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Drought-Sensitive Machine Learning for Robust Water Level Forecasting in the Chitra and Nabaganga River Basins

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April 2026

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ATTESTATION

We understand that plagiarism is strictly against the rules and regulations of Independent University, Bangladesh and is not tolerated. We certify that this thesis is an original piece of work and is not being submitted for any degree elsewhere.

We declare that all materials, models or ideas from other sources are properly acknowledged and referenced following the best practices of academic referencing and international standards

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LETTER OF TRANSMITTAL

Md. Najmus Sakib Sourov
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To
Md. Tarek Habib, PhD
Associate Professor
Department of Computer Science and Engineering
Independent University, Bangladesh

Subject: Submission of Final Undergraduate Thesis

Dear Sir,
I would like to present our undergraduate thesis entitled "Drought-Sensitive Machine Learning for Robust Water-Level Forecasting in the Chitra and Nabaganga River Basins", as part of the coursework for the Bachelor of Science in Computer Science & Engineering.

This study suggests a machine-learning approach for multi-river, drought-sensitive water level forecasting, using long-term water level data (2000-2025). We tested models such as Random Forest, Gradient Boosting, Extra Trees, XGBoost, ANN, LightGBM, and CatBoost, etc. where boosting models performed better in terms of capturing non-linear hydro-climatological interactions and temporal variations.

I would like to thank you for providing continuous guidance, support and feedback during the research. Your guidance was crucial to the completion of this work.

Thank you for your time and consideration.

Sincerely,
Md. Najmus Sakib Sourov
ID: 2221892
On behalf of the group

ACKNOWLEDGEMENT

We first thank God for giving us the strength, patience and diligence to complete this work.

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Finally, we would like to thank our parents for their support, motivation and encouragement. Their sacrifices have provided a source of inspiration and encouragement.

Lastly, we would like to thank all those who have directly or indirectly helped us in the preparation of this research.

ABSTRACT

Accurate water-level forecasting plays a crucial role in proper water resource management, flood control and agricultural planning especially in climate sensitive areas like Bangladesh. Nonlinear interactions and dynamic variability in river systems that exist in increasing levels of drought conditions is usually not well represented in traditional hydrological models. This study suggests a drought-sensitive machine learning system that can be used to enhance water-level prediction in the Nabaganga and Chitra river basin to overcome these issues. The suggested methodology incorporates multi-river data of Bangladesh Water Development Board (BWDB) stations during a 25-year span (20002025) in which the crucial hydrological and climatic variables are involved such as water level, rainfall, lag features, and seasonal indicators. Various machine learning models such as Random Forest, Gradient Boosting, Extra Trees, XGBoost, Artificial Neural Networks (ANN), LightGBM and CatBoost were created and tested to determine the best to use in water-level prediction. The experimental findings indicate that ensemble and boosting-based models are much better than neural network-based approaches. Gradient Boosting has the best performance in the drought-sensitive multi-river framework, with an R^2 of 0.993 and an RMSE of 0.081, and XGBoost has similar accuracy, which indicates that it is highly suitable in terms of discerning cross-basin interactions, seasonal variability, and drought-related low-flow conditions. Further validation on single-river data further supported the dominance of CatBoost, with an R^2 of 0.9982, which is almost perfect predictive accuracy. The results also show the role of time-dependent factors with lagged water-level factors being the most significant predictors, then rainfall and seasonal factors. The long-term trend analysis shows that water levels have been decreasing gradually over the past years, which demonstrates a growing drought stress over the region of study. The multi-river modeling approach has been successful in capturing spatial variability and hydrological connectivity, which can be more generally applicable and robust than single-river models. Overall, the study indicates that multi-river modeling using machine learning in conjunction with drought sensitivity, can be more effective in terms of predictive accuracy, robustness and practicality. The suggested framework offers a flexible and dependable solution to water-level forecasting and aids in making well-informed decisions in the management of water resources, especially in climate-sensitive and drought-affected areas.

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1. Introduction

River water level prediction is an essential aspect of sustainable water resource management, especially in areas where river-based ecosystems and agriculture are significantly relied on. The correct forecasting of water in the rivers leads to proper flood management, irrigation schedules, safety of navigation, and disaster readiness. In developing nations like Bangladesh where a huge percentage of the population depends directly or indirectly on the river systems, the need to have a reliable forecasting becomes even more acute. Bangladesh is located in the delta of Ganges-Brahmaputra-Meghna (GBM), which is among the most active and huge river deltas in the world. Hydrology of the country is defined by the high seasonal variability of the rainfall which is brought by the monsoons, the upstream flows, the transportation of sediments and the tides. This has led to hydrological extremes in river systems such as extreme floods during the monsoon season and extended periods of droughts during the dry season. Over the past years and especially since 2015, the rising rates and severity of droughts have notably changed the river flow regimes, resulting in decreased baseflow, a drop in water levels, and a rise in water resources and agricultural stress. The rivers Chitra and Nabaganga form a hydrologically connected system in southwest Bangladesh, which is crucial for people and agriculture. The rivers exhibit complex behaviour due to hydrological connectivity, siltation and tidal effects. This connectivity makes it possible that any changes in one river can affect the other, especially during low flow when the effects of flow reduction are transmitted throughout the system. This interdependence makes forecasting more challenging because it requires the modeling of both temporal variability and the interaction between the basins. Traditional approaches of forecasting water levels, such as empirical and physically based hydrologic models have been widely used for decades. However, these models are often based on simplifications such as linear relationships and stationarity, which limit their ability to capture complex nonlinear and dynamic relationships in real river systems. Furthermore, they need to be well-calibrated and domain-specific; therefore, they are less flexible to changing climates. The availability of machine learning (ML) methods has provided a robust alternative to forecasting. Machine learning models are able to learn complex nonlinear patterns without any specific assumption of the processes. Random Forest, Gradient Boosting and Artificial Neural Networks are some of the methods that have proven to be effective in capturing temporal variabilities and hydro-climatic relationships. A previous study of the Nabaganga River has shown that ensemble models have achieved high-quality water-level forecasting, which proves the effectiveness of ML models in rivers with dynamic conditions. While these advancements have been achieved, many of the existing studies focus on a single river system, and do not explicitly consider droughts in their forecasting development. However, drought is an important factor that affects water availability, river dynamics and long-term variability, and needs to be considered in water-level forecasting. It is a mistake to assume that drought conditions do not exist and limit the capability of the forecasting systems and its applicability in climate-sensitive regions. To address this, this paper firstly investigates droughts and their impacts on river systems and then proposes water-level forecasting system using machine learning techniques with the consideration of the effect of droughts. The proposed method combines both the multi-river data of Chitra and

Nabaganga basins with the hydro-climatic and temporal characteristics to enhance the accuracy of prediction and the generalization ability.

In general, this study can help to develop data-driven, climate-resilient forecasting systems, which do not only improve the accuracy of water-level prediction but also include the variability due to droughts. The proposed framework can facilitate sustainable water management, enhance agricultural planning, and enhance disaster preparedness among the vulnerable riverine areas.

1.1 Background of the Study

Bangladesh River systems comprise one of the most intricate hydrological systems in the world, which is at the center of supporting agriculture, fisheries, transport, and ecological equilibrium. Water availability (especially in the southwestern region) is very reliant on rivers to provide irrigation and other livelihoods. Nevertheless, over the recent years, the rising climate variability has escalated hydrological extremes, especially drought conditions during the dry season. A significant change in stress during dry seasons since 2015 suggests a change in long-term hydrological processes, which led to a decrease in river flows, a drop in water levels, and an overload on agricultural systems. The Chitra and Nabaganga rivers are among the key river systems in the region that form a hydrologically related basin that experiences strong seasonal variability that is fuelled by monsoon rainfall, upstream discharge, sedimentation, and tidal interactions. The Nabaganga River is a river flowing through agriculturally productive regions and is an important source of irrigation because it has its origin in the Mathabhanga River. The hydrologically related river of the Nabaganga, the Chitra River, brings more complexity with the upstream siltation and downstream tidal effects. This interaction creates a coupled river system in which hydrological processes mutually depend on each other, especially during drought periods, and thus makes it more difficult to predict accurately the water-level than in isolated river systems. Historically, deterministic hydrological models and statistical methods have been used in water-level forecasting. Although these methods offer some insight into the problem, they are frequently not able to reflect nonlinear relationships between climatic and hydrological variables. During the recent years, the development of machine learning methods has become a viable alternative as it can learn complicated patterns directly on historical data without any strict assumptions. Random Forest, XGBoost, and Artificial Neural Networks are among models that have shown high performance in predicting water levels in rivers. Past research, especially that of the Nabaganga River, has indicated that ensemble-based machine learning models can be very highly predictive, and boosting-based methodologies are better than traditional regression methods. However, these studies are typically limited to single river systems, and do not account for the multi-river dynamics and drought sensitivity. This makes them less useful in the real world where river systems interact and are influenced by climate variability. As such, it is clear that there is a pressing need to develop forecasting models that will combine the two parameters of drought sensitivity and multi-river interactions. This research paper will fill this gap by suggesting a machine learning-driven solution that takes into consideration hydro-climatic variability, drought-sensitive characteristics, and cross-basin dynamics in enhancing the strength and precision of water-level forecasting of the Chitra and Nabaganga river system.

1.2 Problem Statement

Proper forecasting of water level in rivers is critical to proper management of water resources, flood control and drought preparedness, especially in climate sensitive areas like southwestern Bangladesh. Higher levels and greater variability of droughts over recent years have greatly influenced the behavior of river flows, complicating the process of reliable prediction during low flow. Nevertheless, even with the improvement in hydrological models, there are still a number of limitations in the existing methods. To begin with, traditional hydrological and statistical models assume linearity and stationarity, which are not considered to reflect the nonlinear and dynamic nature of real river systems. Such models also need a lot of calibration and in most cases they cannot adjust to the varying climatic conditions. Secondly, most of the current studies concentrate on single-river systems, despite machine learning models having proven to show better predictive performance. This method does not portray the interdependence of river basins where hydrological processes like drought transmission, flow changes, and sediment changes affect more than one river at a time. The hydrological linkage of the Chitra and Nabaganga rivers also complicates the situation further, especially when there is a drought in one river where the flow of the river can directly influence the other. Thirdly, drought sensitivity is an important element that is not taken into consideration by the existing forecasting models. Although models can be effective at regular or high-flow conditions, their effectiveness in the case of drought-driven low-flow are not very reliable. This is of great concern in farming areas where dry seasons cause water shortage that may have dire socio-economic implications. Besides, generalized forecasting frameworks that can sustain uniform performance in various rivers and monitoring stations are lacking. The majority of current frameworks are locally focused and fail to extend to connected or heterogeneous river systems. Lastly, it lacks combined methods that integrate machine learning methods with multi-river analysis and drought-aware feature engineering. This weakness restricts the practical usefulness and strength of existing forecasting systems in practice.

Accordingly, there is an urgent necessity of a strong, factual, and drought-sensitive forecasting framework capable of adequately capturing hydrological complications, introduce drought variability, and enhance predictability capabilities across interacting river networks.

1.3 Research Objectives

The overall aim of the research is to build a sound and drought-resistant machine learning model to forecast water-level in interconnected river systems correctly.

Specific Objectives:

- To examine the long-term hydrological trends and determine the trends associated with variability and intensification of drought.
- To test how drought conditions influence the behavior of river flows and the water-level dynamics. Purpose
- To create and deploy machine learning models to predict river water levels with the use of hydro-climatic data.
- To introduce drought-sensitive predictors, such as lagged water levels, rainfall memory into the predictive framework.
- To perform multi-river analysis by merging data of two river basins, Chitra and Nabaganga.
- To compare the results of various machine learning models, such as ensemble and neural network models.
- To determine the strength and generalization potential of models in other rivers and monitoring stations.

1.4 Research Questions

The research questions that will guide this research include:

1. What have long-term hydrological processes, especially after 2015, done to drought and water-level behavior in the Chitra and Nabaganga river basins?

2. Which are the important hydro-climatic processes that contribute to water-level variations under drought sensitive conditions?

3. What is the ability of machine learning models to model the intricate and nonlinear processes of river water levels in a multi- river system?

4. What machine learning models offer the best and strongest predictions to water-level forecasting?

5. What are the impacts of adding drought sensitive attributes on model performance, particularly during low-flow conditions?

6. Will machine learning models trained on one river be effective at other rivers hydrologically connected to the river?

1.5 Scope of the Study

This paper is about the creation and testing of machine learning models to predict water level in Chitra and Nabaganga river basins, southwestern Bangladesh. The historical hydrological and meteorological data available at various monitoring stations under the Bangladesh Water Development Board (BWDB) is analyzed, considering the time frame between 2000 and 2025. The study scope is:

- Combination of multi-station/ multi-river data into one analysis platform.
- Examination of major hydro-climatic parameters, such as the rainfall, water tables, and seasonal signs.
- Creation of drought sensitive functions like lag variables and rainfall memory.
- Application and test of various machine learning models.
- Comparison of the model performance in various rivers and stations.
- Exploration of long-term patterns and droughts.

However, there are some limitations in the research. It doesn't use real-time system, and integration with a physical hydrological simulation model. Also, the results are basin specific and basins and may require some further validation to be applied elsewhere.

1.6 Contributions of the Thesis

The thesis contributes to the area of hydrological forecasting in multiple ways, combining machine learning methods with drought-sensitive analysis in interconnected river networks. To begin with, the study introduces a drought-sensitive machine-learning framework that makes water-level prediction more accurate and robust, especially in low-flow and climate-stress conditions. The framework overcomes a major limitation of most current forecasting models, which mainly deal with normal or high-flow conditions because it explicitly includes drought variability in the forecasting process. Secondly, this study presents a multi-river model that takes into consideration the hydrological connectivity of the river basin of Chitra and Nabaganga. This is an aspect that is not evident in traditional studies of single rivers as it takes into account cross-basin interactions, which enables the model to more closely resemble the real-world process of hydrology where changes in one river system can affect another, particularly during dry years. Furthermore, the paper incorporates drought-sensitive feature engineering, such as lagged hydrological variables and rainfall memory, to successfully model temporal correlations and persistence in the river flow pattern. Such characteristics are important to enhance the model in representing lagged responses and cumulative impacts related to hydro-climatic conditions. In addition, several machine learning models are thoroughly considered, such as ensemble-based and neural network models, to select the best methods to use in water-level forecasting. The results indicate that boosting-based models would perform well in nonlinear relationships that are complex in the data. The other contribution of the thesis is the scaling-up of multi-river forecasting to the previously done work on the

Nabaganga River. This progress highlights the need to develop local models to a better framework that has the ability to deal with complex river processes. The study also contributes to a better understanding of the long-term hydrologic trends by identifying trends associated with an increase in the intensity of droughts, particularly since 2015. These observations can be applied to provide meaningful insights into the shift of river behaviour which can be better predicted.

Finally, this research presents a scientific and climate-smart water level forecast, which can help in effective decision-making in water resources management, agricultural planning and disaster management in vulnerable riverine regions. Generally, the suggested framework fills the need to bridge the gap in the analysis of drought and predictive modeling because the proposed framework offers a holistic approach to reliable and adaptive water-level forecasting in the complex hydrological systems.

2. Literature Review

Recent developments in machine learning have greatly revolutionized the areas of drought assessment and water-level forecasting by allowing modeling of complex, nonlinear hydro-climatic interactions unattainable with traditional approaches. Flood management, agricultural planning and sustainable water resource management require accurate prediction of river water levels and drought conditions especially in regions that are susceptible to climatic changes. The rising access to hydrological data and computing capabilities has given rise to the rapid evolution of machine learning (ML), deep learning (DL) and hybrid systems, all of which show better results than traditional statistical and physical models.The literature on this field presents a broad overview of methods, such as conventional hydrological models, machine learning algorithms, deep learning structures, hybrid optimization-based models, and drought prediction models. Though these studies have been remarkably successful in enhancing predictive power, there are a number of limitations, especially in incorporating drought sensitivity in the prediction of water levels and in the interaction among rivers. In this chapter, a thorough review of the current research is provided to determine the significant progress and gaps in research.

2.1 Traditional Hydrological Models

Historically, traditional hydrological models have been used as a basis of water-level prediction and river-flow simulations based on physical principles and statistical correlations of hydrological variables. These models usually make the assumption of linearity and stationarity thus restricting their capacity to model the nonlinear dynamics of the real-world river systems especially when the climatic conditions are varied. Consequently, they tend to deteriorate in their predictive performance when used in environments with high dynamics and uncertainty in data.

Auto-Regressive Integrated Moving Average (ARIMA) and regression-based models are some of the statistical methods that have been extensively used in hydrological forecasting. The use of ARIMA and Artificial Neural Networks (ANN) in SARIMANN models has been more effective in forecasting monthly water levels in structured environments, such as the Yom River basin [1]. These models, however, have problems with nonlinear relationships and long-term temporal correlations.

Physical hydrological models are also physically based, require substantial calibration and data sets, which makes them difficult to use in data-scarce regions. It has been shown that streamflow simulation models such as the Modified Simulation Model (MSM) are more efficient than the classic models, as they can consider drought as well as flood events [2]. However, they are unable to adjust to rapidly changing environments.

Furthermore, there have been additional limitations observed on a hybrid optimization-based drought model, where traditional models do not accurately model complex interactions between climatic and hydrologic parameters [3]. Previous studies have demonstrated that modern data-driven models are superior to physics-based models. It can be shown that Multi-Layer Perceptron (MLP), Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) models are more accurate in prediction and adaptable than other models such as HEC-RAS [4].

Overall, while traditional hydrological models played an important role in the evolution of forecasting models, their incapability to model nonlinear dynamics, data variability and climate uncertainty has shown a trend towards machine learning, and hybrid modelling. The modern methods are more adaptable and have better prediction performance and are therefore more suitable for modern hydrological issues.

2.2 Machine Learning in Water Level Prediction

Machine learning as a water-level forecasting technique has already been an extremely effective approach as it can capture nonlinear relationships and learn to forecast patterns explicitly through previous hydrological data. Machine learning methods compared to the older statistical and physically grounded models do not have rigid assumptions regarding how the system behaves, thus, are more adaptable to changes and unpredictability of the environment. They have thus been widely applied in predicting river water levels, floods and hydrological variability.

One of the earliest applications is Artificial Neural Networks (ANNs) and these have demonstrated to be very successful in nonlinear prediction of hydrological variables, such as rainfall, discharge and temperature. ANN-based models have been proved to be rather effective in the river systems, and can learn the hidden patterns, basing them on the historical data [5]. To further enhance the performance of the models, hybrid methods with ANN and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) have been suggested.These models combine the interpretability of fuzzy systems with the learning ability of neural networks leading to better robustness to uncertain hydrological situations [6].

Random forest and Extreme Gradient Boosting (XGBoost) are tree-based ensemble learning models that have become extremely popular since they have high predictive accuracy and noise resistance. These models have shown good performance in the predictability of extreme water levels and flood events, which are usually superior to the traditional regression-based prediction methods [7]. Ensemble techniques enhance the reliability of a prediction as a result of a combination of decision trees, which reduces variance and enhances generalization. Specifically, the Random Forest models have demonstrated high effectiveness in river prediction activities, with the R^2 values ranging between 0.87 and 0.92 [8] and the ensemble techniques have even obtained a higher level of accuracy (R^2 is as high as 0.995) in multifaceted river systems [9].

Machine learning models can be extended with deep learning models to enhance forecasting performance by modeling time-dependences in sequential data. Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models have proven to be exceptional in modeling time-series hydrological data. Specifically, LSTMs have demonstrated very high prediction accuracy ($R^2 = 0.998$) and low error in large river systems, and thus they are one of the most effective methods in the prediction of water-level [10].

Machine learning has also been applied successfully in real time flood prediction systems so that they can provide early warning systems in flood prone areas like India and Bangladesh [11]. These systems highlight the relevance of machine learning models in the actual world of operations where disaster mitigation largely relies on timely predictions.

The latest developments have also improved the performance of machine learning by integrating the newest techniques such as transfer learning and multi-station model. Studies on the multi-station river systems have shown that the precision of the Random Forest models can even be near absolute (R^2 0.99) when trained with large scale datasets [12]. Transfer learning techniques have been utilized to boost prediction in ungauged or data-scant river basins through borrowing of information in neighboring regions thereby avoiding the need to have vast volumes of local data [13]. In addition, hybrid ensemble techniques have been found to be stronger and resistant to varying environmental conditions [14], a fact that reinforces their applicability to complicated hydrologies.

The second commendable development in machine learning is explainable AI methods to improve model transparency. Traditional machine learning models can be considered black boxes, but emerging models have included interpretability systems such as SHAP to understand the impact of individual features on prediction outputs. XGBoost models have been effectively applied to predict significant hydrological variables and refine predictions in drought-based studies using SHAP analysis [15]. In addition, machine learning models have demonstrated effectiveness in prediction of streamflow in data-scarce situations that highlights their flexibility and resilience [16].

Overall, machine learning has played a significant role in the advancement of water-level forecasting by providing versatile and data-oriented solutions capable of detecting complex hydrological patterns. Integrating neural networks, ensemble methods, extensions of deep learning, and explainable AI models have created highly precise and reliable prediction systems. More advanced deep learning and hybrid solutions are based on the developments and are discussed in the following section.

2.3 Deep Learning and Hybrid Models

This has enhanced water-level forecasting using deep learning and hybrid modeling that can model intricate spatiotemporal relations that are present in hydrological systems. Unlike more traditional methods of machine learning, deep learning systems will have the ability to automatically discover hierarchical aspects of raw data, and in such a manner, will be able to learn both short-term and long-term changes in river flow patterns. This aspect makes deep learning incredibly helpful in the processing of high-sized, nonlinear, and nonstationary hydrological data. Among the models of deep learning, Long Short-Term Memory (LSTM) networks have become one of the most popular architectures of time-series forecasting. They are able to model sequential hydrological data such as a rainfallrunoff process, river discharge pattern because they have memory cells to store their long-term dependence. Hybrid methods that combine optimization methods with LSTM have also enhanced a better prediction by fine-tuning the model parameters and minimizing forecasting errors [17].

Convolutional Neural NetworkLong Short-Term Memory (CNN-LSTM) and Convolutional LSTM (ConvLSTM) are sophisticated architectures that were created to overcome the weaknesses of entirely temporal models. These models utilize convolutional layers to extract spatial features and recurrent layers to model time, hence they are able to effectively model the spatial and temporal dependencies. Research has demonstrated that CNN-LSTM and ConvLSTM networks are highly effective in flood prediction, with evaluation indices (NashSutcliffe Efficiency (NSE)) and Index of Agreement (IOA) being high [18]. Moreover, new ConvLSTM-based models have also shown better results compared to older LSTM models in terms of fewer prediction attempts and a better spatial representation of rainfall patterns [19].

Deep learning models have also been improved with attention mechanisms that help such models to concentrate on the most important features when making predictions. LSTM models that use spatiotemporal attention dynamically weight the importance of input variables at both time and space and greatly enhance the accuracy of multiple-step predictions [20]. Likewise, hybrid CNN, LSTM and attention mechanisms have been shown to have very high predictive accuracy in flood prediction and enhance model robustness in challenging hydrological contexts [21].

New developments in the recent past have also brought about graph based deep learning models that bring in the aspect of spatial connectivity to hydrological forecasting. GNNs, including FloodGNN-GRU, model river systems as networks, enabling them to learn more about the upstream-downstream relationships. The methods are better in predicting and computing efficiently than traditional deep learning models [22].

Also, Transformer-based architecture has been of interest due to their capability to capture long-term dependencies without using recurrent structures. These models are more efficient in processing sequential data by using self-attention mechanisms and are able to capture complex temporal relationships. Research has revealed that Transformer-based models are superior to the traditional recurrent models in multi-step forecasting tasks and yield more information about important influencing factors [23].

Additional advances have been made on forecasting performances by hybrid decomposition-based frameworks that consider the nonstationary behavior of hydrological data. The machine learning models have been combined with techniques like Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) to break down complex time-series data into simpler components and then predict using the simpler components, with increased accuracy [24]. Further, the use of multi-component hybrid structures with a combination of decomposition techniques, regression models, and optimization algorithms has shown improved short-term forecasting results in intricate hydrological systems [25].

Explainable deep learning has also emerged as an important area of research. SHAP analysis with encoder-decoder LSTM models have been successfully applied to forecast the inflow of reservoirs and the prediction accuracy has been high, as well as the hydrological predictors can be interpreted [26]. Those techniques allow addressing one of the most critical flaws of deep learning models since their predictions are made more transparent and understandable.

Furthermore, recent advances have taken into account innovative architectures such as convolutional models developed with WaveNet which have proven to be more precise and economical in long-term predictions and calculations in hydrological tasks [27]. It is also possible to show that the multi-step forecasting sequence-to-sequence LSTM encoder decoder models are incredibly accurate with the reported R^2 values near to 0.999 [28].

Altogether, deep learning, and hybrid models have been instrumental to enhance the precision of water-level predictions by integrating spatial modeling, time memory, attention modeling, and explainable AI algorithms. These models address most of the limitations of the classical approaches and provide highly accurate, scalable and flexible solutions to complex hydrological processes. They will also continue to improve forecasting performance and are useful in more advanced applications in the flood prediction and water resource management area as they develop.

2.4 Drought Prediction Techniques

Drought prediction issue has turned out to be one of the most pressing areas of research because the impact of climate change, water shortage, and the devastating fluctuations of the environment on the hydrology have become more prominent. Unlike a flood event (which typically can be instantaneous and short-lived), drought is a slow phenomenon, which varies over time and depends on a complex interaction between meteorological, hydrologic, and environmental factors. Accurate drought forecasting therefore requires long-term temporal dependencies, nonlinear relationships and large scale climate patterns to facilitate the use of models with modeling capacity. The recent years have seen machine learning and hybrid modeling become powerful to improve the accuracy and reliability of drought prediction.

The forecasting of drought indices such as the Standardized Precipitation Index (SPI) and Palmer Drought Severity Index (PDSI) have also been effectively predicted by machine learning (SVM), Random Forest and Gaussian Process Regression models. These models have been shown to be very predictive since they are useful in modeling nonlinear relationships between climatic variables, which are rainfall, temperature and soil moisture. Particularly, ensemble methods and SVM have shown excellent accuracy in drought prediction and recorded R^2 values have reached the 0.984 mark [29]. These approaches are especially useful in the modeling of multivariate data as well as in the discovery of unobservable trends within complex hydrological systems.

In addition to data-driven models, there are climate-based models that have also helped in forecasting drought. Those studies that depend on teleconnections based on teleconnections have demonstrated the importance of large scale atmospheric patterns, such as the Indian Ocean Dipole and Rossby wave trains in the formation of droughts. The models make it possible to identify drought conditions at early stages of its development by considering long-range climatic interactions, which are not necessarily considered in conventional hydrological models [30].

Recent developments in remote sensing have also increased the monitoring of drought. GRACE (Gravity Recovery and Climate Experiment) is one of the examples of satellite-based methods implemented to monitor the state of drought in groundwater with the help of machine learning models. GRACE based XGBoost models have demonstrated high predictive accuracy with R^2 nearly reaching 0.99 and also identified lag relationships between the meteorological variables and groundwater storage [31]. These results indicate the relevance of using a combination of machine learning algorithms and remote sensing data in order to predict drought.

There are also artificial intelligence-based drought indices that have been created to address the shortcomings of conventional indices. These indices offer a better representation of drought conditions and are more accurate in prediction because they include various hydrological and climatic variables. Correlation coefficients have been reported to be as large as 0.97 between AI-based indices and measured drought conditions indicating that they are useful in capturing the complex drought dynamics [32].

By integrating multiple algorithms, hybrid modeling techniques have also enhanced the performance of drought prediction. Some of the models like ANN-SVR-ANFIS combine neural networks, support vector regression and fuzzy logic to be able to capture nonlinear relationships. Such hybrid models have been very accurate in prediction of agricultural drought with reported R^2 of about 0.99 [33]. In the same manner simulations of hydrological processes in different climatic conditions have been performed with hybrid ML-SWAT models with high performance with R^2 values ranging between 0.93 and 0.94 [34].

Drought classification and risk assessment have been done using machine learning models. Random Forest-based algorithms have been shown to be highly effective in predicting droughts based on the PDSI index with high classification accuracy and ROC-AUC coefficients of about 0.90 [35]. The models can be specifically applied to the identification of drought-prone areas and in the process of making decisions on water resource management.

New trends have integrated deep learning and hybrid structure in drought forecasting. As an illustration, hybrid CNN-GRU models have been employed to discover temporal trends in hydrological data to enhance forecasting capabilities in complex systems [36]. Moreover, explainable AI models like KAN-SHAPs have been developed to understand the significant environmental factors that drive droughts, e.g. temperature, humidity and precipitation, which enhances predictive and interpretative performances [37].

Along with the technical modelling techniques, recent research has also highlighted the need to integrate drought prediction and water resource management. The role of human intervention, decision making and adaptive water resource management in mitigating the effects of droughts and improve the resilience of the system has been observed [38]. The findings suggest that the approach to predicting droughts has to rely on both proper drought prediction models and integration in decision-making.

Moreover, recent studies in machine learning have found that AI-based solutions have always been more effective at predicting droughts in the long run as compared to traditional statistical techniques. Comparative analysis has revealed that SVM based models can perform better than Random Forest under some situations, especially when it comes to modeling long-term drought patterns [39]. Besides this, extensive review studies have also indicated the utility of machine learning models like LSTM, XGBoost, and Random Forest in enhancing the accuracy of drought prediction in various climatic regions [40].

In general, machine learning and deep learning methods, as well as hybrid modeling, have transformed the drought prediction methods. The techniques yield more precise, strong and scalable solutions to comprehend and foresee drought conditions. There are however issues in the way drought predictions can be incorporated to water-level forecasting systems which creates the need to have integrated structures that incorporate drought sensitivity and hydrological modeling as discussed later.

2.5 Multi-River Forecasting Studies

Most of the current studies on water-level prediction have conventionally focused on single rivers, which calibrate and predict on the basis of a given river basin. While this approach may be very effective for local predictions, their predictability is weak for other river basins. The reality is, that the hydrological processes are not independent and the information on one river can help to predict the other basins through the common climatic influences, upstream-downstream interaction and environmental connectivity. This resulted in an important branch of research into multi-river forecasting, to improve the power and generalizability of prediction systems.

The research on water management among river basins has recognised the importance to consider the hydrological and ecological interactions between basins. They reveal that river basins can no longer be regarded as closed systems, but as a part of a larger system that is influenced by climatic and environmental factors [41]. The consideration of these interactions in water level forecasting models can help to better represent the hydrological processes and improve overall forecast accuracy.

River forecasting with tidal influence has improved the accuracy of the hybrid models with tidal features of phase and amplitude. The models are particularly relevant to the coastal and deltaic locations where water levels are not only governed by the river discharge, but also the marine processes. These models improve the prediction accuracy of the existing models that are only based on river inputs, by combining hydrologic and tidal inputs [42].

The findings of studies in other places also highlight the variations in models' performance in river systems. For instance, Support Vector Regression (SVR) has been proven to be useful for multi-step forecast with low data input in the Mekong Delta, and Multi-Layer Perceptron (MLP) has been shown to be better than LSTM and XGBoost in some seasonal variations [43], [44]. These findings underline that the suitability of models depends on the characteristics of the region, and it is important to have adaptive and generic forecasting systems.

It has also applied deep learning models in large-scale hydrologic systems beyond rivers. For example, LSTM models have been successfully used in complex wetland systems, such as the Everglades with a high capacity to capture spatial and temporal interactions between large-scale, heterogeneous systems [45]. This study shows that deep learning models can be used to develop models of large-scale hydrologic systems.

Recent developments in multi-river forecasting have been directed towards enhancing generalization and applicability based on recent machine learning approaches. Transfer learning has now become a potent method of overcoming the issue of data scarcity and cross-basin prediction. Transfer learning models can also be used to predict water levels in ungauged or data-limiting areas by utilizing the experience of river systems that have abundant data, thus eliminating the need to retrain on large datasets [46]. This can greatly improve the practical applicability of forecasting models.

Moreover, multi-step forecasting models which combine both meteorology and tidal variables have shown better results in intricate river systems. These models identify the mutual interaction effect of climatic and oceanic processes, and thus more effectively predict the levels of water in those areas where rainfall and tidal processes interact [47].

Other similar hydrological processes that machine learning techniques have been applied to include salinity intrusion in coastal areas. Model-based studies based on XGBoost and neural networks have shown the capability to represent interactions among water levels, salinity, and environmental variables as well as enhance understanding at the system level [48]. In addition, recent studies in the field of river discharge predictions have presented more advanced machine learning models which improve the accuracy and reliability of predictions over a long period and are used to improve water resource management plans [49].

The multi-river forecasting still has a lot of challenges despite these progresses. The current models are still based on small datasets and are not able to capture the full spatial dependencies and hydrological connectivity among river basins. Also, real-time data, climate variability, and multi-source data are not very well integrated, which limits the use of these models in real-life applications. To solve these issues, it is necessary to design coherent frameworks, which combine multi-river data, advanced machine learning methodologies, and environmental variables to enhance accuracy in predictions and generalization.

2.6 Research Gaps

While considerable improvement has been made in water level and drought prediction using machine learning, deep learning and hybrid models, there are still some research gaps that play a key role in the performance and applicability of existing techniques.

The current machine learning, deep learning, and hybrid modeling methods used to forecast hydrology have progressed very fast, but a number of research gaps remain critical and limit the efficacy, scalability, and practicality of existing applications. Even though most models can be very predictive in closed-systems and laboratory-like environments, they do not tend to be able to cope with the dynamic, interconnected and complex nature of the real-world hydrological system.

The absence of the interconnection between drought prediction and water-level forecasting is one of the biggest gaps. The two domains are typically considered separately in most studies, with drought prediction models, which are based on machine learning methods, aiming to estimate indices, including SPI or PDSI [14], [15], [16], and water-level forecasting models, which are mostly based on hydrological and meteorological input [20], [21]. In spite of the fact that both methods are very precise in their respective fields, they do not show a direct and dynamic correlation between drought conditions and river water levels. As a matter of fact, drought has a great impact on the river discharge, groundwater availability and the hydrodynamics of a basin. The lack of built-in modeling structures restricts the capability to model these interdependencies, making it less reliable to forecast in extreme climatic conditions.

The second limitation is another crucial aspect of single-river or single-basin studies dominance. A large number of machine learning models are trained on data of a particular river system, where they have high performance because of local calibration and data consistency [23], [24], [25], [26], [27]. Nevertheless, these models are not generalized in other river systems that have different hydrological properties. Likewise, drought prediction research has a tendency of being specific to regions, and based on localized climatic data [29], [30], limiting their transferability. This poses a significant research gap in the establishment of generalized models that can learn across river basins and translate across-basin hydrological relationships.

Another weakness is the minimal use of spatial relationships and the hydrological connectivity. Even though real-world river systems are networked together, by both upstream-downstream connections, and basin-level interactions, most current models concentrate exclusively on temporal dependencies [33]. Even more sophisticated deep learning models are likely to focus on time-series forecasting but forget about the spatial relationships among river nodes. This leads to models which are unable to capture the physical behaviour of hydrological systems, particularly in multi-river or deltaic systems where river-interaction is also important.

Another evident weakness is the absence of focus on drought sensitive feature engineering and long-term temporal memory. Although lag-based characteristics and sequential learning have been included in some models [36], numerous methods of predicting droughts are still based on the use of static indicators without taking into account the cumulative and delayed hydrological impacts. Indicatively, the long-term effects on water levels of past rainfall, soil moisture retention, and evapotranspiration rates cannot be well represented in most of the existing models. This limits the ability of models to predict long term drought and slow response.

Another research gap is the high complexity of advanced models and the high computational demands. Recent hybrid and deep learning models (e.g. decomposition-based or optimization-based models) have achieved outstanding prediction accuracy [39], [40]. But the models are often computationally expensive, require a large amount of data and are hard to calibrate. This constrains their application, particularly in poorly developed regions, where there is a deficit of computing power and high-resolution data sets.

There is also a lack of data. Certain hydrological models are developed with the help of large-scale historical data of good quality, and these data might not be available in smaller rivers and remote regions. Although there are some studies that aim to solve this issue by adopting adaptive and machine learning models [43], the robustness of these models in the presence of limited data is not satisfactory. The need, therefore, is for models that can operate with limited data.

Another major limitation is the fact that climate variability and long-term changes are not taken into account. While other authors consider climate-related factors and seasonal variations [44] as the primary causes of the water-level forecasting, most of the water-level forecasting models do not explicitly consider the long-term climate change and extreme events. This reduces their potential to provide reliable forecasts in a changing climate, which is becoming important in climate vulnerable regions.

Lastly, predictive models and real-world decision-support systems are not integrated. Though most of them are very accurate in an academic context, they are seldom applied in operational frameworks to flood control, agricultural planning or water resource management. The lack of user friendly, real time and decision-oriented systems restricts the practicality of the available researches. To overcome these shortcomings, our study suggests a drought-sensitive machine-learning framework that considers multi-river datasets, temporal lag features, and indicators of climate. The proposed solution to drought prediction should enhance predictive accuracy, model generalization, and practical use because it will be based on forecasting of drought and water levels, and the hydro scientific interconnectedness of river basins.

2.7 Issues with Existing Data

Although machine learning and deep learning methods are rapidly evolving to be used in hydrological forecasting, the quality, structure and access to available datasets are still considered one of the greatest obstacles that influence model performance and generalization significantly. Issues related to data are usually disregarded, and yet they are important in establishing the success of predictive models.

One of the primary concerns is the inaccessibility of the routine and quality long-term data. The anomalies during the recording, poor coverage over time, and variability among different monitoring stations are typical in most hydrological data sets [9]. These inconsistencies introduce ambiguity in model training and reduce predictability. Even advanced models such as LSTM and GRU which are expected to be used with sequential data [12] may not perform well in the dirty or incomplete data.

The other notable challenge is that there were missing values and gaps in data. Hydrological data collection is mostly done through manual data collection, sensor-based data collection, and environmental observations, all of which are susceptible to measurement errors and disruptions. Despite the frequent use of preprocessing methods like interpolation and imputation [15], they can create bias and unrepresentative underlying patterns. Although certain machine learning models prove to be resilient to these conditions [18], their accuracy is still affected by the quality and continuity of input data.

Another crucial drawback is the absence of feature diversity. Most studies use water level or rainfall as the main source of information [21], but they do not include other relevant hydro-climatic variables like soil moisture, groundwater levels, temperature and evapotranspiration. These factors contribute greatly to the formation of drought and water-level processes. Lack of multi-dimensional features means that models are constrained by the capability to describe interactions among different environmental components and that there is poorer prediction accuracy.

The other critical concern is the lack of representation of temporal dependencies. Hydrological processes are time dependent in nature whereby the existing conditions are a result of past occurrences like rainfall accumulation, upstream flow, and seasonal variations. Nevertheless, long-term temporal dependencies and lag effects are not structured in many datasets [24]. Whereas there are deep learning methods that seek to overcome this issue, effectiveness is limited by quality and format of the input data.

Moreover, the absence of multi-station and multi-river data is a major limitation to spatial variability and hydrological connectivity of models. The majority of available literature is based on single station or single river data [25], which restricts model externalization to other areas. The absence of spatial diversity means that models cannot learn interactions among interlinked river systems as well.

There are additional challenges of data heterogeneity and scaling inconsistencies. Hydrological data usually contains variables that have varying units, distributions, and measurement scales [28]. These inconsistencies may adversely affect the model performance and result in unstable predictions without proper normalization and preprocessing.

Finally, the real-time and high-frequency data is not integrated, which limits the applicability of the existing models to the operating environment. Near real-time forecasting can be carried out using some systems [31], [32] but the vast majority of datasets are historical and cannot be updated in real-time. This restricts the use of models in early warning and real-time decision-making.

To address these problems such as multi-river data, temporal lag data and drought related data, this study uses a structured and enriched dataset. The solution offered will improve the data quality, the number of features, and integrate the spatial and temporal data to develop a more effective and stable water-level forecasting system that can be effectively deployed in the real-life circumstances.

3. STUDY AREA & DATA DESCRIPTION

3.1 Study Area

The Chitra and Nabaganga river basins of the southwest part of Bangladesh are the subject of this study and the area is a hydrologically active and climate sensitive region with a high degree of seasonal variability. Over the past years, this region has been witnessing rising hydrological stress especially in the shape of drought during dry season that has greatly affected the water availability, agricultural productivity and ecosystem stability. These river regimes are of immense importance in the management of water resources in the region and they are very susceptible to climatic variability as well as anthropogenic impacts.

The rivers are highly affected by monsoonal rainfall, upstream flow inputs, sedimentation and in some regions by tidal interaction due to their position in a low-lying deltaic environment. All these lead to complicated hydrological processes, in which the level of water in the rivers changes significantly over the year, with the highest flows during the monsoon and the lowest at long dry intervals. The Chitra River is a river of the Madhumati River and is in the districts of Narail and vicinity. It also shows a strong seasonal fluctuation whereby it is heavily discharged during the monsoon season and much less during the dry season. The river is very susceptible to drought conditions especially in the recent years due to low rainfall and thus the baseflow decreases and the irrigation systems become stressed. The hydrological characteristics of the Chitra River are determined by the variability of upstream inflows, rainfall distribution, and local climatic conditions and are sensitive to both the short-term variability and long-term environmental changes. The river Nabaganga which hydrologically connected with the river Chitra went through Jhenaidah and Jessore. Similar to the Chitra River, seasonal variations are very high; however, it is not sensitive to rainfall and drought conditions as this channel is sensitive due to the morphology of the channels, flow processes and basin characteristics. Past research demonstrated that machine learning models can be effectively used to predict the water heights at this river even though these studies have typically looked at the analysis of individual river separately, and not cross-basin interactions and drought sensitivity. The hydrologic connectivity of the Chitra and Nabaganga rivers is one of the key characteristics of this work. The network of these rivers is not isolated in hydrological processes such as the spread of flows, seasonality and drought conditions. The change of the rainfall or even the discharge of any basin or the intensity of drought of one basin could directly affect the water level of the other basin, particularly during extreme hydrological events. This interdependence is increased during drought conditions whereby low flow conditions become spread out in the system.

This interdependence emphasizes the necessity to treat the same with a multi-river modeling approach, rather than considering each river individually. The two river systems will be integrated into one analysis concept in this paper to quantify cross-basin interactions, increase water-level forecasting accuracy, and resilience in drought sensitive environments.

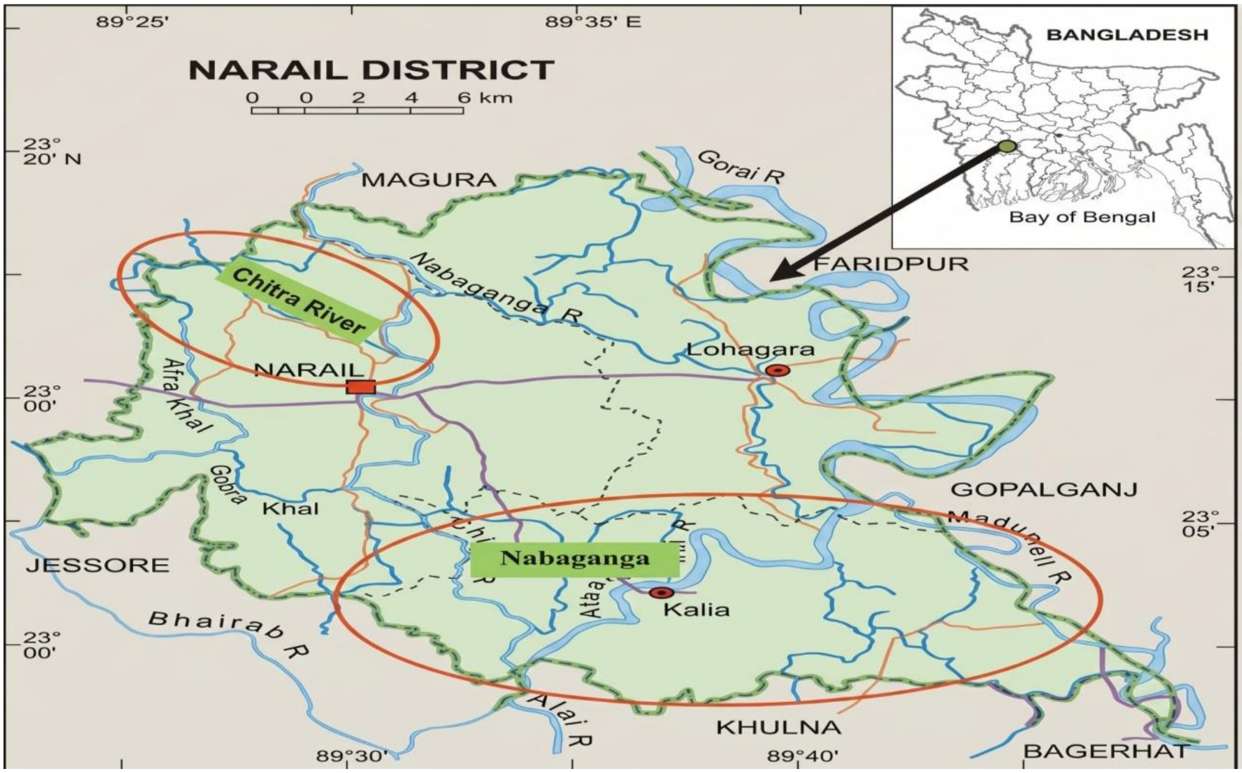

Figure 1. Hydrological connectivity map of Chitra & Nabaganga rivers

3.2 Data Sources

The data used to analyze was obtained in Bangladesh Water Development Board (BWDB) which is the primary organization that carries out hydrological surveillance and data gathering in Bangladesh. The hydrological data that BWDB possesses are long-term, quality-controlled and have been extensively used in both academic and practical water resource management. The data is a 2000 to 2025 or approximately 25 years of uninterrupted data observation in form of a time series. This is a long time horizon that is particularly useful to document the long-term hydrological patterns, seasonal variations and extreme events, including flood and drought periods. Long-term data will be essential in this study to analyze the trends of drought and how long-term low flows affect water levels in rivers. This rich historical information makes machine learning models more reliable and robust, as it allows the learning of time dependencies and variability driven by climate.

In this research, the data will be used in six monitoring stations that will be located within the river systems of Chitra and Nabaganga. These stations were chosen to give extensive coverage of space, which covers upstream, midstream, and downstream of the rivers. The chosen stations are: Kalachandpur, Khatur-Magura, Lohagara, Narail, and Ratandanga with Kalachandpur being found in both river datasets because of hydrological overlaps between the two basins. This common station is significant in the process of capturing the inter-river connectivity and the manner in which hydrological processes spread throughout the system. Multiple monitoring stations can be used to provide a deeper study of the spatial variability of water levels and this is vital in a multi-river modeling framework. It also increases the generalization of the machine learning models as the models are subjected to varied hydrological conditions in different locations. Moreover, the dataset includes the use of related hydro-climatic variables, such as rainfall and seasonal indicators, which are important to reflect the underlying processes that drive river dynamics. The variables are especially significant in capturing the delayed and cumulative effect of rainfall and in identifying patterns that are related to drought conditions.

In general, the combination of long-term, multi-station, and multi-river data offers a good basis to create a robust and drought-sensitive water-level forecasting framework.

Table 1. BWDB Monitoring Stations Used in This Study

Station Name	**River**	**Description**
Kalachandpur	Nabaganga	Upstream/ Shared
Khatur-Magura	Nabaganga	Midstream
Lohagara	Chitra	Upstream
Narail	Chitra	Midstream
Ratandanga	Chitra	Downstream
Kalachandpur	Chitra	Downstream/ Shared

These stations are to provide a comprehensive spatial representation and enable the study to include the variations in water levels across rivers as well as over time, which is crucial to multi-river forecasting and drought-sensitive analysis.

3.3 Dataset Description

The data sample of this study is a full spectrum of hydrological and climatic variables which can reflect the processes of time as well as environmental factors influencing level of rivers. It is formatted in a multivariate time-series data with each observation being associated with a specific date and monitoring station. This framework enables the model to learn the temporal correlations as well as the spatial changes between the Chitra and Nabaganga river systems. The 25-year (20002025) long-term dataset provides sufficient temporal richness to capture the short-term variability, seasonal variability and long-term hydrological dynamics, particularly useful in the development of drought-sensitive forecasting models. W water level (WL) variable is the most important variable to be predicted and is the central variable in the dataset. This is the daily recorded river stage at each of the monitoring stations and it is an indicator of combined effects of upstream flow, precipitation, and basin characteristics. Since there is a direct relationship between water level and flood and drought, it is among the key considerations to evaluate the performance of a model. The data range includes an extremely wide range of hydrological scenarios, including peak flows in monsoon seasons to extremely low values in drought events, which provides the model with the opportunity to familiarize itself with a wide range of river behaviour. Other than the water level, rainfall information is also added as one of the explanatory variables. The primary source of river discharge and a very significant contributor to water-level changes is rainfall. The daily rainfall measurements are also included into the dataset and it is possible that the model will be able to record the instantaneous hydrological response to precipitation. However, the physical processes such as infiltration, storage and slow run off imply that not all of the impacts of rainfall on the river water levels can be instant.

In order to capture these temporal relationships, both water level and rainfall lagged features are added to the dataset. Persistence and continuity in river behavior are represented by the water-level lag variables (e.g. lag1, lag2, lag3) since present water levels are highly dependent upon past levels. On the same note, lagged rainfall variables are incorporated to capture memory effects of rainfall, and the model can learn delayed hydrological responses and cumulative effects with time. Such characteristics are especially essential in the modeling of drought conditions where an extended cycle of low rainfall has a cumulative effect on the river flow. The temporal features included in seasonal variability are month and seasonal features. These characteristics help in separating various hydrological seasons, such as monsoon, post-monsoon, and dry seasons, that can enable the model to learn cyclic behavioral patterns of rivers. Drought conditions have a strong association with seasonal variability hence these characteristics are important in the drought sensitive modeling. Spatial identifiers are also included in the dataset, i.e. River ID and Station ID, and they allow the model to distinguish between the observations of the various rivers and the monitoring sites. These identifiers enable the model to model spatial heterogeneity and locus-specific patterns, which is critical in a multi-river framework wherein hydrological behavior differs at various stations and basins.

In addition, derived indicators of hydrology are also included to furnish context information on the initial conditions of rivers. The characteristics assist the model to realize deviation of normal trends, which is essential in detecting extreme hydrological events like floods and droughts. The dataset was also preprocessed to ensure that the data quality and consistency were given to the model training. The lack of values has been dealt with through the appropriate interpolation or drop approaches and outliers have also been considered to avoid learning bias in the models. In addition, everything was standardized to a standard scale to facilitate model convergence, stability and general predictive performance.

Overall, the data set provides a very descriptive data on hydrological, climatic, time series, and spatial data, which is a good foundation to develop a sound and drought sensitive multi-river water-level prognostic model.

Table 2. Summary of Dataset Features

Category	Variable(s)	Description
Target	LWL	Low water level (m), drought-sensitive river stage
Hydrology	HWL, Avg_LWL_Monthly	High-flow condition and monthly baseline
Rainfall Forcing	Rainfall, Avg_Rainfall_Monthly	Monthly precipitation drives runoff and drought
Hydrological memory	LWL_Lag1, LWL_Lag2, LWL_Lag3	Short- and long-term water-level persistence
Rainfall memory	Rainfall_Lag1, Rainfall_Lag2	Cumulative drought signal
Seasonality	Month_num, Season_Moonsoon, Pre-moonsoon, post-moonsoon	Seasonal and monsoon regime
Spatial identity	River_ID, River_Name, Station_ID	Multi-river and station-wise differentiation
Time	Year	Long-term climate trend
Metadata	Multi_River_Case, Data_Source_Assumption	Multi-river structure and data traceability

3.4 Exploratory Data Analysis

The Exploratory Data Analysis (EDA) was conducted to examine the current structure, trends and associations in the data prior to the creation of a model. The main objective of the analysis was to understand the temporal variations, seasonal fluctuation, spatial changes and drought behavior of river levels in Chitra and Nabaganga basin.

The findings revealed that there were strong seasonal patterns in the amount of water in the two rivers. The monsoon season causes the level of water to shoot up due to downpour and inflow upstream resulting in the best discharge conditions. On the other hand, during a dry climate the amount of water decreases considerably and in most instances, is extremely low and is associated with the drought conditions. This prominent seasonal variation underscores how reliant river behaviour is to climatic cycles and confirms the need to include seasonal aspects in the predictive model. The analysis of the long-term trends during the 25-year interval (20002025) showed that there was a significant inter-annual variation in water levels, which was evidence of the impact of the changing climatic conditions. Specifically, over the past years, a gradual decrease in the water levels during the dry season was noted, which suggests the growing severity of drought and decreasing baseflow. These tendencies indicate that there is a change in hydrological behavior that is essential to comprehend the long-term water availability as well as to create powerful drought-sensitive forecast models. There was a strong positive correlation between rainfall and water level but the effect was not immediate. There was some noticeable time lag between rainfall occurrences and rise in river water levels. Hydrological processes that cause this delay include infiltration, surface runoff and basin storage. The existence of such a lag is a strong argument in favor of the lagged rainfall and water-level features in the dataset which undergo through delayed responses and time-dependent dependencies to the model. Spatial analysis among various monitoring stations demonstrated that there is a great variation in water-level behavior. The upstream stations were more responsive to rainfall events whereas the downstream stations were smoother with delayed responses because of the flow accumulation and channel properties. As well, some stations were more affected by drought, which implies spatial heterogeneity in the hydrological sensitivity of the basin. This variability highlights the relevance of multi-station and multi-river data in order to obtain an accurate portrayal of complex hydrological processes.

On the whole, the EDA proves that the river water level depends on the complex of seasonal variation, long-term climatic changes, delayed effects of rainfall, and geographical changes. These results form a solid basis of feature selection and model design, especially when creating a multi-river framework that is sensitive to drought.

4. METHODOLOGY

4.1 Overall Framework

This paper suggests an integrated drought-sensitive machine-learning model to predict water levels in an inter-basin river system. The model aims at capturing hydrological variability caused by droughts and subsequently uses the data to enhance predictive values of the river water levels. The framework will improve reliability when there is a low flow (drought conditions) and when there is a normal flow by incorporating awareness of drought in the model. The entire workflow is comprised of a sequence of organized steps that are: data integration, preprocessing, feature engineering, normalization, model training and performance evaluation. The stages are meticulously planned to convert raw hydro-climatic data into a structured form that can be read by machine learning yet maintain a temporal dependence and spatial variability. The use of a multi-river learning paradigm is one of the main elements of the suggested methodology, as both the Chitra and Nabaganga rivers data sets are incorporated into a single modeling system. In contrast to traditional methods, which consider river systems in isolation, this framework allows cross-basin learning, which can be used to model interdependencies between rivers. This is of special concern to hydrologically related systems, where changes in the level of rainfall, upstream flow, or drought severity in one basin could affect water-level conditions in another. Besides multi-river integration, the framework is also explicit in the application of the principles of drought-sensitive modeling. There are temporal lag characteristics, rainfall memory and seasonal indicators to capture delayed hydrological responses and seasonal drought persistence. These characteristics allow the models to capture short-term variations and extended periods of low flow, which is important in drought conscious predictions. Moreover, the framework will be able to deal with spatial and temporal complexity. The spatial variability of multiple monitoring stations is represented by the integration of station-level data, whereas time-series features are used to represent the dynamics of the process over time. Such dual ability enables the system to generalize over the river segments and to adapt to the different hydrological conditions.

In general, the suggested framework gives a scalable and data-driven solution to the problem of integrating the drought analysis with machine learning-driven water-level prediction, which will be the basis of the further modeling and evaluation steps of the proposed study.

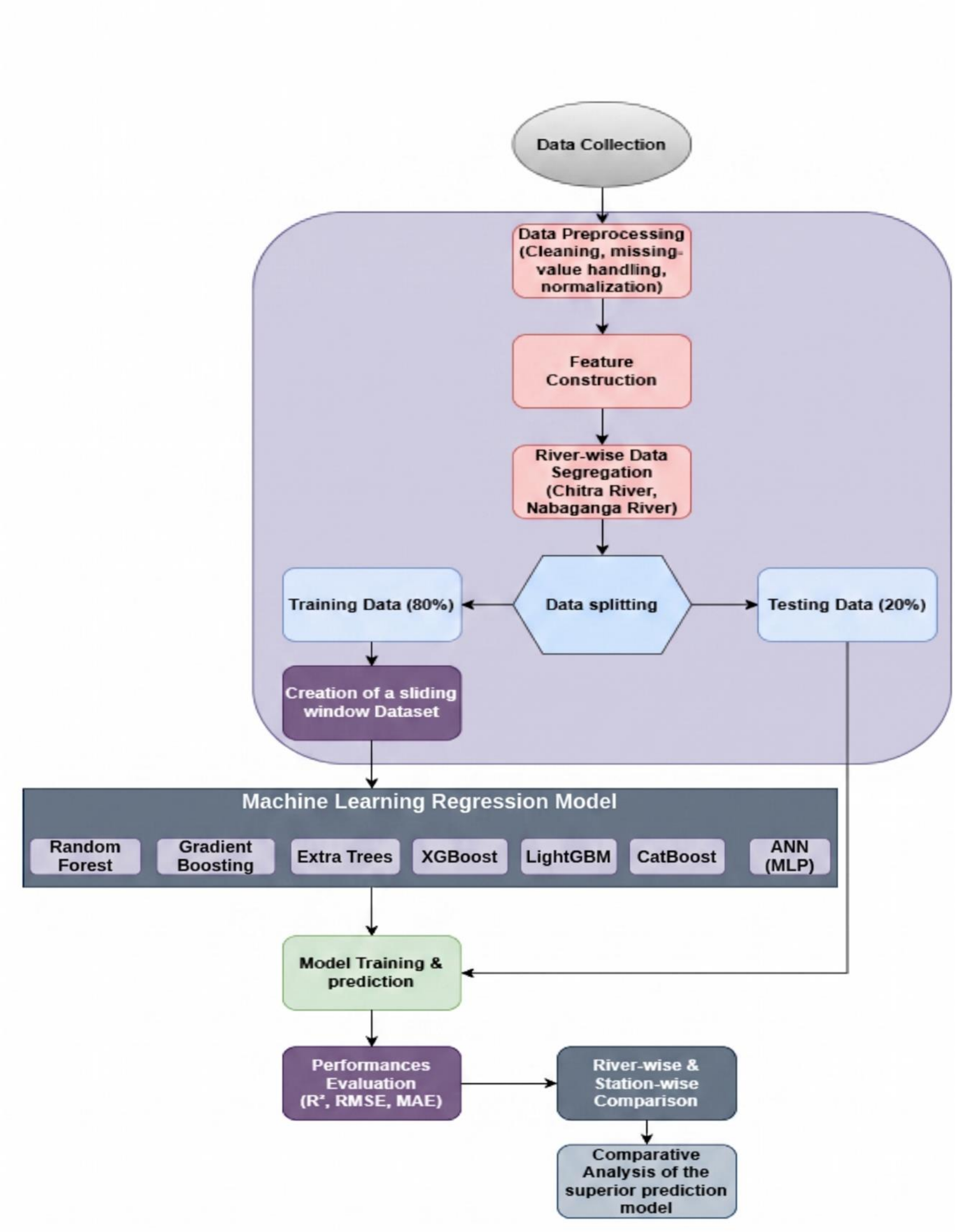

Figure 2. Overall Methodology and Machine Learning Framework for Drought-Sensitive Water-Level Forecasting

4.2 Data Integration

The process of data integration is very important as it converts various station-level datasets to a single multi-river dataset that can be used to make predictions using machine learning techniques. The first step involved hydrological data was processed into six BWDB monitoring stations and compiled into independent time-series data sets of the various sites of the river systems of Chitra and Nabaganga. These data sets were then combined into one consolidated data set to be able to run a comprehensive spatio-temporal analysis. In the course of the integration, it was assigned an observation ID (River ID) and a Station ID (a categorical identifier) that denotes the river basin and monitoring point, respectively. These features enable the machine learning models to distinguish between spatial context and learn location-specific hydrological patterns. Also, each dataset was time-warped with a common temporal index (date), which made them consistent over time and allowed performing multi-station analysis in a synchronized manner. The integration process is successful in changing the isolated time-series observations into a structured spatio-temporal dataset with each data point possessing both the temporal features (e.g., lag features and seasonal indicators) and the spatial features (e.g., river and station identifiers). Such representation enables the model to presently explain both temporal relationships and spatial variability and the cross-basin relationships. The primary advantage of this sort of strategy is that it considers hydrological connectivity of rivers. Changes in the behavior of one river may occur as a result of changes in rainfall, upstream level of drought or other river in a system that is interconnected such as the Chitra and Nabaganga basins. The model is able to learn these interdependencies through integrating information on multiple rivers, rather than studying rivers as single systems.

Moreover, the consolidated information facilitates modeling of drought-sensitive conditions since it enables the extrapolation of low-flow conditions in a spatial dimension. This is very crucial when it comes to the dynamics of the effects of droughts, and their spread across interconnected basins over a period of time. Consequently, the process of integration not only increases the richness of the dataset but also the model generalization and predictive performance of the model in complex and climate-sensitive conditions of hydrology.

4.3 Data Preprocessing

Preprocessing of data is a vital process in determining the quality, consistency and reliability of the data before developing a model. The raw hydrological data obtained in BWDB can have irregularities which include absent values, redundancy and noise in measurements due to limitation of the sensors or errors in record taking. It is necessary to conduct proper preprocessing to reduce the number of biases in the data and enhance the reliability and correctness of machine learning models. Missing data have been treated using appropriate interpolation techniques to any minor time gaps that arose without significantly disrupting underlying patterns in the time-series data. In cases where there were large gaps or bad segments it was either omitted or estimated carefully based on values available and trend nearby. This will ensure the integrity of the dataset and prevent distortion of hydrological signals. An intense identification and eradication of redundant records and inconsistencies of the data were conducted to give data integrity. The importance of maintaining clean and non-redundant data in time-series analysis is particularly important since repeats and misaligned data points can negatively impact the learning of the model. Outlier was identified to distinguish the important extreme events with the false data points. Hydrological extremes such as floods and low water level due to droughts are significant to the model training and they were not eliminated in the dataset. The sensor faults or flaws in data recording gave aberrant values which were filtered out with the assistance of statistical techniques. These conservative approaches will ensure that the dataset is hydrologically valuable in variability and will eliminate noise that can negatively impact model performance. Consistency checks were also performed to ensure consistency in data formats, units and time consistency across all the stations. This is particularly important in the case of a multi-river structure, where inter dataset differences can hamper effective integration and analysis.

Overall, the preprocessing stage ensures that the data set is clean, consistent and realistic to real-life hydrological conditions. The processed data set provides a good foundation to develop powerful and drought sensitive machine learning models via preserving the normal and extreme events including drought conditions.

4.4 Feature Engineering

One of the most important aspects of this study is feature engineering because it directly will dictate how well machine learning models can capture complex hydrological dynamics and drought-related behavior. The feature engineering process in this research was specifically designed to consider the temporal dependencies, environmental influences and the spatial variability with specific consideration given to the representation of drought sensitive conditions. Lag features of water level were also created to capture the temporal dynamics and they include LWL_Lag1, LWL_Lag2 and LWL_Lag3 which represent past-day observations. These lag variables allow the model to acquire persistence and continuity in the behavior of rivers, with the present water levels being highly dependent on the historical situation. This is particularly crucial in cases of drought where long periods of low water table will be the signs of water scarcity and slow response by the system instead of sudden changes. In the same way, lagged rainfall effects were also introduced to show the effects of rainfall memory. These characteristics enable the model to determine delayed hydrological responses, because the effect of the rainfall on the river water level depends on processes like infiltration, runoff and basin storage. The model can learn cumulative and delayed effects of precipitation by including rainfall lag variables, which are critical to the proper modeling of both recovery following drought and change to low-flow conditions. The variability of the seasons was included in terms of temporal encoding like month and seasonal features. These characteristics help the model to differentiate various hydrological regimes such as monsoon, post-monsoon, dry seasons among others. Due to the close relationship between drought conditions and seasonal patterns, especially in extended dry seasons, these characteristics are important in enhancing model sensitivity to seasonal drought cycles. Besides the time and weather factors, the spatial context was maintained by providing the River ID and Station ID, which enabled the model to distinguish between locations and observe spatial variability in hydrological patterns. This is more so when the framework is that of a multi-river, where each river and station might have a different response to the rain and drought environments. One of the most important contributions of the given study is that the implicit description of drought conditions in terms of combinations of features is performed instead of using predetermined drought indices. The model can learn both short-term variations and long-term drought patterns directly by using the data, by combining lagged water levels, rainfall memory and seasonal indicators. This data-driven approach makes this approach more flexible and adaptable and therefore the model can be generalized to other hydrological conditions and river systems.

The entire process of feature engineering provides a strong representation of the underlying hydrological system that is drought-sensitive, which forms a strong foundation of accurate and reliable water-level prediction.

Table 3. Engineered Features for Drought-Sensitive Modeling

Feature Type	Description	Purpose
Lag WL	Previous water levels	Capture temporal dependency
Lag Rainfall	Past rainfall values	Capture delayed rainfall effect
Seasonal Features	Month/Season	Capture seasonality
River ID	River identifier	Enable multi-river learning
Station ID	Station identifier	Capture spatial variability

4.5 Data Normalization

In order to ensure the model training was effective and stable, the model training was in fact data normalized to ensure that all the input features are in the same numerical scale. The data set contains variables that are not of the same unit and magnitude e.g. water level and rainfall and unless they are properly scaled, the variable with high values will have inappropriate influence in the learning process. This approach preserves the relative ranking and association of the data and, in addition, normalizes all the characteristics equally. Normalization is particularly important with machine learning models such as Artificial Neural Networks and gradient boosting algorithms which are vulnerable to feature scaling. It will prevent numerical instability in the training process, and will also make the training process quicker and more efficient. In addition, normalization ensures that drought-related factors, e.g., lagged water levels and rainfall memory are equally considered in training the model. This assists in maintaining the balance of the different input variables as well as the appropriate capture of drought sensitive patterns. Overall, the standardization of the feature space normalization, the enhancement of model stability and the enhancement of predictive performance are introduced in the proposed drought-sensitive forecasting framework.

4.6 Dataset Splitting

The data was divided into training and test data to reach predictability and the ability to generalise of the machine learning models. Where, it was trained on approximately 80 % of the data and the remaining 20 % held back to being tested. Since the dataset is a time series (a multivariate one) a splitting policy based on time (i.e. chronological policy) was used instead of random sampling. Previous observation was used to train and more recent observations were used during testing. The approach does not lose time order and does not leak data that the models are being tested on future unknown data, as would be the case in real-life forecasting. The spatial diversity was also to be of the process of splitting. The training and testing sets contained the data of Chitra and Nabaganga rivers, and all the monitoring stations. This will ensure that the models are trained on a wide range of hydrological conditions and tested on numerous spatial environments.

This approach provides a realistic and valid assessment of model performance since it preserves the time continuity and spatial variability. It also ensures that the trained models can effectively generalize to other periods in time and to other river sites, a requirement to build a powerful and drought sensitive forecasting system.

4.7 Machine Learning Models

This study uses machine learning models to understand the complicated and nonlinear relationship between hydrologic and climatic variables to make precise water-level forecasts. The traditional modeling techniques do not give reliable predictions due to dynamic nature of river systems and because of interaction of various factors that affect the river systems like rainfall, seasonality, drought conditions and upstream flow. In order to overcome these issues, this study will use an integrated set of machine learning models in a single framework. In this study, eight machine learning models are used, which include ensemble learning methods and neural network-based methods. Such models are Random Forest (RF), Gradient Boosting Regressor (GBR), Extra Trees Regressor (ETR), XGBoost (XGB), LightGBM (LGBM), CatBoost and Artificial Neural Network (ANN - MLP). Having various models enables a comprehensive assessment of the various learning strategies and guarantees strength in a wide range of hydrological situations.

Ensemble-based models, especially tree-based, are highlighted based on their high capabilities of dealing with nonlinear relationships, noise, and high-dimensional data. Random Forest, Gradient Boost, Extra Trees, XGBoost, LightGBM, and CatBoost can be used to model such complex interactions among hydro-climatic variables, without compromising predictive power or overfitting. These models are particularly useful in the modeling of drought-sensitive behavior, where nonlinear dependencies and gradual changing are likely to be significant. Besides the ensemble approaches, an Artificial Neural Network (ANN) takes the shape of a Multilayer Perceptron (MLP) to represent complex nonlinear patterns and latent relationships in the data. When dealing with interactions of features in complex interactions, neural networks offer another learning mechanism that further complements the tree-based models. The models are trained and tested on the multi-river dataset, which facilitates them to learn the temporal correlation, as well as the spatial variability among the Chitra and Nabaganga river systems. Such an integrated approach to modeling will facilitate a systematic comparison of the merits of various algorithms and provide an opportunity to capitalize on their benefits in one drought-sensitive prediction system. In general, the application of several machine learning models increases the credibility of the study since it offers a comparative analysis in relation to each other and guarantees strong performance in a variety of hydrological and climatic conditions.

Random Forest (RF)

Random Forest is an ensemble learning model which builds a plethora of decision trees through bootstrap sampling and by chance sampling of features. The individual trees are trained on the various subsets of the data and the overall prediction is achieved by averaging the results of all the individual trees. This randomization of data and features selection is useful in reducing overfitting and enhancing the model generalizatio [50].

Mathematically, the prediction of Random Forest is expressed as:

$$y = \frac{1}{T}\sum_{t=1}^{T} h_t(x) \qquad (1)$$

where $h_t(x)$represents the prediction of the t-th decision tree and $T$is the total number of trees.

Random Forest can be successfully used in hydrological forecasting because it can have nonlinear relations between the input variables (rainfall, lagged water levels, and seasonal indicators). It is especially strong in working with noisy and high-dimensional data, which are typical of river basin analysis. Additionally, its ensemble character enables it to be used to model complicated processes in multi-river systems and can give stable predictions both in flood and drought periods.

Gradient Boosting Regressor (GBR)

Gradient Boosting is an ensemble learning algorithm which constructs models in a sequence with each new model trying to rectify the previous models. Gradient Boosting is also used in contrast to Random Forest which constructs trees independently, with the goal of reducing prediction error, through the minimization of a loss function [50].

The model can be expressed as:

$$y(x) = F_0(x) + \sum_{m=1}^{M} \gamma_m \, h_m(x) \tag{2}$$

where $F_0(x)$is the initial model, $h_m(x)$represents the weak learner (decision tree), and $\gamma_m$is the learning rate controlling the contribution of each tree.

Such a sequential learning process enables Gradient Boosting to learn the fine details in the data, such as small variations that are related to drought conditions. It is especially efficient in the description of complicated hydrological time series, when a gradual change in rainfall and water levels needs to be precisely monitored. It is suitable in drought-sensitive forecasting as it focuses on hard-to-predict situations.

Extra Trees Regressor (ETR)

Extra Trees or Extremely Randomized Trees is a variation of ensemble learning that adds extra randomness to Random Forest. In this technique, the feature selection as well as the split thresholds are randomized, enhancing model diversity and minimizing variance [50].

The prediction function is given by:

$$y(x) = \frac{1}{T} \sum_{t=1}^{T} h_t(x) \tag{3}$$

The difference between the two though they are similar in the formulation, is in the construction of the trees. Extra Trees requires the full dataset (no bootstrap sampling) and randomly selects the split points, which results in less time training and better generalization. Extra Trees is especially effective in hydrological contexts where data is both very variable and noisy, e.g. data affected by irregular rainfall and seasonal variations. It is useful in forecasting multicast rivers, where the spatial variability is important because it has a tendency to generalize well.

XGBoost Regressor (XGB)

XGBoost (Extreme Gradient Boosting) is a new version of gradient boosting, which represents regularization, parallel processing, and optimization of tree construction. It is considered to be one of the strongest machine learning algorithms on structured data [51].

The objective function of XGBoost is defined as:

$$obj(\theta) = \sum_{i=1}^{n} L(y_i \, , y'_i) + \sum_{k=1}^{k} \Omega(f_k) \tag{4}$$

where Lrepresents the loss function measuring prediction error, and $\Omega(f_k)$is the regularization term that penalizes model complexity.

The regularization part of XGBoost helps avoid overfitting. XGBoost is very useful when working with variable data. It is good at forecasting drought- water levels. This is because it can handle interactions between rainfall and seasonal variations. XGBoost is one of the models used in this study. It is chosen because it is efficient and accurate.

LightGBM (Light Gradient Boosting Machine) – Regression Model

LightGBM is a new and extended framework of gradient boosting, which is aimed to enhance the capability of computation and scale, especially in large and high-dimensional data. In contrast to the traditional boosting algorithms that expand trees at a level, LightGBM uses a leaf-wise tree expansion approach to grow the model, expanding the leaf that reduces losses the most. This enables it to concentrate on the most informative parts of the data, hence convergent faster and more accurately. LightGBM is an effective regression model that can be used to predict continuous values like river water level. It is especially applicable in time-series forecasting activities, in which huge amounts of past data need to be handled effectively. Histogram-based learning is also included in the algorithm which minimizes on memory usage and increases on the speed of training and is feasible in real-world hydrological applications. LightGBM in the framework of this research is a supporting model to measure the efficiency of boosting-based algorithms to work with multi-river data and time dependencies. Its capability to identify nonlinear relationships among rainfall, lagged water levels and seasonal variations renders it helpful in identifying not only short term fluctuations but also the long-term hydrological trends. [51]

The mathematical formulation of the model is given as:

$$y = \sum_{m=1}^{M} \alpha_m T_m (x) \tag{5}$$

MLP Regressor (Multi-Layer Perceptron) – Regression Model

The Multilayer Perceptron (MLP) Regressor is a kind of feedforward artificial neural network that is developed to model complex nonlinear relationships between the input features and continuous output variables. It comprises of a series of layers with an input layer, one or more hidden layers and an output layer, with every neuron being fully connected to neurons in the next layer. The model is adjusted by the weights and biases by the backpropagation algorithm and gradient descent optimization. Being a regression model, MLP is especially good at modeling complex interactions among hydrological factors like historical water levels, rainfall, and seasonal indicators. Its nonlinear activation functions can model very complex functions and thus it is the appropriate model to use in models of dynamic river systems where the relationships between variables are not linear. The MLP is adopted as a supportive model in this study to compare the approaches based on neural networks with the ones based on ensemble learning. On the one hand, it is very able to learn complex patterns, but its performance is extremely sensitive to the parameters tuning and quality of data. However, it is quite informative on the performance of deep learning models in water-level forecasting, particularly during different climatic and drought conditions [51].

The mathematical representation of the model is given as:

$$y = \sigma(W_1 . x + b_1) + b_2 \tag{6}$$

CatBoost (Categorical Boosting) – Regression Model

CatBoost is a type of boosting algorithm. It is designed to work with features that need little preprocessing. CatBoost uses a method called ordered boosting. This method reduces prediction bias. Prevents overfitting. CatBoost can work directly with variables. It does not need a lot of encoding. This makes it very useful for datasets with types of features. CatBoost is a type of regression model. It is good at predicting values like river water levels. It is especially useful when the sample contains clues like seasonal labels and river identifiers. CatBoost can link numerical variables. This increases the precision and interpretation of the model. CatBoost is a model in this study. It performs well in addressing temporal variations in the dataset. This is helpful in river settings where categorical variables are needed to represent spatial differences. [51].

The mathematical formulation of the model is given as:

$$y = \sum_{m=1}^{M} \alpha_m T_m(x) + b \tag{7}$$

4.8 Model Evaluation Metrics

The performance of the proposed machine learning models was evaluated using three regression metrics. These metrics are Mean Absolute Error, Root Mean Square Error and Coefficient of Determination. These metrics were chosen to give an evaluation of model performance. In forecasting it is not just about the average deviation between predicted and observed values. It is also about the sensitivity of the model to values like flood peaks and low-flow conditions. The chosen metrics represent areas of model performance. Mean Absolute Error is a measure of average error. Root Mean Square Error focuses on deviations. It is helpful when evaluating a models performance during events. Coefficient of Determination measures how well a model explains the variability in data. Using these three metrics together provides a high-quality evaluation framework. This framework allows for a comparison of different machine learning models under various hydrological conditions. It is especially important in drought- forecasting situations. Models should be accurate not just when the flow is normal but when it is at a low level for a long time. Using evaluation measures reduces the chances of biased model evaluation. It provides a credible foundation, for choosing the most effective model for predicting water levels in interconnected river systems.

Mean Absolute Error (MAE)

Mean Absolute Error (MAE) is the mean absolute deviation between the predicted and observed water levels. It gives an easy to understand and interpret error of a model by showing how much, on average, the forecasts do not match the real numbers. Because MAE does not differentiate among the errors, it is not sensitive to extreme values as RMSE is, and as such is a more resilient measure of the overall model performance. MAE finds application especially in hydrological studies where it is necessary to determine the overall reliability of water-level forecasts in various seasons. It captures the goodness of the model in normal flow conditions and gives a clear picture of the average forecasting error [50] .

The mathematical expression of MAE is given by:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - y'_i| \tag{8}$$

Where, $y_i$represents the observed water level, $\hat{y}_i$represents the predicted value, and $n$is the total number of observations.

Root Mean Square Error (RMSE)

Root Mean Square Error (RMSE) is used to estimate the square root of the mean squared errors between the predicted and observed values. In contrast to MAE, RMSE punishes bigger errors more severely because of squaring the differences. This is why it is especially sensitive to extreme deviations, and it can be used to analyze the performance of a model during the most crucial hydrologic events. RMSE is important in the context of this study to determine the extent of capture of extreme conditions like flood peaks and drought periods by the models. A smaller RMSE implies that the model can be used to predict normal and extreme variations in water-level well [50].

The mathematical formulation of RMSE is given by:

$$RMSE = \sqrt{\frac{1}{n}}\sum_{i=1}^{n}(y_i - y'_i)^{2} \tag{9}$$

Where, $y_i$and $\hat{y}_i$denote the observed and predicted values, respectively.

Coefficient of Determination (R^2)

The Coefficient of Determination (R^2) is used to determine the percentage of variance in the data observed that is accounted by the model. It also gives an idea of the correspondence of the predicted values to the actual observations. R^2 can be between 0 and 1 with the higher the value of R^2, the better the performance of the model and the ability to predict. In hydrological predictions, the R^2 high value means that the model is effective in explaining the variability of the water levels with time including seasonal and long-term trends. It also indicates the capacity of the model to capture the underlying physical and climatic processes that affect the behaviour of rivers [50].

The mathematical expression of R^2 is given by:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - y'_i)^2}{\sum_{i=1}^{n}(y_i - y'_i)^2} \tag{10}$$

Where, y_i is the observed value, $\hat{y}_i$ is the predicted value, and $\bar{y}$ is the mean of the observed value

5. RESULT ANALYSIS

This paper provides an in-depth discussion of the experimental findings of the suggested drought-sensitive machine learning system to forecast water levels in the river basins of Chitra and Nabaganga. The analysis is performed based on a multi-river data set that combines hydrological and climatic data of the two river systems in a long time interval. This chapter aims to determine the effectiveness, strength, and generalization ability of the developed models in different hydrological and climatic conditions. The analysis starts with the assessment of the main machine learning models used in the multi-river framework and how they predict with high accuracy and their capability to observe nonlinear hydro-climatic relationships. This is followed by a close study of performance by river where model behavior is investigated individually in Chitra and Nabaganga rivers to determine the spatial consistency and capability of cross-basin learning. Besides this, the paper also measures the capacity of the models to recreate the observed water-level patterns by visual means such as observed and predicted comparisons. One of the main points of this chapter is the evaluation of drought-sensitive performance where the long-term water-level patterns and the variability of the stations are examined to determine the trends in decreasing flow and rising drought stress across the basin. Moreover, the validation is conducted in the long-term by applying other machine learning models to test the model consistency and reliability of the proposed framework. The relationships of the features, the temporal variations, predictive stability are also examined to gain a better insight into the model behavior. On the whole, this chapter illustrates why the suggested multi-river, drought-sensitive method enhances water-level forecasting by accounting for intricate temporal, spatial and climatic interactions and as such is a more reliable and scalable hydrological prediction and water resource management solution.

5.1 Overall Model Performance under Drought Conditions

The predictive accuracy of the chosen machine learning models was measured on the basis of the mixed multi-river dataset comprising of the Chitra and Nabaganga river systems. This analysis will determine the suitability of the drought-sensitive framework suggested to model the complex hydrological processes in integrated basins, especially when climate variability and drought stresses occur. Table 5.1 summarizes the performance of the five major models namely, Random Forest (RF), Gradient Boosting Regressor (GBR), Extra Trees Regressor (ETR), XGBoost (XGB) and Artificial Neural Network (ANN).

Table 4. Overall Performance of the models

Model	**MAE**	**RMSE**	R^2
Random Forest	0.045	0.120	0.984
Gradient Boosting	0.057	0.081	0.993
Extra Trees	0.060	0.127	0.982
XGBoost	0.052	0.084	0.992
ANN (MLP)	0.242	0.333	0.875

The findings provide a clear indication that the ensemble and boosting-based learning models are much better in comparison to those of neural network-based methods when it comes to multi-river water-level forecasting. This is a performance shortfall that underscores the highly nonlinear, dynamic and nonstationary nature of hydrological processes, especially during drought periods. Such complexities can be well represented by tree-based ensemble models as they can model interactions between features and can accommodate irregular patterns of tabular hydro-climatic data.

The Gradient Boosting Regressor (GBR) model was the best overall model as it has the highest coefficient of determination ($R^2 = 0.993$) and lowest RMSE (0.081). This model is probably very good at reproducing the short term variations and long-term relationships (such as drought persistence). Gradient Boosting uses an iterative learning process and is able to learn from recent predictions to focus on new complex relationships of low-flow and drought events. XGBoost also showed good results with a high R^2 (0.992) and RMSE (0.084) value. Hence it can well generalize under different conditions due to regularization techniques and pruning of trees. The model can well capture the seasonality, rainfall and low flows (drought) in the two river systems. The Random Forest and Extra Trees models are good (R^2 value of 0.984 and 0.982 for both the models). These are the most interesting models as they have an ensembled averaging (a statistical principle) which reduces the variance and hence stabilizes the prediction. However, they are not as efficient as boosting, as they do not have a sequential increasing of the model fit (and hence can predict only complex drought patterns). But the weakest model was the Artificial Neural Network (ANN) with an R^2 of 0.875 and a much lower RMSE value of 0.333. This indicates the poor representation of the long-term memory and drought sensitive variability by a feed-forward neural network for tabular data. Perhaps lack of memory and sensitivity to scaling in inputs lead to the relatively poor results. Overall, the study indicates the best performance of boosting and ensemble tree-based modeling for parched rivers. The fact that they can capture dynamic temporal and spatial relationships, as well as an inherent nonlinearity makes them the preferred models for multi-river systems. Finally, the higher accuracy of the merged dataset shows the potential to increase the accuracy of multi-system models by using many river systems, rather than adding noise to achieve higher generalisation to multi-climate-sensitive systems.

This is evident in this study, as boosting-based models can be the most accurate and reliable models to develop to predict parched multi-river water-level in the Chitra-Nabaganga basin.

5.2 River-Wise Model Performance Analysis under Drought Conditions

In order to assess the performance and reliability of the suggested drought-sensitive multi-river framework further, river-wise performance analysis was carried out. In this analysis, the performance of the individual machine learning models using the Chitra and Nabaganga river datasets are analyzed. Through the analysis of the model behavior at the single river scale the spatial robustness, cross-basin generalization and the capacity of the models to reproduce localized hydrological dynamics in a changing climatic and drought environment is possible. This is especially critical when dealing with multi-river systems, in which rivers are characterised by distinct morphological and hydrological features.

5.2.1 Performance Analysis for Chitra River

The performance of the machine learning models for the Chitra River is presented in Table 5.

Table 5. Model Performance for Chitra River

Model	MAE	RMSE	R^2
Random Forest	0.068	0.130	0.972
Gradient Boosting	0.077	0.119	0.977
Extra Trees	0.045	0.122	0.976
XGBoost	0.059	0.112	0.979
ANN (MLP)	0.309	0.421	0.710

The findings reveal that XGBoost was the most accurate predictor of the Chitra River as shown by the highest R^2 value of 0.979 and the lowest RMSE of 0.112. It shows that it has a high potential in learning complex nonlinear relationships among rainfall, river flow, and drought conditions in a morphologically dynamic river system. This characteristic of XGBoost to capture both short-term variability and long-term hydrological relationships is especially valuable in capturing the low-flow patterns and slow water-level change associated with droughts. The performance of the Gradient Boosting Regressor ($R^2 = 0.977$) and Extra Trees ($R^2 = 0.976$) were also high, which once again supported the suitability of ensemble-based models to predict seasonal fluctuations and drought-induced fluctuations. The models can simulate interactions among several hydro-climatic factors such as delayed rainfall impacts and seasonal changes, which are important in precise forecasting of droughts. Random Forest model demonstrated a steady, and viable performance with an R^2 value of 0.972. Whereas it is a little less accurate compared to boosting-based approaches, its ensemble averaging mechanism also offers consistent predictions under different settings. The same stability is advantageous when it comes to dealing with general hydrological variability, but it can also smooth out smaller-scale drought-related variations in water tables. Conversely, the ANN (MLP) model showed much worse results, having an R^2 of 0.710 and RMSE of 0.421. This suggests that feed-forward neural networks can not capture long-term hydrological memory and drought persistence as well when using structured tabular data. Performance of ANN is constrained by the fact that it does not effectively capture temporal dependencies and nonlinear interactions especially in a situation where there is a gradual change in drought and there is long low flow.

The overall findings of the Chitra River indicate that boosting-based models are more useful to support complex hydrological behavior in a river that is a variable and sensitive system to the drought conditions.

5.2.2 Performance Analysis for Nabaganga River

The performance results for the Nabaganga River are presented in Table 6.

Table 6. Model Performance for Nabaganga River

Model	**MAE**	**RMSE**	R^2
Random Forest	0.062	0.122	0.984
Gradient Boosting	0.063	0.091	0.991
Extra Trees	0.076	0.131	0.981
XGBoost	0.057	0.087	0.992
ANN (MLP)	0.401	0.538	0.679

In the case of the Nabaganga River, XGBoost was once again the best performer and the R^2 value was found to be 0.992 and the RMSE was found to be 0.087. The outcome also proves the excellence of boosting-based models in terms of representing hydrological variability, such as seasonal variations, sediment-related variations, and the impact of droughts. The accuracy of XGBoost is high, which means that it can model regular flow behavior and extreme conditions with the smallest error, significantly enhancing its relevance in practice as a forecasting tool. Gradient Boosting model (R^2 = 0.991) also showed excellent performance as it is close to XGBoost. This consistency confirms the fact that the boosting techniques are especially efficient when working with complex and nonlinear hydrological data, in particular, in cases when the drought conditions are recorded, when the level of water varies slowly with time. Random Forest ($R^2 = 0.984$) and Extra Trees ($R^2 = 0.981$) also performed well, but a bit worse than boosting-based models. These models are also reliable because of the ensemble character of the models, which gives consistent forecasts under various hydrological conditions. Nevertheless, they cannot record finer scale variations in a continuous fashion due to their inability to correct their mistakes in sequence and hence are only effective in capturing variations when there is a low flow or drought. The ANN (MLP) model was once again the least performing with an R^2 of 0.679 and an RMSE of 0.538. This shows that there is a lot of hard work in modeling drought conditions and tidal-related changes in flow variability in Nabaganga River. The large values of RMSE show that ANN is not capable to perform good in extrapolations over complex hydrological processes, for nonlinear interactions and time lags. Also, the error performance metrics of Nabaganga River are comparatively better than Chitra River, which means that the system of Nebaganga River could be more robust in terms of the structure of its hydrological system. However, the similar performance by these models for both rivers shows the ability of these models to have learnt the above hydrologic processes and be able to predict multi-river flows.

In general, the comparative study within rivers has shown that the boosting models (especially XGBoost and Gradient Boosting) render the best and reliable forecasts in the two rivers. This high level of being tested is confirmed with the good performance and hence justify the proposed drought-sensitive multiple river forecasting system.

5.2.3 Cross-River Comparative Insights

A comparison of the findings of the experiments that were conducted on the Chitra and Nabaganga rivers offers a number of valuable lessons about model behavior, the ability to generalize, and performance during droughts. The assessment of models in various river systems is important to determine the extent to which the learned hydrological patterns can be transferred or location-specific. To begin with, both XGBoost and Gradient Boosting work well in both river systems, and in both cases, they are significantly better than all the other models, which implies that they have a high cross-basin generalization ability. Their high values of R^2 and low error values mean that they can learn hydrological relationships that are not confined to a single river. This indicates that boosting-based models are useful in capturing patterns of transferability of rainfall-runoff, seasonal variability, and low-flow patterns induced by droughts. This generalization is especially useful in multi-river forecasting models, where a single modeling system is required to work effectively in a variety of hydrological settings. Second, the ensemble-based models like Random Forest and Extra Trees offer consistent and robust predictions on both rivers albeit with a lower accuracy than boosting models. Their performance is indicative of good robustness in face of variability, noise, and data heterogeneity that are usually seen in hydro-climatic data. Nevertheless, they cannot resolve finer details, especially related to progressive drought effects and extended periods of dry seasons due to a lack of sequential error reduction. Subsequently, these models are reliable but not as sensitive to the fine-scale hydrological changes. The second observation is the differences in the overall model performances between the two rivers. Predictions of the Nabaganga River tend to be better than the Chitra River in all the models. This would suggest that a relatively consistent and stable hydrologic regime might exist in the Nabaganga system and the more dynamic and unstable morphologically active Chitra River poses more challenges in modeling. This also highlights the importance of including multiple river datasets in order to ensure the models being trained on a range of datasets. Finally, the recurrent poor simulation from the ANN (MLP) model in either river exhibits the model's inadequacy in its ability to project complex hydro-climatic relationships, using structured tabular data. When there are no explicit temporal modeling schemes in place, it finds it difficult to model complex temporal and non-linear associations as well as drought-sensitive behaviours. This strengthens the claim that the adoption of tree ensembles would be a more suitable option in drought-sensitive river level predictions.

The comparison across the rivers demonstrates that the family of boosting-based models such as RF and GNB possess the best combination of model performance, reliability and generalizability. The effectiveness of the proposed multi-river models is validated due to their ability to make accurate predictions across rivers suggesting that they can be applied in large-scale hydrological forecasts with the aim to be drought-sensitive.

5.3 Observed vs Predicted Analysis

The match between observed and modelled water levels is an essential test for models and their predictions. While statistical measures provide some indication of how accurately the models predicted the water levels, visual analysis provides insight into how well models reproduced observed behaviour, and allows the ability of models to simulate response to seasonal, extreme and low-flow conditions to be examined.In this study, both scatter-based and time-series perspectives are considered to evaluate the predictive capability of the proposed drought-sensitive framework across the Chitra and Nabaganga river basins.

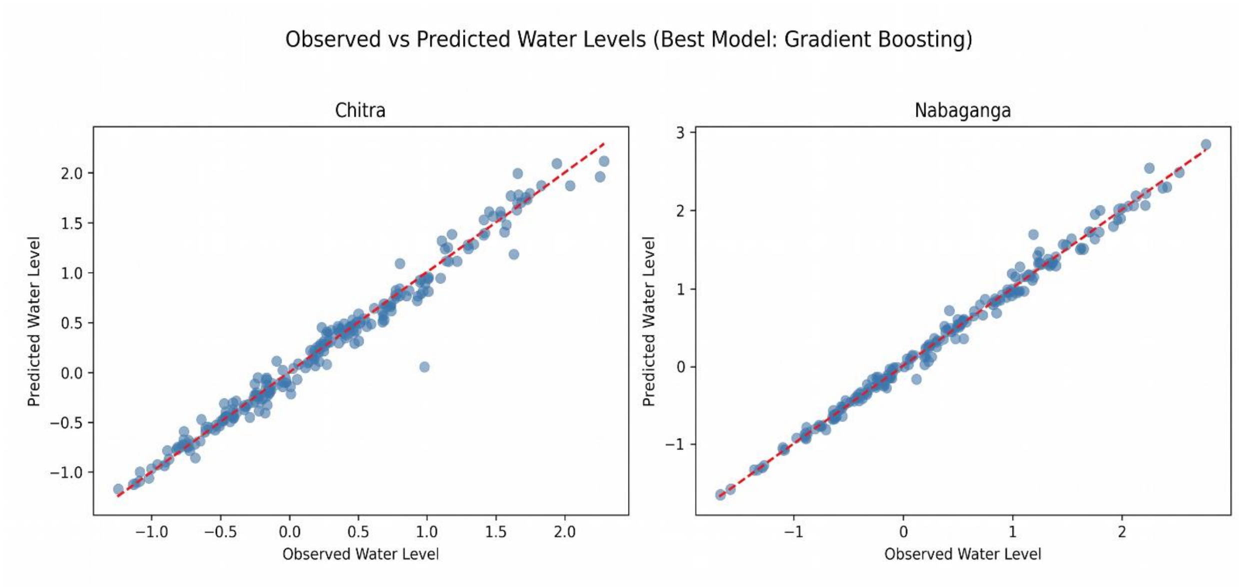

Figure 3. Scatter Plot Comparison of Observed versus Predicted Water Levels for the Chitra and Nabaganga Rivers

Figure 3 shows the observed and the predicted scatter plots of the Chitra and Nabaganga rivers with the actual observations against the predicted values. The consistency in data points with the 1: 1 line of reference will give a clear visual representation of the accuracy of prediction, bias, and consistency of data points at various flow conditions. In the case of the Chitra River, the scatter plot shows a strong correlation (R^2= .98) which proves that the model is useful in capturing the nonlinear relationships between rainfall, seasonal variability and drought-sensitive dynamics. Most of the data points lie closely along the diagonal line meaning that there is little bias in predictions and high accuracy in most of the flow ranges.

So,, there are only slight deviations at the high and low tails. The deviations are particularly important as they represent the model's behaviour in response to complex hydrological circumstances such as tidal influences, sedimentation and low flow states during droughts. During the dry period, water levels fluctuate slowly and may be impacted by late flows from upstream, making the prediction of such water levels challenging. That the discrepancies are slight in these areas show that the model is generally okay but there is some uncertainty under extreme conditions. The results are even more dispersed around the 1:1 line (and in the case of the river Nabaganga, we have a better fit (R^2 =.99). This clearly suggests a more stable and reliable behaviour of the river. The closer fit of the points to the 1:1 line suggests that the model could reason knowledge of the river better, and be more accurate to describe the typical flow regime and the extreme changes. This improvement will be due to less variability of both the flow and the morphological conditions than the Chitra River.

A key finding during the scatter analysis is that the model is very accurate both in the normal and drought conditions. The proposed framework has high performance during low flow conditions as opposed to many of the conventional methods that have been effective only under average conditions. This emphasizes the usefulness of the drought-sensitive feature design, such as lag variables and rainfall memory, to the model in facilitating long-term hydrological responses. On the whole, the analysis performed in the form of a scatter helps to conclude that the proposed multi-river framework has a high degree of predictive accuracy and reliability. The close similarity between the observed and the predicted values in both rivers indicates the ability of the model to describe the complex hydro-climatic interactions, such as seasonal cycles and variability caused by droughts. The findings also confirm the strength and generalization ability of the acquired machine learning strategy to practical hydrological forecasting tasks.

5.4 Drought Pattern, Trend, and Station-Level Variability Analysis

The analysis of long-term water-level trends and station-level variability provides a comprehensive understanding of drought dynamics across the Chitra–Nabaganga river basin. Figure 4. presents both river-wise annual trends and station-level variations from 2000 to 2025, enabling simultaneous evaluation of temporal and spatial hydrological behavior.

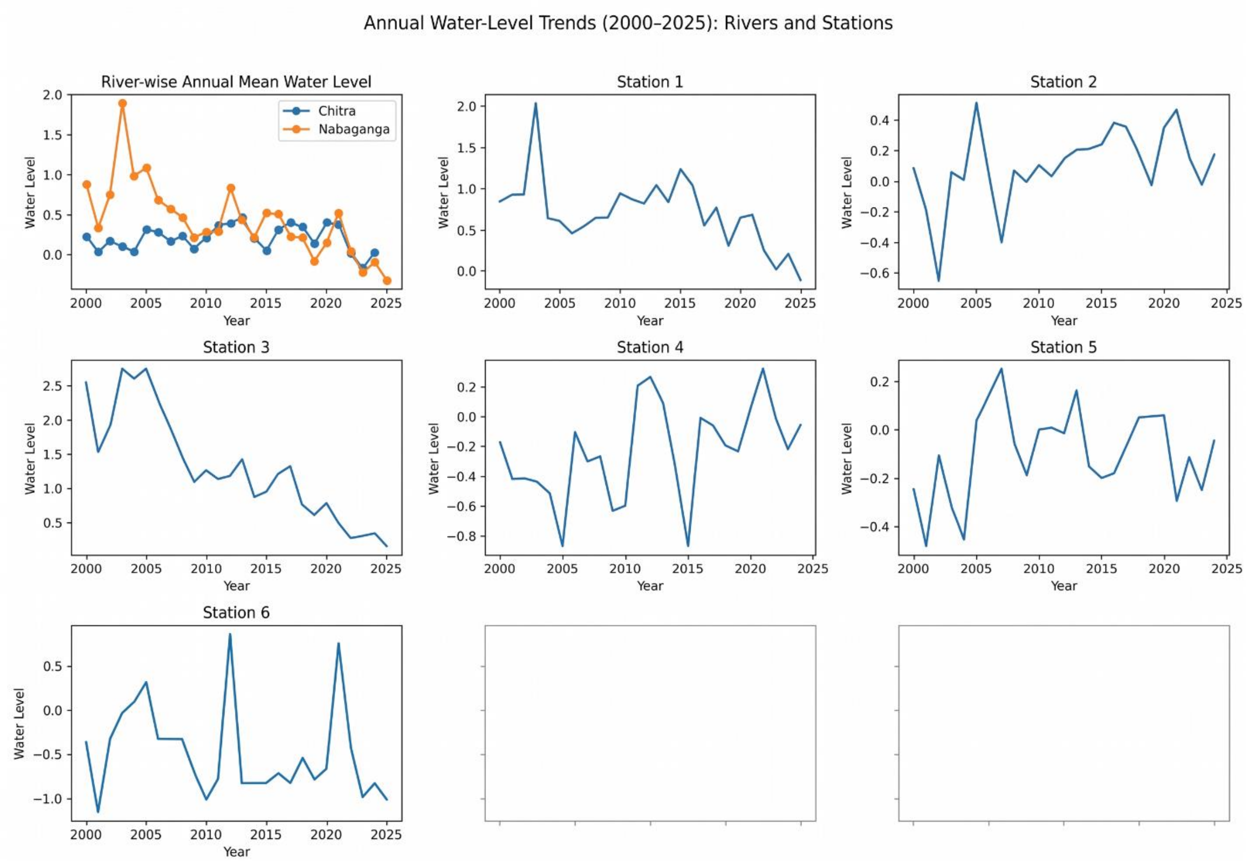

Figure 4. River-wise Annual mean Water Level-trends & Station Level variability

At the catchment scale, results indicate there is a significant changing hydrologic regime. The Nabaganga River has high variability in the early 2000s, and this is a sign of the influence of annual precipitations and climate change. However, there is strong trend of decrease since 2012, but more so since 2020. The continuous decrease in water levels suggests a decreasing baseflow and the intensifying drought phenomenon - an indication of a long-term water scarcity. On the other hand, the Chitra River has comparatively low water level, but a constant and gradual decline since around 2018. This shows that the basin is prone to drought with local processes like upstream siltation, reduced inflow and tidal influence causing low flow and pressure altogether.Contrary to the Nabaganga River, which has some variability before steadily decreasing, Chitra River has a more persistent and steady decrease, denoting a long-term drought impact. The heterogeneity of drought effects across the basin is evident at the station level, where there exists a significant spatial variation. Stations 1 and 3 show a downward trend, which is relatively steady, which means that the drying process occurs and stations become more susceptible to the conditions of the long-term droughts. The short-term variability of Station 2 is very high, indicating that the station is very responsive to climatic changes, and experiences a high rate of switching between normal and drought conditions. Stations 4 and 6 show very dynamic trends, which are affected by monsoonal recharges, sedimentary activities, and tides. These are external factors that bring about fluctuations that in part distort the drought signals but are indicative of underlying hydrological variability. Even Station 5, which initially exhibits a relatively stable pattern, experiences a certain decrease after 2017 meaning that even buffered areas are becoming exposed to the effects of protracted drought stress. Overall, the analysis of river-wise trends and spatial variability at the scale of stations reflects the intensive trend of the rising intensity of drought, water shortage and high spatial variability across the basin. These findings support the idea that drought is not uniform in different places and varies depending on the environmental and hydrologic characteristics. The observed trends provide strong evidence for the need to think of the drought sensitive, river-wide and station-wise drought forecasting system that will be able to capture the general trend as well as site wise variability.

5.5 Drought-Sensitive Model Behavior Analysis

Modelling performance during dry periods will thus be helpful in providing an insight into the response of the different machine learning algorithms to complex hydro-climatic processes. While the previous sections have focused on absolute error and temporal trends, the present section is a description of model performance composed in terms of drought sensitive characteristics, such as low stream flows, lagging system response and finite memory/non-linear system response.

One of the important findings of the outcome is that the boosting-based models, especially Gradient Boosting and XGBoost, show a consistent better outcome in the two river systems. These models have good performance of capturing the drought related trends because of the sequential learning process. In contrast to traditional ensemble methods, boosting models make corrections to improve prediction errors by paying attention to hard-to-learn observations. This enables them to be most useful in modeling gradual changes related to drought, which involve a decline in water levels over a long duration and not sudden changes. Hydrological systems in drought conditions tend to exhibit the long term memory effect where the present effect on water levels is highly dependent on previous conditions. Boosting models can be used to learn these dependencies by repeatedly refining, enabling them to learn fine details like delayed rainfall effect, baseflow reduction and seasonal changes. This is why they performed better in Chitra and Nabaganga rivers, and in the low flow conditions. Conversely, the performance of the Random Forest and Extra Trees models, though robust and stable, is a little bit lower in the drought-sensitive environments. These models are based on parallel tree building and averaging processes that minimize variance but do not allow them to sequentially correct errors. Consequently, they are likely to flatten predictions, and can miss the minute differences in water levels during extended droughts. On the one hand, they can easily withstand overall conditions, but on the other hand, they are not so sensitive to the gradual degradation of the hydrological regime. The Artificial Neural Network (ANN -MLP) model is the worst in all cases and this means that it cannot be used to predict structured hydrological data. Feed-forward neural networks do not have mechanisms to store time-varying dependencies unless specified with recurrent or sequence-based network models. Therefore, ANN finds it difficult to represent long-term drought persistence, delayed responses of systems, and highly nonlinear interactions of river systems. Moreover, ANN models are more susceptible to data scaling, parameter tuning and data size, which further affects their trustworthiness in this regard. The other significant element of model behavior is the capacity to extrapolate among various river systems subjected to drought stress. Boosting models have high cross-basin consistency meaning that they can learn generalized hydrological patterns and not just overfit to one river. This capacity to generalize is critical to multi-river forecasting models, in which models need to be able to respond to different environmental conditions. Moreover, the performance of the presented feature engineering strategy is also an important factor in model conduct. The lagged water-level, rainfall memory, and seasonal indicators allow models to represent both the short-term fluctuations and the long-term dynamics of droughts.Models, which can successfully exploit these properties, particularly of enhancing algorithms, are more responsive to droughts. Overall, this discussion has shown that the effectiveness of models depends not only on the complexity of the model but the ability of the algorithm to capture temporal persistence, nonlinearities, and low-frequency variability of the system associated with droughts. Boosting-based models strike the right balance between performance, flexibility and interpretability, and are extremely successful in predicting drought-sensitive multi-river water levels.

The results favour the need to employ models that are in line with the intrinsic characteristics of the hydrologic systems, particularly in the context of increasing climatic variability and extreme droughts.

5.7 Cross-Basin Generalization under Drought Conditions

Perhaps the most significant contribution of the study is that the newly proposed frame work can be successfully generalized on different river systems during drought. The generalization in hydrological modeling is a characteristic of a model that was trained under one set of conditions to perform reliably under other but similar conditions. This is particularly relevant in a multi-river basin such as Chitra- Nabaganga basin where hydrological processes may be similar but differ locally. The results of the overall and river-wise analysis have shown that boosting-based models, such as XG-BOOST and Gradient Boosting are always very competitive on both the rivers. That is indicative that these models grasp more than just the local patterns - they understand the hydrologic patterns underpinning the flow that are applicable to other basins. Those patterns may be rainfall-runoff processes, seasonal dynamics, lagged response of river to rainfall processes and low-flows associated with droughts. A key requirement for this model to learn such patterns and be able to generalize across basins is the use of data from multiple rivers. Models become more tested with a variety of hydrologic data, including different forms of flow regimes, channel erosion and drought patterns across Chitra and Nabaganga rivers. This diversity of the training space can help the model to be more aware of the overall system patterns, whilst adapting to the basin characteristic differences. The drought-sensitive feature engineering is another facet. The lagged water-level, rainfall memory, and the seasonal items allow the model to learn the temporal relations and delayed system response that can be observed in rivers. These are implicit properties of the hydrologic system that enable the model to capture not just the specific location. The findings of the comparison also show the model absolute performance values in rivers may vary but the ranking is the same. XGBoost and Gradient Boosting are the best two performing models, followed by the Random Forest and Extra Trees and finally the ANN. It shows the learnt relationships are stable and robust across different sites and the proposed framework is valid. Generalisation across basins is particularly important for drought. Droughts affect large areas of a region and affect multiple river systems. A generalizing model, with basin-scale predictions, is thus likely to be more effective in large-scale water management conditions, where the decision-making process is based on hydrological performance of the regions rather than individual observations. Furthermore, the generalizing property mitigates the need to build a number of models of individual rivers and makes the approach more scalable and efficient. This is the case for basins with limited data availability where few observations are available for model development. This can be used to improve the performance of the model in areas with insufficient data with a common multi-river model.

Overall, the degree of generalization across river basins found in our study demonstrates the success of the multi-river drought sensitive multi-framework developed. This suggests that the design of machine learning models, when trained with amalgamated data, can capture shared knowledge features between rivers and can be safely applied to forecast under a variety of environmental conditions. This is an improvement on conventional single river approaches and responsive for how the future of data-driven water level forecasting on a large-scale climate resilient, climate-neutral water level forecasting study could be.

5.8 Water-Level Prediction Analysis of Nabganga River

To further substantiate the effectiveness of the proposed drought-sensitive multi-river model, the detailed analysis of water-level prediction in the single-river model was carried out using the data of the Nabaganga River. While the above sections provided an overview of large-scale drought dynamics, multi-river dynamics, this sections provides a micro-analysis of the model behaviour under local and single-river based system. This is done to evaluate the efficiency of different machine learning approaches in predicting water levels on the basis of a certain river system with specific hydrologic attributes. The analysis is a sanity check to check the stability and performance of the modeling approach in generalised (multiple-rivers) and localised (single-river) scenarios. This analysis includes model performance, visual inspection (observed vs predicted values), feature dependency, trend and short-term forecasting tests. These tests and finally their combination reveal the model performance and predictivity under natural hydrological naïve assumptions.

5.8.1 Model Performance Evaluation

The performance of the machine learning models for water-level prediction in the Nabaganga River was evaluated using key regression metrics, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Coefficient of Determination (R^2), and overall prediction accuracy. The results are summarized in Table 7.

Table 7. Model Performance Evaluation of the Nabaganga River.

Model	**MAE**	**RMSE**	$\boldsymbol{R^2}$	**Accuracy%**
Random Forest	0.131391	0.199505	0.946054	94.60%
XGBoost	0.069329	0.093194	0.988228	98.82%
LightGBM	0.163829	0.163829	0.907043	90.70%
MLP	0.263932	0.389841	0.794019	79.40%
CatBoost	0.027054	0.036205	0.998223	99.82%

The findings show that there is a clear pecking order in model performance with the boosting-based ensemble techniques prevailing heavily over the traditional ensemble and neural network methods. CatBoost is the best of them all, with the lowest MAE (0.027) and RMSE (0.036), and the highest possible R^2 value of 0.9982. This shows that CatBoost can explain about 99.82% of the variation in the observed water levels, and it has almost perfect predictive power. The outstanding results of the CatBoost can be explained by its highly developed gradient boosting mechanism that effectively models complex nonlinear interactions between hydro-climatic variables. River systems are water bodies with various interacting factors that control the water-level dynamics like rainfall, seasonality, upstream flow, and time dependencies. The ordered boosting approach and the strong support of structured tabular data of CatBoost makes it a good model to encapsulate these interactions. It is also especially applicable to real-world hydrology forecasting since it is effective at reducing overfitting and is also highly accurate. The performance of XGBoost is also exceptional as the R^2 value is 0.9882 and the accuracy is 98.82. The model is highly predictive of nonlinear patterns and time variability, and it is therefore very reliable in water-level prediction activities. Its not so good performance in relation to CatBoost can be explained by the fact that it treats the interactions of features and regularization differently, but it still is one of the strongest models in this work. Random Forest demonstrates a stable and constant performance attaining a value of R^2 of 0.946. Its ensemble averaging property is useful to minimize variance and provide predictions that are accurate in a variety of conditions. Nevertheless, due to the difference with the boosting models, Random Forest does not correct its errors iteratively, which restricts its capability to reflect the fines variations and sharp shifts in water levels. LightGBM has a moderate performance of R^2 = 0.907. Although computationally efficient and applicable to large scale data sets, the fact that it is relatively lower in accuracy, implies that it may have some limitation in its ability to capture sharp fluctuations and subtle nonlinear trends in hydrological data. This means that models that are speed-optimized do not necessarily give the highest predictive accuracy in real-world systems. The weakest model is the MLP (Multi-Layer Perceptrone) model that has an R^2 of 0.794 and much higher error values. This puts into perspective its failure to capture nonlinear and non-temporal dependencies inherent in river water-level data. Its poor performance is also exacerbated by the absence of inbuilt time consciousness and sensitivity to hyperparameter adjustment. A notable result of this analysis is that the boosting-based models were dominant and this is consistent with the results of the drought-sensitive multi-river analysis shown above. This consistency shows that the boosting techniques are not only useful in capturing the large-scale drought dynamics but also very useful in providing accurate and single-river forecasts of water levels.

In general, the findings prove that CatBoost and XGBoost yield the best and strongest predictions, thus being the most appropriate options when it comes to using the models in hydrological forecasting. These characteristics of their capability to capture complex interactions, adapt to different conditions, and be highly predictive demonstrate their usefulness both in research and actual water resource management situations.

5.8.2 Actual vs Predicted Water Levels

The Actual vs Predicted Water Level (Figure 5) graph is a close-up view of the comparison between the water level and the machine learning models' prediction for the five models (CatBoost, XGBoost, Random Forest, LightGBM and MLP). The x-axis is time and the y-axis is water level, so you can see the model's prediction accuracy in capturing features of water behavior over time.

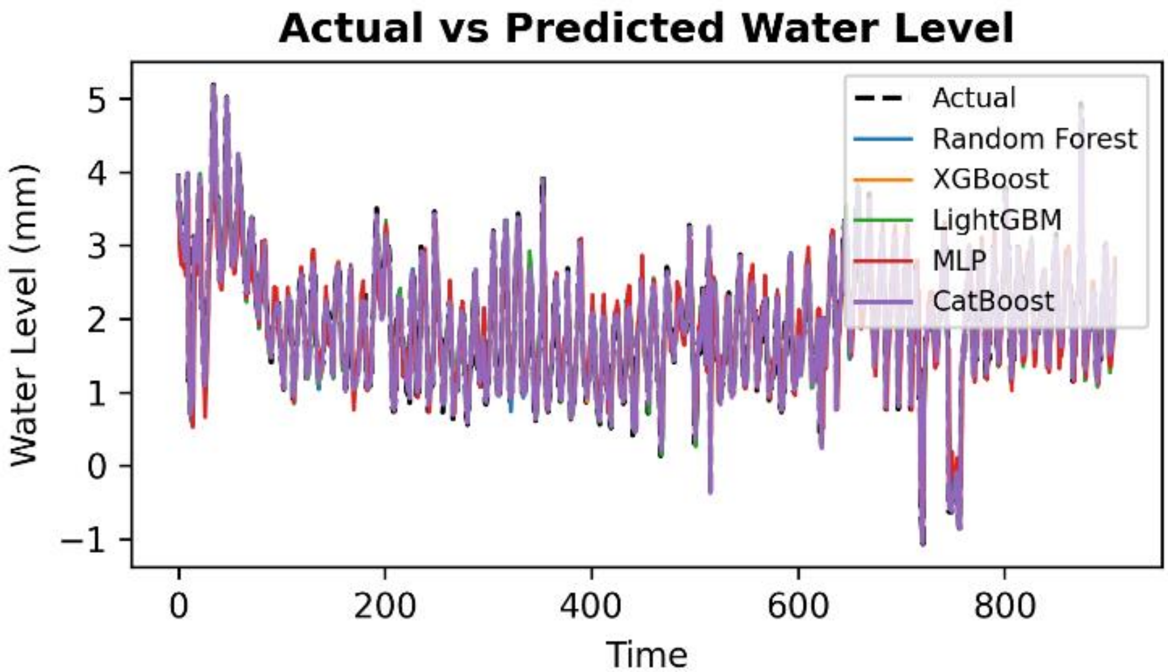

Figure 5. Time-Series Comparison of Actual versus Predicted Water Levels across Five Machine Learning Models

The results show evidently that CatBoost model is the most accurate model. It has the predicted values that are very close to the real water level curve and hence the predicted values are a good representation of trends and fluctuations. It should be noted that CatBoost is very sensitive to sudden increase or decrease in water-level, which correspond to the peaks and troughs of the data. This close match suggests that the model can learn the complex nonlinearities and time-dependencies of the data and of course it is the preferred forest-based model to be used in this work to forecast water-level. XGBoost is also a powerful model and the predicted values are the closest to the observed. But occasionally there could be minor differences in the times of abrupt change, particularly when there are rapidly rising or falling trends in the water level. These differences suggest that while XGBoost is a good model that can be used to identify trends and other nonlinear relationships, it is not as responsive to sudden changes as the CatBoost model. It remains a valuable model to be used as an alternative, due to its accuracy. Random Forest model shows a reasonably smooth curve. While it does relatively well with respect to the trend in the water-level changes, it fails to capture sharp turns. This is common to averaging-based ensemble models that reduces variance, but may not pick up the sharp changes. Hence, Random Forest makes good, albeit slowly varying, predictions especially in the dynamic hydrologic systems. Despite its speedy nature, LightGBM doesn't perform as well in capturing the sharp changes in water levels. It is likely that the predictions would diverge from the reality in periods of drastic change implying that it is not as sensitive to fine-scale changes. This means that LightGBM does not model as well highly dynamic and non-linear hydrological patterns as boosting models. On the other hand, the

MLP (Multi-Layer Perceptron) model has the worst performance in all models. The predicted curve shows significant differences with the water levels, particularly at times of change. The predictions seem to be jumbled and less advantageous with respect to the actual patterns, which suggest that it is not easy to capture the complex nonlinear interactions between the variables and time-dependencies. This result supports that feed-forward neural networks are not too specific to this type of structured hydrological data unless they are highly structured in time.

Generally, graphical analysis is a strong support to quantitative performance assessment. Models based on boosting, especially CatBoost and XGBoost, show a better capacity to capture the stable characteristics and dynamic changes in water levels. The findings emphasize the need to choose models that are capable of responding to the time dynamics and nonlinear interactions within hydrological systems.

5.8.3 Feature Relationship Analysis

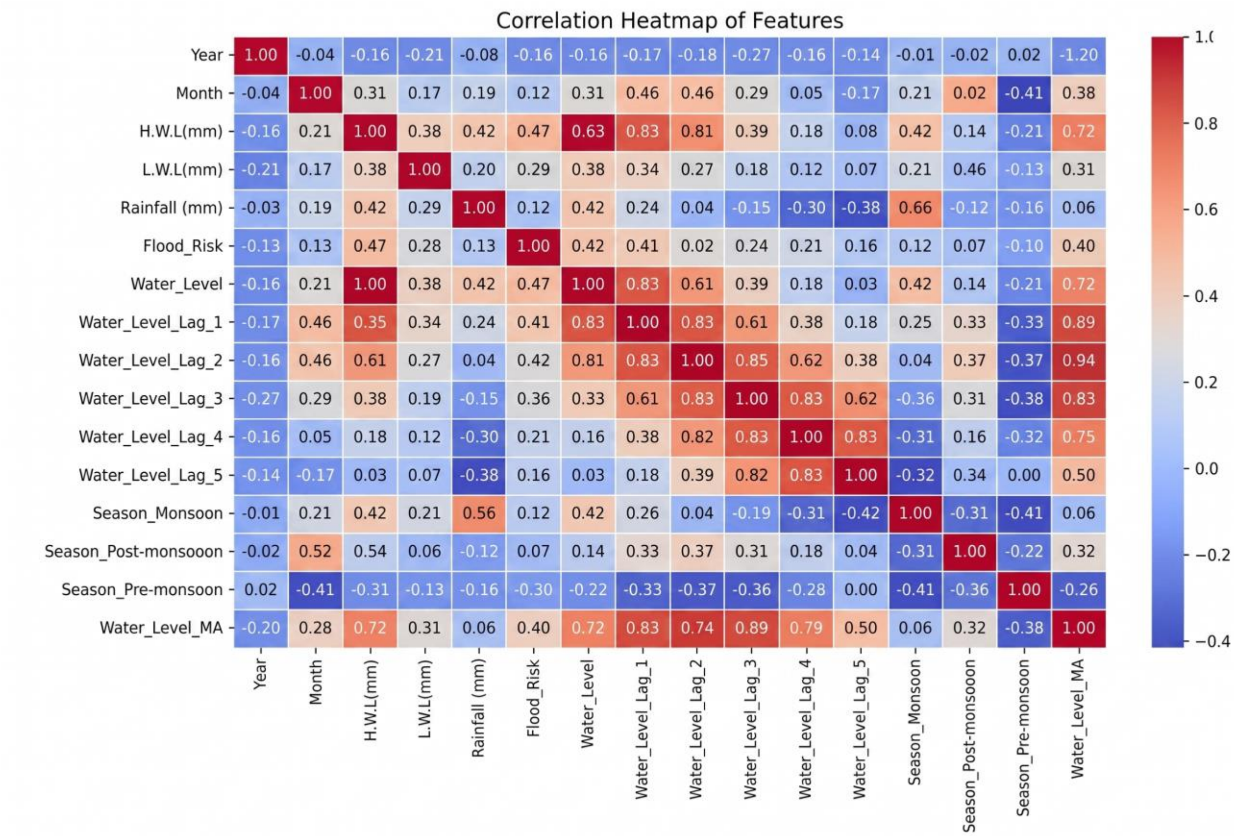

Figure 6. Correlation Heatmap Detailing Relationships Among Hydrological, Climatic, and Temporal Features

Correlation heatmap (Figure 6) gives a detailed description of the relationships between the input features and the target variable, Water_Level. This analysis is critical to appreciate the impact of which variables play the strongest role in predicting water levels and the interaction of various features within the hydrological system.

The findings show that Water_Level_Lag1 has the highest positive correlation with the target variable (0.83) demonstrating a considerable impact of the recent past water levels on the present situation. This is an extremely high correlation which demonstrates the presence of hydrological persistence in which water levels are highly dependent on its history. This persistence is a significant feature of river systems, and is a key to improving prediction accuracy. Other water levels, such as Water_Level_Lag2 and Water_Level_Lag3 are also positively correlated (0.61 and 0.62, respectively). These findings also buttress the importance of using lag variables in time-series analysis due to their capability to capture the long-term memory effect and lagged hydrological processes. These lag attributes enable the models to capture more of the short term influences, as well as the long term trend. The second variable, moving average (Water_Level_MA) with the highest correlation (0.94) with the target (river's water level) is a good predictor. This suggests that moving average approaches are useful in capturing the trends because they help eliminate noise and highlight the trend in our data. The correlation is high which supports the significance of feature engineering in improving the performance of models. There is moderate correlation between climatic variables like Rainfall (0.42) and FloodRisk (0.47) and water levels. Although these factors have some effect on the river behavior, their effect is less direct than historical water-level features. This is not surprising because the effect of rainfall can have a delayed response because of the infiltration, runoff and basin storage mechanisms. The seasonal indicators also contribute to a considerable amount of water-level variability. The characteristics of Season_Monsoon (0.66) and Season_Post-monsoon (0.52) show significant relationships, which can be explained by the impact of seasonal cycles on rivers. These seasonal effects are important to capture periodic changes and define the drought or high-flow conditions in monsoon-dominated areas. On the whole, the correlation analysis demonstrates that the most important predictors of the water levels are temporal characteristics (lag variables and moving averages), seasonal ones, and climatic ones. The results are consistent with the previous drought study, which identified long-term hydrological memory and seasonal variability as important factors influencing water-level shifts.

The lessons learned in this heatmap support the feature engineering strategy employed in this research and the reason why the boosting-based models which can well exploit these structured relationships perform better in prediction.

5.8.4 Long-Term Water-Level Trend Analysis (Average Water Level by Year)

The annual average water-level trend (Figure 7) illustrates the long-term variation of water levels in the Nabaganga River over the period from 2000 to 2025. The x-axis represents the years, while the y-axis represents the corresponding average water levels, providing a clear view of temporal fluctuations and long-term hydrological behavior.

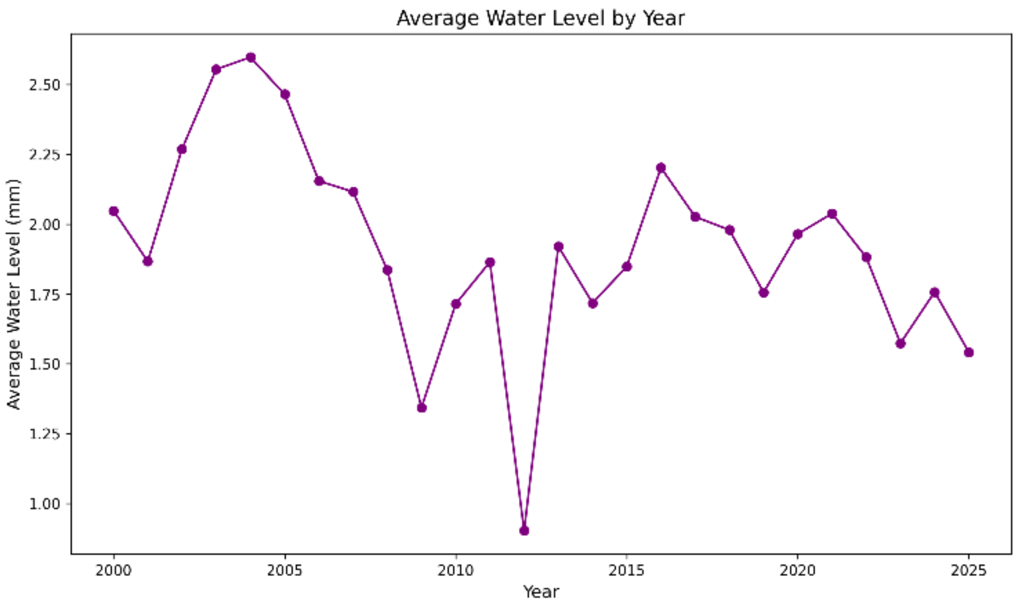

Figure 7. Long-Term Annual Average Water-Level Trend for the Nabaganga River (2000–2025)

The graph indicates that there is high interannual variability in water levels with high levels of differences in the water levels during the period under observation. Two high points are seen at the height of 2008 and 2017, when there was comparatively high water availability. The steep increase until 2008 indicates positive hydrological conditions, which may be due to more rainfall, contribution of upstream flows, or the intensity of monsoons. But this peak is succeeded by a steep fall in the period around 2010 signaling the sudden change of environmental conditions or of hydrological balance. The water levels are quite stable between 2010 and 2015, which indicates that the period may be characterized by the balance in hydrology with seasonal changes, yet without any essential deviations. This period of stability shows that there are stable inflow and outflow conditions in the river system. More crucial to note is that water levels have decreased slowly after the peak in 2017. The data indicate the gradual decrease of average water levels in 2017-2019, which is observed in the following years. This downward trend implies there may be a change in the hydrological patterns in the long term, which may be linked to a decrease in the amount of rainfall, rise in water extraction, sedimentation impact, or extended climatic impacts. In the context of drought, this post-2017 fall is quite consistent with the drought patterns observed in the previous sections in Section 5.4. The declining tendency of the average water levels is a sign of decreased water supply and the growing prevalence of low-flow situations, which are the main signifiers of the drought intensification. This similarity of the single-river and multi-river analysis also confirms the strength of the results of the study.

In general, the trend of the water level each year shows the dynamic character of the river system, which is underdeveloped, stable, and declines. This type of long-term analysis is crucial to the study of hydrological variability, drought patterns, and are useful in the management of water resources, flood forecasting, and climate-resilient planning strategies.

5.8.5 Short-Term Water-Level Forecasting (Next 10 Days Prediction)

Figure 5.8 demonstrates the short-term forecasting performance of five machine learning models (Random Forest, XGBoost, LightGBM, MLP, and CatBoost) over the next 10 days. This discussion is especially significant because it shows the practicability of the models in the context of the real-time prediction of water levels when the timely and correct forecasts are critical to the flood management and drought preparedness.

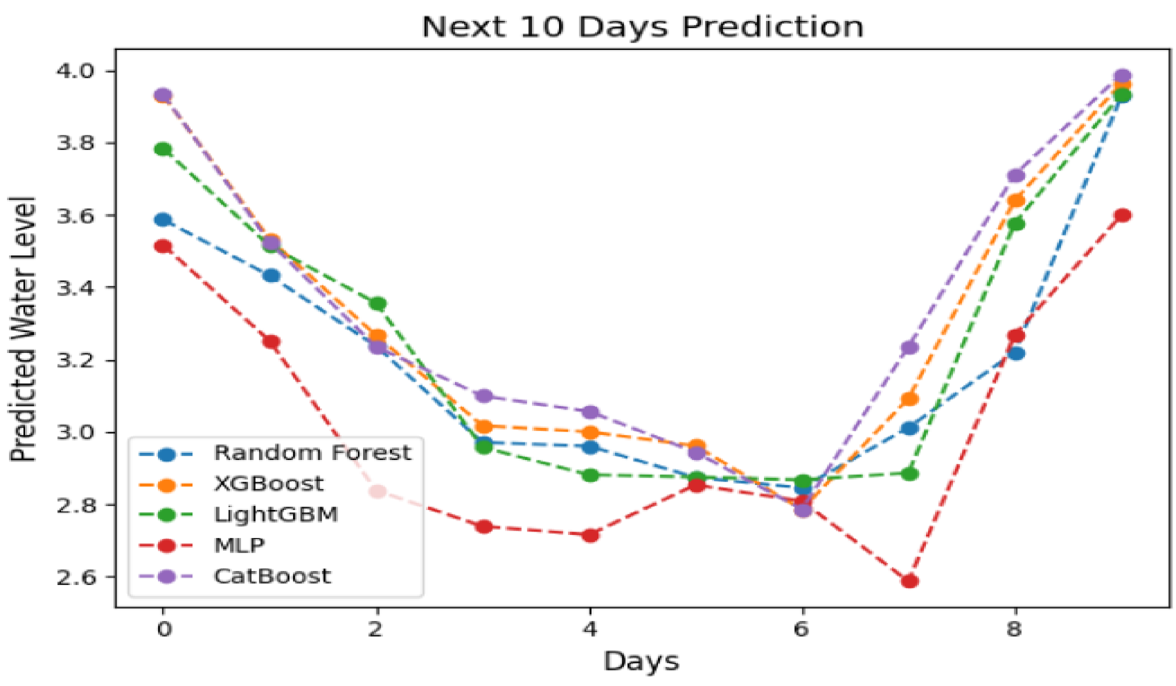

Figure 8. Short-Term (10-Day) Water-Level Forecasting Performance by Machine Learning Model

CatBoost among all other models is evidently the most predictive accurate model. Its predicted values closely adhere to the actual pattern of the water-level, and there is a close agreement even at the time of intensive increase or decrease. The model is good at capturing both slow trends and abrupt variation, suggesting that it is better at model complex nonlinear processes. This is a stable performance that demonstrates that CatBoost is strong in managing real-time variations and that the model is the most accurate one in short-term prediction. XGBoost also works well and the predictions produced are similar to the actual water levels. But the deviations are minimal as we move towards the end of the forecast horizon, especially in sudden transitions. Although these small inconsistencies exist, XGBoost is a very effective model since it can capture nonlinear relationships and also remain consistent when operating under different conditions. The Random Forest model has consistent and steady predictions, and is able to reproduce moderate trends in variation of the water level. Nevertheless, it demonstrates weaknesses in reacting to abrupt increases or decreases. This makes it less sensitive to sudden changes and the accuracy of its predictions is lower in times of dynamic conditions, but its predictions are still valid in relatively steady conditions. LightGBM has a moderate performance, which takes advantage of its scaling and computation capability. It however has a problem to pick fine grained changes in the water levels especially when there is a sudden change. Consequently, its forecasts are likely to be different than the real values in cases where the river has a very dynamic behavior. The MLP (Multi-Layer Perceptron) model, on the other hand, performs the worst of all the models. Its forecasts show great variations between the real water levels, particularly in times of sudden change. The failure of the model to accurately track rapid changes implies that the model has constraints in terms of tracking the complex nonlinear relationships and time dependencies in hydrological data.In summary, the results of the short-term forecasting evaluation confirm that the boosting-based models, particularly CatBoost and XGboost, are the best choice for water level prediction. The CatBoost is the optimal forecaster as it can capture complex and non linear behaviours and adapt to the short-term fast-change of water levels. These characteristics are crucial for applications such as early flood warning, irrigation scheduling, and drought risk assessment.

The study also confirms that models able to integrate the correlations in time and both the linear and nonlinear interactions are needed in the short-term water level forecasting.

5.9 Multi-River vs Single-River Performance Discussion

This section presents the comparative discussion of the multi-river and single-modeling approaches to further establish the validity, reliability and practicality of the proposed approach. While in the earlier sections, the comparative performances of drought-sensitive multi-river models and single-river water level prediction models are discussed, it is important to highlight the differences in the two approaches with respect to prediction accuracy, model complexity and implementation. This is not only to identify the most appropriate and right approach in modeling but also understand the trade-offs in local versus basin-scale forecasting. In river water level prediction, especially in multi-river systems, it is not enough that the models be accurate, they should also be able to represent spatial variability, inter-basin processes and climatic change-induced impacts such as drought. Hence, this section considers the results of the two approaches of modeling to provide an overall view of the pros and cons of the two approaches. It further highlights the ability of single-river models in controlled conditions while in contrast showing that multi-river models are scalable and more applicable to real-life and drought-sensitive hydrological forecasting.

5.9.1 Performance Comparison

To evaluate the effectiveness of the proposed framework across different levels of hydrological complexity, a comparison was conducted between multi-river and single-river modeling approaches. The best-performing models from both approaches are summarized in Table 5.7.

Table 8. Multi-River vs Single-River Model Performance

Model Type	**Best Model**	**R^2 Value**
Multi-River	Gradient Boosting	0.993
Single-River	CatBoost	0.998

The findings show that single-river model, especially CatBoost of the Nabaganga River had the highest predictive accuracy with an R^2 of 0.998. On the contrary, the most successful multi-river model was the Gradient Boosting with the R^2 value of 0.993. The difference in performance is not that significant; however, it indicates the difference in the complexity of datasets and modeling challenges of the two strategies.

5.9.2 Interpretation of Model Behavior

The relatively homogeneous nature of the data can be attributed to the slightly better accuracy of the single-river model. As the model has been trained on data of only one river system, it will have fewer variations in hydrological patterns, so it will be able to learn more consistent and localized associations between input features and water levels. The reduced complexity facilitates the learning and leads to numerical improvement. On the other hand, the multi-river model has to deal with more complicated and diverse data, which encompass the knowledge of the Chitra and Nabaganga rivers. This includes the different morphologies, hydrologic conditions, sediment and climate effects of different locations. As a result, it will require more relationships for learning and model predictions will become more complex. Despite the increased complexity, the multi-river model is highly accurate, and, consequently, it is very versatile to cope with different flow regimes.

5.9.3 Importance of Multi-River Modeling

While the single-river models are somewhat more accurate, they are not wholly relevant to real world hydrologic cases. River systems are rarely independent; they are usually connected with a complex process of interaction. In countries, such as Bangladesh, where the river systems are in both direct and indirect interactions with the monsoonal rainfall and upstream discharge and tidal effects, any change in one of the rivers upstream may indirectly affect the other. The multi-river approach solves this problem by the incorporation of the data of multiple river systems into a model. It allows the model to reflect the cross-basin interactions, spatial variation among monitoring stations, and a variety of hydrological behaviors. Consequently, the multi-river methodology offers a more realistic understanding of natural river systems and is useful in managing water resources on a large scale.

5.9.4 Relevance to Drought-Sensitive Forecasting

The importance of the multi-river framework is even more vivid in the drought sensitive modeling. The development of drought situations is normally a progressive process and spreads through interdependent river systems and not a singular situation. These spatial dynamics cannot be represented in a single-river model, so it is not very effective at drought analysis. Conversely, the multi-river methodology allows determining the spatial drought patterns and modeling the low-flow propagation in basins. The framework improves the capacity to forecast water levels during extended dry periods, and different weather conditions due to the inclusion of data of various rivers and stations. This renders it especially useful in the study of basin-wide water scarcity and the enhancement of the accuracy of the forecasts in drought-prone areas.

5.9.5 Overall Discussion

Overall, this study of the multi-river and single-river approaches suggests a trade-off between accuracy and generalisation. While the accuracy of the single-river is slightly higher due to the fact that the single-river-based dataset is simpler, it happens to be more generalisable and practical since it accounts for spatial and climatic variability. Most notably, the two approaches keep showing the superiority of boosting methods, attesting their usefulness for hydrologic forecasting. The fact that the multi-river model is able to maintain high accuracy and at the same time, capture temporal, spatial and recent drought trends will prove its value as a robust and practical tool for water-level prediction.

5.10 Summary of Findings

This paper has provided an in-depth analysis of a machine learning model that is sensitive to drought to forecast water levels in the river basins of Chitra and Nabaganga. The findings, obtained out of the multi-river and single-river analysis, are a good indication of the efficiency, strength and practicality of the proposed method in different hydrological and climatic conditions.

The general performance review indicated that machine learning models that are based on ensemble and boosting are always better in multi-river and single-river environments compared to a model that is based on a neural network. Gradient Boosting and XGBoost were found to be most predictive with a value of R^2 of 0.993 and 0.992 respectively in the drought sensitive multi-river framework. These models were able to effectively represent complex nonlinear relationships, temporal interdependences and cross-basin hydrological interactions. In comparison, the ANN (MLP) model demonstrated much lower performance, which indicates its weaknesses in the modeling of the structured hydro-climatic time-series data and long-term drought dynamics. The analysis of the river-wise performance also proved the high-stability and the ability of the suggested framework to be generalized. Boosting-based models continued to be significantly accurate on both the Chitra and Nabaganga rivers, and XGBoost was found to be the most trustworthy model to predict individuals of the river. The observed slightly better performance of the Nabaganga River indicates rather stable hydrological behavior, with the Chitra River being more variable and complex to model. Although these variations exist, the fact that the models are consistently ranked in both rivers shows high cross-basin learning and confirms the usefulness of the multi-river method. Graphic analysis, observed versus predicted, showed that there was a close match between the predicted and actual water levels with p value of correlation near to 0.98-0.99. The models were able to model long-term trends and short-term variations, including the low-flow conditions due to droughts. The fact that minor deviations occur when the conditions are extreme implies that there is inherent uncertainty in the highly dynamic hydrological processes but this does not pose a significant problem to overall model reliability. The importance of this study is the trend analysis of drought patterns and trends that indicated definite evidence of rising drought severity throughout the basin. The Nabaganga River experienced a strong decrease in water levels afte012, with more drastic decreases after 2020, whereas the Chitra River experienced a consistent decrease starting around 2018. At station level, it was found that there was a significant space variation with some places becoming progressively drier and others being sensitive to climatic variations. These results verify both that the drought behavior is a temporally changing and spatially heterogeneous behavior and that necessitates multi-river, multi-station modeling methods. The model behavior analysis during drought conditions showed that the boosting-based algorithms are especially effective to capture gradual hydrological changes related to the long periods of low-flow. Their serial learning process allows them to model delayed responses, rainfall memory effects, and time persistence, which are essential in drought sensitive forecasting.

Conversely, classical ensemble models and neural networks did not perform as well in terms of the ability to capture these small-scale dynamics. The cross-basin generalization analysis also confirmed the power of the proposed framework. The data consolidation of several river systems allowed the models to acquire transferable hydrological information, such as rainfall-runoff, seasonal, and drought propagation. This aspect can greatly increase the scalability of models and eliminate the necessity of having individual models per river making the method more applicable to large-scale applications. Another proof of model accuracy was the test with a single-river dataset (Nabaganga). CatBoost showed the best performance here with a high $R^2 = 0.998$ (close to perfect) predictive power. It also helped to identify that the most important predictors are the temporal factors (lagged water levels and moving averages, then seasonal and climatic factors). This results in the need for feature engineering undertaken in the study and explains the superiority of the boosting algorithms. The dynamic variations in river systems were also revealed in the long-term and short-term studies. The long-term results exhibited increases, stagnation and decreases, but showed a drastic decline beginning 2017 coinciding with drought. The short term forecasting results proved that CatBoost and XGBoost are extremely efficient in capturing short term variations and hence they can be used in operational forecasting such as flood forecasting and drought management. Finally, the analysis of multi-river versus single-river provided a trade-off between accuracy and complexity. While the single-river models are accurate and less complex compared to the multi-river models, the latter are more generalizable, scalable and applicable. The ability of the proposed framework to maintain good accuracy in predictions as well as capturing spatial variation, temporal dependency and drought sensitive patterns demonstrate the potential of the proposed framework as a global initiative in the field of hydrologic forecasting.

Overall the findings of this study suggest that a machine learning based multi-river model that is particularly sensitive to droughts has a clear edge in forecasting water levels by making use of temporal, spatial and climatic information. The study also demonstrates that the characteristic of ensemble complexity and feature engineering should be exploited to overcome the impacts of climate change and increasing droughts. This study will support the development of reputable, data-driven and climate robust forecasting systems that can aid in sustainable water resource management, farm planning and mitigation strategies for vulnerable riverine regions.

6. COMPARATIVE ANALYSIS

6.1 Framework-Level Comparison

Table 5. presents a comparative overview of the proposed framework with existing studies in terms of research focus, modeling techniques, scope, and performance. The comparison highlights that most previous works primarily focus on either drought analysis or water-level prediction independently, without integrating both aspects into a unified system.

Table 9. Framework-Level Comparison of the Proposed Study with Existing Literature

Study	**Focus**	**Models**	**Scope**	**Best Performance**	**Main Gap**
Pande et al. [1]	Drought index (SPI)	SVM, ensembles, GPR	Single region	$R^2 \approx 0.87$	No river-level prediction
Ahmadianfar et al. [3]	River water levels9	SVD-KR + LGBM	Single basin (Canada)	$R \approx 0.97$	No drought awareness
Bassah et al. [13]	Regional water levels	ConvLSTM	Everglades	MARE 0.38–1.40%	Requires gridded data
This Study	Drought-aware multi-river forecasting	RF, GB, ET, XGBoost, ANN	Chitra & Nabaganga	$R^2 = 0.993$, RMSE = 0.081	—

It was evident in the comparison that the available studies have a shortfall in either a very limited scope of focus on drought indices without operational prediction or in an inability to forecast the drought conditions of an individual river. Conversely, the study is unique to combine the drought sensitivity with multi-river water-level forecasting to provide the ability to make robust generalizations of the model across hydrologically linked basins. This combined system enables the framework to be effective when it is stressed by climate and offers valuable information about the way water should be managed in practice.

6.2 Model-Level Performance Comparison

To further evaluate predictive performance, a detailed comparison with existing machine learning approaches is presented in Table 10. This comparison focuses on model accuracy, features used, and real-world applicability.

Table 10. Model-Level Predictive Performance Comparison with Existing Machine Learning Approaches

Factor	**This Study**	**Durian Tunggal River (Ahmed et al. [1])**	**Malwathu Oya River (Rathnayake et al. [2])**	**Flood Prediction (Islam et al. [3])**	**PSO-LSTM Bangladesh (Ruma et al. [5])**
Models	CatBoost, XGBoost, RF, LightGBM, MLP	ANN, RF, SVM, Gradient Boosting	Hybrid ANN + ANFIS	XGBoost, RF, MLP	PSO-LSTM
Key Features	Past WL, Rainfall, Seasonal Indicators	Past WL, Rainfall, Seasonal	ANN, ANFIS, Uncertainty	Rainfall, Extreme WL	WL, Long-term dependencies
Best Performance	**CatBoost R^2 = 0.9982 (99.82%)**	ANN 99.09%	Hybrid ANN	XGBoost 88%	PSO-LSTM 96%
Real-World Application	Flood risk, agriculture	Flood prediction	Uncertain forecasting	Extreme events	Long-term prediction
Model Strength	Captures complex nonlinear patterns	Good nonlinear modeling	Handles uncertainty	Extreme prediction	Optimized long-term learning

The results show that the proposed CatBoost model is the most accurate model for water level forecasting among all the methods considered, and has a value of the R^2 coefficient of 0.9982. This demonstrates that it can remarkably model the nonlinear relationships between the hydrologic variables, such as past water levels, rainfall and seasonal flags. Our model has a better performance and stability in complex seasonal conditions compared with the popular ANN methods (99.09%), and the recent PSO-LSTM models (96%).

6.3 Integrated Discussion

The framework-level and model-level comparisons combined analysis demonstrates an essential gap in current research. The majority of the studies only analyze drought and make no actionable water-level predictions or include drought-sensitive features but do not analyze drought prediction accuracy. This isolation restricts their usefulness in practical uses especially in climate sensitive areas. Contrastingly, this work fills such a gap by combining drought-conscious multi-river models with highly accurate single-river forecasts. The drought analysis component is robust to low-flow and climate-stress environments, and the water-level prediction component is highly precise and operationally suitable. Combined, these elements constitute an overall hydrological forecast system that can manage variability of the environment and the accuracy of prediction.

6.4 Overall Contribution Positioning

On the whole, the suggested framework will further the current studies by incorporating several strengths into one integrated system. It does not only enhance the accuracy of prediction using hi-tech boosting based models, but also increases robustness by using drought sensitive features and multi-river interactions. This study is a holistic solution to hydrological modeling, unlike the past studies that focus on individual elements of the model, this study is accurate and climate conscious. This combined method has been shown to greatly enhance the applicability of machine learning to real-world water resources management, which is vital in such critical applications as flood risk assessment, agricultural planning, and climate-resilient decision-making. The possibility of being extremely accurate and at the same time taking into account spatial variability and drought conditions makes this study a valuable contribution in the field of hydrological forecasting.

7. DISCUSSION

7.1 Key Findings

The goal of this project was to develop a machine learning water-level prediction model resistant to drought in the Chitra and Nabaganga rivers basins. The findings of experiments provided some insight on the model behaviour, hydrology and the effectiveness of proposed multi-river strategy. Some of the key findings are that the ensemble and/or boosting-based machine-learning models are always superior to the neural network-based machine-learning models in both multi- and single-river predictions. GradBoost and XGBoost were very effective predictors of the drought-sensitive multi-river strategy ($R^2 = 0.993$) but CatBoost was the most effective predictor of the single river case ($R^2 = 0.998$). This consistent performance suggest that boosting-based models are good at incorporating complex non-linear relationships, interaction among features and temporal dependencies in the hydrological system On the other hand, the relatively unsatisfying performance of MLP model suggests that it may have limitations in capturing the properties of time-series data when no specific time-series handling is used. The other key finding is that temporal effects have a strong influence on the water-level forecasting. This is also underscored by the correlation analysis showing that the lag features (especially the one lag (Lag1) i.e. water level previous to the predicted value) are the most important features for prediction . This proves that hydrological memory does exist in the river systems whereby the state of the current water is highly dependent on the previous state of affairs. The introduction of lagged variables and moving averages greatly contributed to better performance of the models by allowing them to capture continuity short-term and long-term trends. The significance of climatic and seasonal factors in the variability of water-level is also noted in the study. The indicators of rainfall and floods exhibited moderate correlations, which means that they are external factors of hydrological change. Seasonal characteristics, especially indicators related to monsoon showed a high impact on water levels, which indicated the dominant role of monsoonal rainfall in the dynamics of rivers. Even though these factors are less dominant than the temporal features, they are needed to capture sudden changes and enhance the model robustness in changing climatic conditions. Spatially, the findings indicate great variability of the various river systems and monitoring stations. The multi-river analysis indicated that hydrological behaviour is not homogeneous with some stations having homogeneous behaviour and some having high variability and responsiveness to environmental factors. This spatial non-homogeneity highlights the fact that a multi-river, multi-station framework should be adopted as opposed to single-river models. One of the most important results of this research is that the long-term tendencies of decreasing water levels are observed, which means that drought is getting more and more intense throughout the basin. The Nabaganga River exhibited a significant decrease since 2012, then more since 2020, whereas the Chitra River had a progressive decrease since around 2018. These tendencies indicate the increasing drought stress and water scarcity which is in line with the observed climate variability and local hydrological changes.

Also, a comparison between the multi-river and the single-river models revealed that there is a clear relationship between the accuracy and generalization. While both the models were accurate, because of less complexity, the single-river model has been found more accurate, the multi-river model also demonstrated very good ability to various hydrological situations. In other words, not only is the proposed approach accurate but also can be generalized for the real world.

7.2 Practical Implications

Our research has important practical applications for water resource planning, flood and drought management, and agriculture, especially in vulnerable regions like Bangladesh.

First, the framework developed in this study allows for precise and dependable predictions of drought and water-level fluctuations, facilitating early warning systems for extreme water events. The model's ability to represent long-term drought variability and short-term fluctuations can help policymakers to take proactive measures to mitigate flood and drought impacts. Second, the capacity to accurately forecast water-levels under different climate scenarios makes the proposed framework suitable for irrigation and agricultural management. This helps farmers and decision-makers effectively manage water resources, minimize crop losses and enhance agricultural output, especially in drought-affected areas. The multi-river water level forecasting framework facilitates integrated water management, as it takes into account the interdependence of multiple river systems. This approach captures inter-basin effects and spatial variability, allowing for better regional-scale integrated water resource management. Further, incorporating recent advances in machine learning offers a scalable and data-intensive approach that can be applied to other river basins with similar hydrologic regimes. This framework can be expanded to real-time monitoring, increasing its usefulness for real-time forecasting and monitoring. And finally, the inclusion of features that are sensitive to drought stress makes the proposed system highly relevant in the face of climate change, which brings more variability and extreme events, requiring more robust and flexible forecasting systems. The fact it performs well even under drought conditions suggests the approach could be used to help implement sustainable water resource strategies and improve climate resilience.

7.3 Limitations of the Study

Even though the proposed framework demonstrates good performance and capacity in water-level prediction of drought-prone areas, it has some limitations that could be considered as an opportunity for improvement. Two river basins Chitra and Nabaganga are used for the study focusing on two selected monitoring stations. While this research shows good transferability between these connected river systems, it could be improved if a wide variety of river systems could further prove that the framework is scalable and adaptable to the different river systems. Second, it uses primarily data-driven machine learning models, which do not explicitly represent physical processes. While this leads to high performance for the models, this could be improved using mixed approaches that combine data-driven and physical models to have more explainability and robustness in the real world. Third, the features used in this paper primarily include the key hydro-climatic components such as water level, rainfall and seasonality. The addition of other environmental indicators, such as soil moisture, upstream discharge or groundwater level, to the model will also aid in the understanding of hydrological processes. The paper also examines the models' performance using historical data and model testing with simulated test prediction. The use of the suggested framework in a real-time monitoring system would also make the framework more applicable for real-time forecasting and management. Finally, while the models in this paper have been tested and demonstrated their fair performance under normal and drought conditions, further tests on the models under extreme or rare events would provide more insights into the stability and robustness of the models.

Overall, these limitations do not undermine the potency of the proposed framework; rather it suggests the potential future advances to improve its generality, interpretability and realism.

8. CONCLUSION AND FUTURE WORK

8.1 Conclusion

The current study developed a multi-objective machine learning-based framework for water-level forecasting in Chitra and Nabaganga river basins to address the high demand for accurate water-level prediction frameworks that can adapt to the climate changes. The system developed integrates data of multiple rivers, a consideration of droughts in feature engineering and the use of the latest machine learning methods, which is a robust approach to modelling dynamic and complex river systems under various climatic conditions.

The results demonstrate that the hydro-climatic and machine learning, with emphasis on ensemble methods, show the impact. In the multi-river setting, the prediction accuracy of the Gradient Boosting and XG Boost were also high ($R^2 = 0.993$), showing that they are transferable to interrelated rivers and also able to capture the spatial variability and interactions of the rivers. On the other hand, the single-river CV and training accuracy were also high, with CatBoost having a high accuracy ($R^2 \approx 0.998$) moving towards near-perfect prediction accuracy in a controlled environment. This twin-level testing shows the strength and correctness of the suggested system. A key contribution in this study is that drought sensitivity is incorporated in water-level forecasting under a single multi-river model. This study is unlike the traditional studies, which consider drought analysis and water-level prediction as two different phenomena since all the spectrums of hydrological behavior are only realized through this type of approach. Cross-basin interaction, drought conditions, and low-flow modeling capabilities are a considerable improvement in the realism and applicability of the forecasting system. The results also show that the most significant influences in the prediction of water-level are the temporal dependencies with the dominant role played by the lagged water-level features. This proves the existence of high hydrological memory in river systems. Concurrently, climatic and seasonal factors, especially on rainfall and monsoon signals, play a significant role as they capture the external environmental drivers. The temporal, climatic and spatial characteristic combination allows the models to learn both short-term variations and long-term trends effectively. Moreover, the long-term trend analysis shows that the level of the water decreases gradually on the territory of the study, especially since 2012 and 2018, which speaks of the growing drought intensity and less water availability. The implications of these findings are that climate variability is increasingly affecting river systems and there is a need to integrate drought-conscious processes into the predictive model. The relative analysis with the current literature further attests the relevance of the work. Although earlier studies tend to concentrate on either drought modeling or high-accuracy prediction on its own, the study is able to combine the two in a single framework. Not only does this increase the accuracy of prediction, but also increases the model robustness in situations of climate stress, as the proposed approach would be more applicable to the real world. Generally, the proposed framework has a high level of accuracy, generalization and robustness. Its capacity to manage multi-river interactions, high sensitivity to droughts, and provide high predictive accuracy makes it a broad and scalable water-level forecasting tool. Findings of this research are relevant in developing data-based hydrological modeling and a viable base to inform sustainable management of water resources, agricultural planning, and disaster preparedness in climate-prone areas.

8.2 Future Work

The approach could be expanded by using more sophisticated deep-learning approaches, such as long-short-term memory (LSTM) and hybrid networks, which could consider temporal relationships in streamflow. Other variables (soil moisture, groundwater and land-use) could also be added as predictors. The real-time prediction system would verify the forecast potential of the approach for floods, as temporal and sensor variability can influence the results. The method could be applied to larger, more complex river catchments (especially with poor observations), limited time and space.

Final Remark

The current study is a good example of the application of machine learning to manage complex hydrological issues in the face of climate change. The integration of drought-sensitivity, multiple-river and high-precision forecasting techniques provides a more realistic approach to water level forecasting, as demonstrated in this study. Not only does the new approach improve prognostication efficiency but also research in hydrological responses under climate stress. It is particularly relevant in the real world in the sphere of water resource management, agriculture and disaster risk management due to the ability to introduce increased robustness and accuracy. The pressing need in the field is likely to be a great need for effective and data-driven drought forecasting systems because of increasing climate variability. In this vein, the findings of the present study contribute to the development of applicable and scalable solutions and climate-proof solutions to support water resource management and decision making in low-lying areas.

PUBLICATIONS

This thesis has resulted in the following publications:

[1] Drought-Sensitive Machine Learning for Robust Water-Level Forecasting in the Chitra and Nabaganga River Basins
Conference: 5th International Conference on Sentiment Analysis and Deep Learning (ICSADL 2026)
Date: 18–20 February 2026

Published in: IEEE Xplore 31 March 2026

DOI: 10.1109/ICSADL67539.2026.11452092

This paper presents a drought-aware multi-river machine learning framework for accurate water-level forecasting. It integrates hydrological and climatic features across interconnected river basins and demonstrates the effectiveness of ensemble and boosting-based models in capturing complex hydro-climatic relationships under drought conditions.

[2] Machine Learning Modeling for Predicting Water Level in the Nabaganga: A Typical River in Bangladesh
Conference: 2025 International Conference on Intelligent Computing, Information and Control Systems (ICOIICS)
Date: 19–21 November, 2025
Location: Lalitpur, Nepal
Published in: IEEE Xplore 24 February 2026
DOI: 10.1109/ICOIICS67115.2025.11390660

This paper focuses on single-river water-level prediction using machine learning models such as CatBoost, XGBoost, Random Forest, LightGBM, and MLP. The study demonstrates high predictive accuracy, with CatBoost achieving the best performance, and highlights the effectiveness of machine learning techniques in modeling nonlinear hydrological patterns.

Both publications are directly derived from the research work presented in this thesis. The first publication focuses on drought-sensitive multi-river forecasting, while the second emphasizes machine learning-based water-level prediction in a single-river context. Together, they validate the robustness, accuracy, and applicability of the proposed framework.

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