CGIAR Initiative on Asian Mega-Deltas

Technical Brief

Using Machine Learning Tools for Salinity Forecasting to Support Irrigation Management and Decision-Making in a Polder of Coastal Bangladesh

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Key messages

- River salinity poses a critical threat to livelihoods and food security in the polders of Bangladesh.
- Irrigation in these polders heavily depends on river water, but allowing unsuitable saline water into the polders can severely jeopardize agriculture.
- Despite Bangladesh's advanced flood forecasting system, no operational mechanism exists for river salinity forecasting.
- A data-driven Machine Learning (ML) system for river salinity forecasting has been developed for polder 34/2P located in Khulna district in collaboration with the Institute of Water Modelling (IWM) in Bangladesh.
- The ML model demonstrated strong performance during testing, accurately forecasting salinity levels in the Rupsa-Kazibacha River systems flowing through the eastern side of the polder, signifying readiness for operational pilot testing for the upcoming season.
- This forecasting tool enhances agricultural decision-making by allowing farmers to adjust their planting schedules based on anticipated salinity changes, thereby minimizing crop yield losses.

Introduction

The Ganges-Brahmaputra delta is a globally significant region known for its high population density, intense agricultural production, and diverse ecosystems, which are crucial for the livelihoods of millions (Rahman et al., 2019). However, it increasingly faces hydrological stresses such as flooding in the wet season, water scarcity, and salinity intrusion in the dry season. In Bangladesh, part of the Ganges-Brahmaputra delta, over 30% of its cultivable land is in coastal areas, with approximately 53% of this land affected by varying degrees of soil salinity. Agricultural land use in these coastal zones is significantly lower than the national average cropping intensity. This is primarily due to the non-availability of fresh water for irrigation and the accumulation of excessive salts in the soil in the dry season (Shawkhatuzamman et al., 2023). The limitations on crop production due to salinity are compounded by inadequate irrigation infrastructure, the lack of salt-tolerant crop varieties, the prevalence of traditional crop types, increasing occurrences of climate change-induced natural disasters, and insufficient adoption of improved agricultural technologies.

Salinity disrupts the necessary agroecological and hydrological conditions for optimal crop production. The primary drivers of salinity development include direct inundation with saline water and the upward or lateral movement of saline groundwater during the dry season (November/December - May/June). The severity of salinity can lead to crop yield reductions of 20 to 40%, with extreme cases resulting in total crop failure. These issues are becoming more severe due to altered precipitation patterns and rising sea levels.

Since 1960, large embankments have been constructed around arable lands bordering rivers, known as polders, to reduce loss of life and support agricultural activities in the coastal belt by protecting it from flooding and salinity intrusion. These embankments were designed to shield the land from tidal flooding. Sluice gates were installed within the embankments to connect the internal canal systems formed by former river distributaries to the surrounding rivers. By strategically operating these sluice gates, excess water can be drained from the polders during low tide, while water can be brought into the polders during high tide, facilitating effective water management for agricultural purposes. While Bangladesh boasts a robust flood forecasting system, there exists a gap in forecasting river water salinity for the farmers to adapt their planting schedule.

A machine learning-based short-term river salinity forecasting system for the polder 34/2P was developed in close collaboration with IWM, Bangladesh, to address this key gap. The river salinity forecasting system predicts the time windows during which salinity levels will be below acceptable thresholds for irrigation (<4 ds/m), enabling the operation of sluice gates. These systems utilize machine learning algorithms to forecast salinity levels in advance, providing farmers with a critical decision-making window. In the polder 34/2P, this forecasting technology will enable farmers to plan and adjust their agricultural practices by anticipating changes in salinity, allowing them to adjust planting times to minimize yield losses associated with increased salinity and avoid delays in planting windows. The modeling framework aims to integrate the salinity forecast with existing advisory services available to farmers in polders, enhancing their resilience under increasingly variable climatic conditions (Jampani et al., 2023).

Discharge and salinity forecasting

This pilot study focused on developing and validating an ML-based salinity forecasting model near selected sluice gates in polder 34/2P near Khulna City, southwest Bangladesh (Figure 1). The study utilized discharge and salinity data from July 2011 to June 2022. The data for model training covered the period from 2011 to 2020, while validation was conducted using data from 2021 and 2022. The forecasting model employed reference flow discharge data from the Hardinge station to forecast discharge rates at the sluice gate locations, which were then used to forecast salinity levels at each gate.

The forecasting framework employed an ensemble of advanced machine learning algorithms, including Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), Recurrent Neural Networks (RNN), Convolutional Neural Networks (CNN), and hybrid CNN-LSTM models (Jampani et al., 2023). These algorithms were designed to effectively capture the temporal and spatial relationships between river discharge and salinity. Additional covariates, such as the discharge rate at the reference station, were found as critical inputs for predicting discharge at the sluice gate locations.

The model implementations were carried out in two stages: a) discharge forecasting (30 days in advance), which includes a sequential additive model approach utilizing time-lagged discharge data with a 5-day lag. The models followed the structure: $Qt=g(Qt-30)$; $Qt=g(Qt-30, Qt-35)$; $Qt=g(Qt-30, Qt-35, Qt-40)$ and $Qt=g(Qt-30, Qt-35, Qt-40, Qt-45)$). Five machine learning algorithms were assessed, and the best-fit model for each gate was selected using the Akaike Information Criterion (AIC), and b) a salinity prediction model based on the above AI/ML algorithm was applied, incorporating discharge and salinity time-series data.

The methodology was systematically applied across all 24 (1-15 western and 21-29 eastern sides of the polder) sluice gates, ensuring comprehensive model evaluation and implementation. By leveraging historical discharge and salinity data, the ML-driven model provides reliable salinity forecasts, which are crucial for managing water resources and mitigating the impacts of salinity intrusion in the region. The study also found that observed discharge at the Hardinge Bridge station is highly correlated with the GloFAS v4.0 (Global Flood Awareness System) produced by the European Centre for Medium-Range Weather Forecasts (ECMWF) under the Copernicus Emergency Management Service. This correlation indicated the feasibility of replacing Hardinge discharge data with the open-access GloFAS data. Including GloFAS data as complementary to IWM discharge data further enhanced the model's robustness and ensured continuity in forecasting, even during data shortages.

GloFAS data also exhibited a strong correlation (Figure 2) with reconstructed discharge data from the Rupsha River (simulated by the IWM model) at sluice gate locations 1 to 15 within the western side of polder 34/2P (Kazibacha River). This approach enabled the reconstruction of discharge data at these locations using GloFAS as the reference with high confidence. Salinity predictions at these gates were subsequently made using empirical equations, integrating reconstructed discharge data with GloFAS (for the pilot year 2024) and IWM-simulated discharge (2021-22).

In contrast, sluice gates 21 to 29, located on the eastern side, are part of a non-perennial diversion of the Kazibacha River (Pasur segment). This segment is primarily influenced by tidal backwater, resulting in a poor correlation with GloFAS discharge data (Figure 2). Consequently, as the majority of operational sluice gates are situated on the western side, the modeling and forecasting efforts were limited to gates 1 to 15.

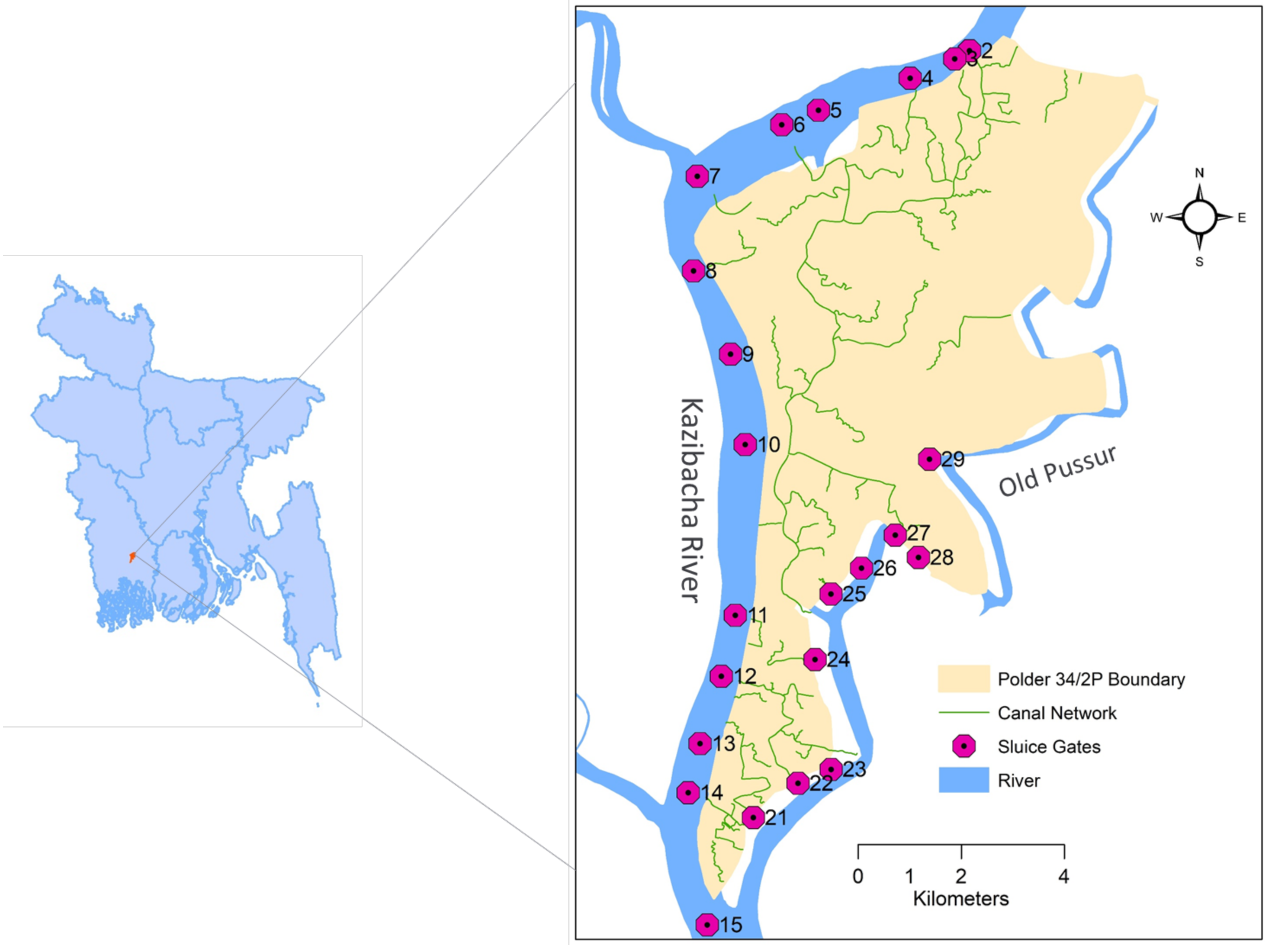


Figure 1. Location of polder 34/2P in Khulna district and sluice gates for water intake into polder channels.

The statistical performance of the models (Figure 3) during the calibration and validation phases was found to be satisfactory. Advanced ML architectures, as mentioned above, were implemented to model salinity dynamics across various sluice gate locations, effectively testing the accuracy of the model. Gates numbered 2 to 15 exhibit high Nash-Sutcliffe Efficiency (NSE) values, indicating satisfactory model performance in predicting salinity concentrations.

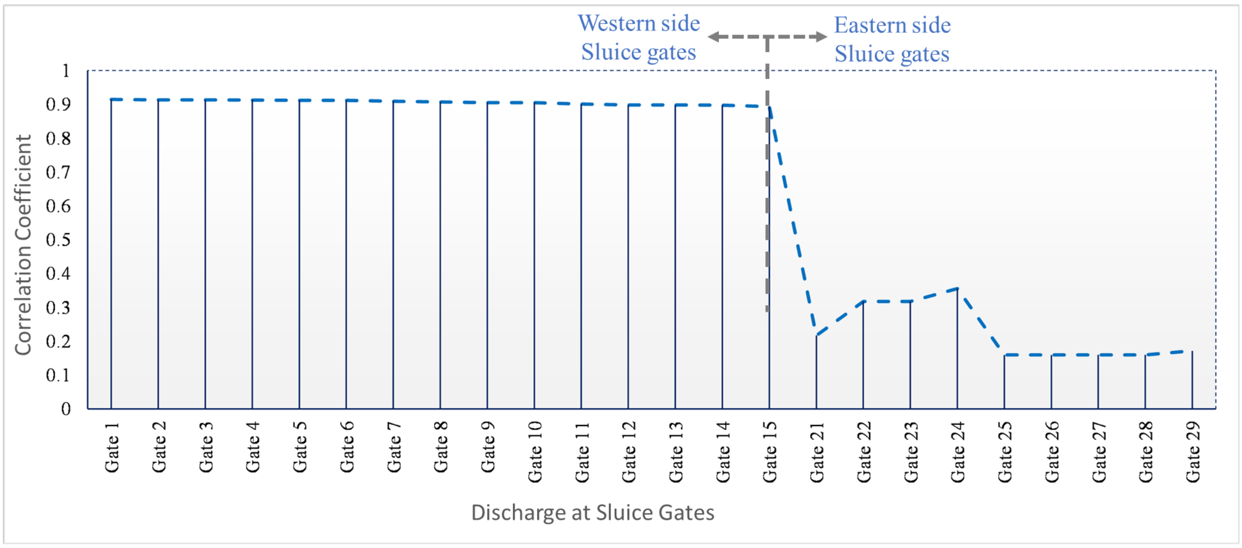
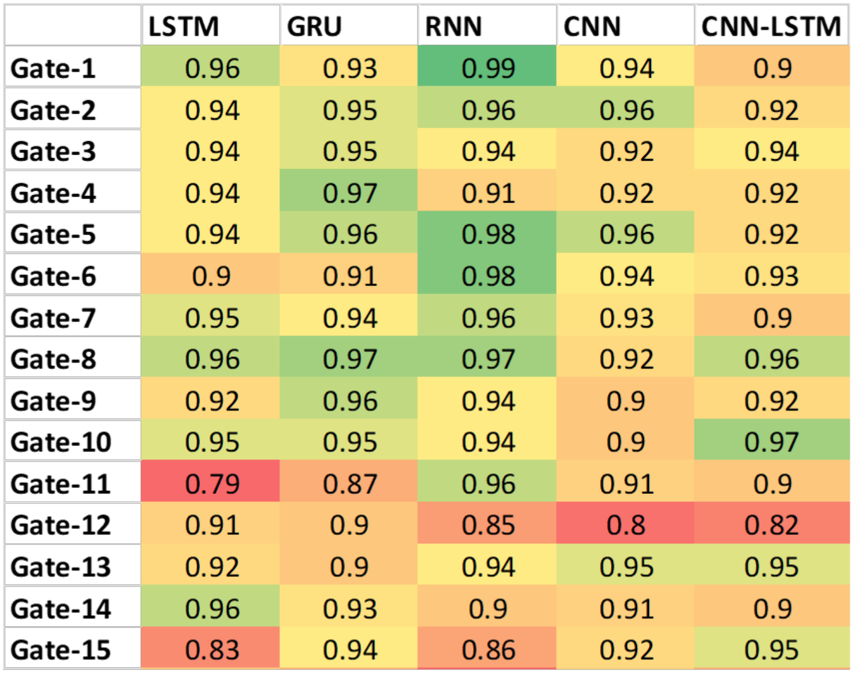


Figure 2. Correlation of GloFAS discharge with discharge rate (reconstructed IWM discharge observation) for all sluice gates.



	LSTM	GRU	RNN	CNN	CNN-LSTM
Gate-1	0.96	0.93	0.99	0.94	0.9
Gate-2	0.94	0.95	0.96	0.96	0.92
Gate-3	0.94	0.95	0.94	0.92	0.94
Gate-4	0.94	0.97	0.91	0.92	0.92
Gate-5	0.94	0.96	0.98	0.96	0.92
Gate-6	0.9	0.91	0.98	0.94	0.93
Gate-7	0.95	0.94	0.96	0.93	0.9
Gate-8	0.96	0.97	0.97	0.92	0.96
Gate-9	0.92	0.96	0.94	0.9	0.92
Gate-10	0.95	0.95	0.94	0.9	0.97
Gate-11	0.79	0.87	0.96	0.91	0.9
Gate-12	0.91	0.9	0.85	0.8	0.82
Gate-13	0.92	0.9	0.94	0.95	0.95
Gate-14	0.96	0.93	0.9	0.91	0.9
Gate-15	0.83	0.94	0.86	0.92	0.95

Figure 3. Forecasted accuracy (2020–2022) of the NSE for different sluice gates (1–15) of various ML algorithms.

Figure 4 depicts the salinity forecasting through the entire hierarchy of process flow at gate 4, i.e., model training (2011 - 2018), testing (2019 – 2020), and forecasting validation for 2020-22. Pilot testing for 2024 was carried out using the predicted discharge data from GloFAS up to May 30, 2024 to forecast discharge and predict salinity from June 30, 2024, onwards for one month during the flood tide salinity period, and from January 1, 2024, onwards for one month during the ebb tide salinity period. The purpose of this integrated predictive framework is to precisely map the windows of availability of river water with salinity levels below the permissible threshold (<4 ds/m), ensuring that the water can be safely diverted to canals connected to various gates.

During the dry period (November 2023 to February 2024), salinity levels exceeding 4 dS/m are observed. Conversely, salinity reduction and irrigation onset are observed during the wet season. Salinity declined rapidly between June 20 and July 7, 2024, which was corroborated by field-level measurements. As observed from the threshold dates of salinity below 4 dS/m, upstream sluice gates (Gate No. 2) have a larger window of access to quality irrigation water (~8 months) compared to Gate No. 15 (~6 months).

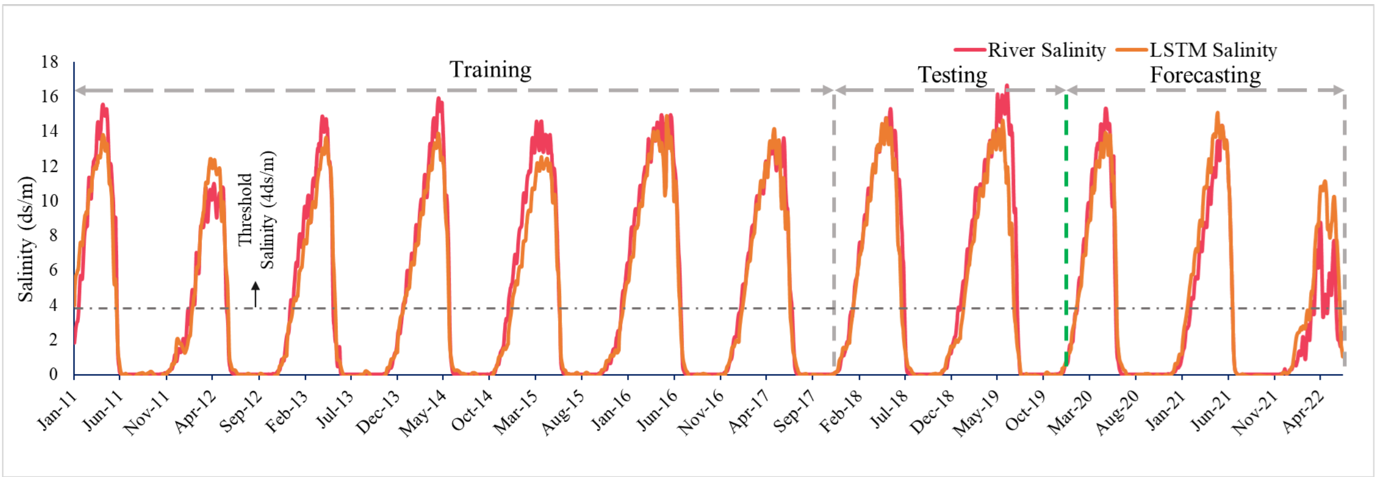


Figure 4. Salinity training (2011–2018), testing (2018–2020), and forecasting (2020–2022) at Sluice Gate 4, based on both river salinity and modeled salinity.

Way forward

Developed Machine Learning (ML) algorithms-based river salinity forecasting framework for the polder 34/2P of Khulna district, effectively capturing the patterns and dynamics of river water salinity through a heuristic data-driven approach. It demonstrated reliable predictive capabilities across key sluice gates, which are critical to the planning of agricultural activities in the polder. These promising results bolster confidence in the framework's potential success in forecasting salinity for the 2025 season as part of ongoing CGIAR activities.

The project outcomes were presented to various stakeholders in Bangladesh, including the Bangladesh Water Development Board (BWDB), the Department of Agricultural Extension (DAE), and other water-focused institutions. Through active collaboration with the Institute of Water Modelling (IWM) in Bangladesh, the framework's capability was enhanced by co-developing the methodological approach and refining it for potential pilot-scale deployment in 2025.

Further development and refinement of the framework depend on the availability of ready-to-use data to improve prediction accuracy. Efforts will also focus on integrating the model into existing operational systems and advisory infrastructures operated by different stakeholders in the polder region of southern Bangladesh. This integration aims to provide near real-time water resource management support and effectively address the salinity challenges of the polders.

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CGIAR Initiative on Asian Mega-Deltas

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Cover photo: Village pond in Khulna polder 34/2P (photo: Dr. Mahesh Jampani)

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