing decreasing trends in the rainfall of western Bangladesh (Hossain et al., 2014). In comparison, the Central and South-West regions exhibit slightly and warming trends (0.20-0.22 °C decade$^{-1}$) and modest rainfall trends (+15 to +18 mm decade$^{-1}$). These findings support earlier reported large increases in temperature for places including Cox's Bazar and Sylhet (Rahman & Sohul Am, 2015). The coastal site is also the most unique, with the highest mean temperature (26.8 °C) and strongest warming rate (+0.25 °C per decade), as well as the largest increase in rainfall (+21 mm per decade). This result is also supported by research that emphasizes more severe monsoon seasons and extreme rainfall events in littoral Bangladesh within the context of climate change (Bhattacharjee et al., 2023).

Climate projections show a straightforward path of increasing temperature and rainfall throughout the 21st century, causing greater overall impact, especially under the high-emission SSP5-8.5 pathway. This is in line with studies based on CMIP6 that demonstrate a high increase in temperature and precipitation under high emission scenarios. Jihan et al. (2025) projected temperature increases between 21.6 °C and 23.56 °C under SSP2-4.5 and 26.04 °C for SSP5-8.5 by the end of the century, along with concurrent increases in precipitation. Similarly, Bhattacharjee et al. (2023) pointed out that the northwestern and west-central sectors in Bangladesh may experience more than 3.8 °C of warming according to SSP5-8.5. Assessment of the supervised ML models demonstrates the potential of data-driven methods in representing nonlinear hydro-climatic relationships. In this study, the results of Long Short-Term Memory (LSTM) were better than other models, and it had the minimum errors and the best efficiency scores in streamflow estimation. These results are consistent with those of Luo et al. (2025) and Leščešen et al. (2025), and show how the LSTM model is a powerful forecaster of river discharge. Ensemble methods such as RF and XGBoost also had good performance, which indicates that they can be used in hydrological model. These results confirm the use of ML methods to improve predictability and the application of climate water research. The overall increase in water availability is supported by the estimated changes in river basin flows. These findings are also in accordance with Mamoon et al. (2024) and Basher et al. (2018), who found increasing discharges in Bangladesh due to enhanced monsoonal precipitation and glacier melt in the headwater region. The higher response in the Meghna basin is due to its stronger dependence on rainfall variability and hydrological changes in the upstream.

An analysis of flood frequency reveals the extreme increases to be of alarming concern. Under SSP5-8.5, the scenario becomes much darker, with floods expected every three years in the beginning, then every two by mid-century, and possibly annually by 2100. These results are consistent with Rahman et al. (2020) who reported enhanced monsoon and upstream runoff as the primary contributor to the flood escalation. These projections emphasize the critical necessity for enhanced flood risk reduction policies, early warning systems, and climate-proof infrastructure in Bangladesh. According to the results, the South-West region was identified as the most at risk; consistent with Bhuyan et al. (2023) and Monir et al. (2024), who found a decline in groundwater with reduced replenishment, high extractions, and enhanced evapotranspiration. By mid-century, salinity is also predicted to increase from 5.2 to 7.4 ppt, and by end-century 9.6 ppt. The dissolved oxygen level will drop to 5.7 milligrams per liter from 6.8 mg/L, and the pH will drop to 7.1 from 7.4. Turbidity will increase from 15.2 NTU to 22.4 NTU. These findings are consistent with those of Khan et al.

(2023) and Hossain et al. (2014) who reported a higher trend of salinity intrusion, oxygen deficit, and sediment load in the aquatic systems of Bangladesh than climate change.

The integrated vulnerability index also reflects substantial disparity of regional vulnerability. These results were in agreement with the findings for Ahmed et al. (2024) and Kabir et al. (2024), who emphasized that southwest and coastal Bangladesh were susceptible to water stress due to the sea level rise and over extraction. Finally, the developed modelling system has the potential for use as a climate diagnosis and water resources management supporting tool. Forecasts of streamflow are useful for flood preparedness and find relevance to work that highlights the applicability of ML in hydrologic prediction (Bosompemaa et al., 2025). Groundwater predictions are also of use for irrigation scheduling and predicting shortfalls as in Rahman et al. (2020). Saltwater intrusion mapping maps highlands along the coastline of significance to agriculture and aquaculture (Khan et al., 2023). Integrating all these components directly in a vulnerability dashboard constitutes a useful instrument for the decision support that decision makers can use to prioritize their interventions and investments to be less vulnerable to future climate-related hazards.

## 6. Findings and Recommendations

### 6.1. Findings

a) Moderate levels of warming (+0.19°C/decade) and reduced rainfall (−12mm/decade) are experienced in North-West Bangladesh whereas Higher warming (+0.20–0.25°C/decade) and increased rainfall (+15–21mm/decade) are reported for Central, South-West and Coastal regions.
b) In SSP scenarios, temperature and rainfall are expected to increase under SSP5-8. 5 with the greatest increases (+4.1°C, +13.5% rainfall by 2100).
c) The probability of extreme flood events is expected to rise and, under SSP5-8.5, could become an annual event by the century’s end.
d) The drain on the ground water is high, particularly in South-West and Coastal areas (down to 13.2m).
e) Higher salinity (9.6ppt), lower dissolved oxygen (5.7mg/L), slightly acidic (pH 7.1) water, and higher turbidity (22.4NTU) are expected.
f) The maximum water vulnerability is observed in South-West and Coastal regions (indices 0.7), and minimum in North-West and Central regions (0.5).
g) Among all used models, LSTM achieves better prediction accuracy for flow forecasting; specifically, RF and XGBoost validate these satisfactory results.

### 6.2. Recommendations

a) Adaptation strategies tailored to each region should be executed, with a priority for South-West and coastal areas to the control of flooding, salinity and groundwater.
b) Apply advanced machine learning models (particularly LSTM) for real-time hydrological prediction and early warning systems.
c) Implement prevention measures for salinity, hypoxia, acidification and turbidity by proactive water quality monitoring and pollution control.
d) Encourage sustainable groundwater use, by way of managed abstraction and artificial recharge.
e) Apply decision-support products to inform evidence-based, specific interventions for climate-resilient water resources management.

## 7. Conclusion

The research clearly shows that climate change will have a profound effect on the country's water resources, with large variations in temperature, precipitation, river flows, groundwater levels and water quality across regions. Projections suggest higher temperatures and precipitation, higher river flows, more frequent extreme floods and significant groundwater depletion, especially in the South-West and coastal as well as reduced water quality, including increases in salinity and turbidity, and reductions in dissolved oxygen level. Single LSTM, machine learning model is very strong, which can become preferable in predicting streamflow and water integrated resources management, similarly, all ensemble models (Random Forest, XGBoost) are very successful. The decision-support model designed yields implementable responses for flow forecasting, groundwater monitoring, salinity mapping and vulnerability assessments, leading to regional adaptation strategies based on scientific evidence. Recommendations for further research include incorporating real-time data of climate and hydrology; extending the use of the model to socio-economic and land-use parameters and delineating fully adaptive management strategies for optimal allocation of water under multiple climate conditions, developing resilience of Bangladesh's water resources to climate changes at present and in the future.

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