

DROUGHT-STAGE SEGMENTATION AND XGBOOST-BASED PREDICTION OF IRRIGATION SUPPLY CAPACITY FOR MONSOON-DOMINATED AGRICULTURAL RESERVOIRS IN EAST ASIA

SÉGMENTATION DES PHASES DE SÉCHERESSE ET PRÉVISION À L'AIDE DE XGBOOST DE LA CAPACITÉ D'APPROVISIONNEMENT EN EAU D'IRRIGATION DES RÉSERVOIRS AGRICOLES SOUMIS À LA MONSOON EN ASIE ORIENTALE

Mihye Yang¹, Wonho Nam², Kwangya Lee³, Kwangsik Yoon⁴

ABSTRACT

Agricultural reservoirs in South Korea operate under a highly seasonal hydroclimatic regime dominated by the East Asian monsoon, with a large share of annual precipitation concentrated in summer. This strong seasonality, combined with increasing hydroclimatic variability and recurrent droughts, has intensified the need for more adaptive reservoir drought management. Conventional operation practices often rely on static storage thresholds or fixed rule curves, which may be insufficient for early drought recognition and staged operational response. In this study, a data-driven drought management framework is proposed for agricultural reservoirs by integrating statistical drought stage classification with machine-learning-based short-term storage ratio prediction. Two major agricultural reservoirs in the Yeongsan River basin, Jangseong Reservoir and Naju Reservoir, were selected as case studies. First, reservoir-specific drought stages were defined from long-term storage ratio distributions using percentile thresholds. Second, an Extreme Gradient Boosting (XGBoost) model was developed to predict short-term reservoir storage ratio using antecedent storage, rainfall, cumulative rainfall, and seasonal variables. Third, scenario-based simulations were conducted under representative drought-year meteorological conditions and different initial storage states to assess possible drought stage transitions. Finally, predicted storage ratios were converted to storage volumes and linked to estimates of available agricultural water supply. The framework is designed to support operationally interpretable drought warning and adaptive irrigation management by combining historical drought context with near-term forecast information. The results indicate that the proposed approach can provide a practical basis for reservoir-specific drought diagnosis, forecast-informed response planning, and supply-risk assessment under monsoon-driven and data-limited conditions.

Keywords: agricultural reservoir; drought management; storage ratio; XGBoost; machine learning; South Korea; water supply; monsoon climate.

RESUME

En Corée du Sud, les réservoirs agricoles fonctionnent selon un régime hydroclimatique fortement saisonnier, dominé par la mousson d'Asie orientale, une grande partie des précipitations annuelles étant concentrée en été. Cette forte saisonnalité, conjuguée à une variabilité hydroclimatique croissante et à des sécheresses récurrentes, a renforcé la nécessité d'avoir une gestion plus adaptative des réservoirs en période de sécheresse. Les pratiques d'exploitation conventionnelles s'appuient souvent sur des seuils de stockage statiques ou des courbes de régulation fixes, qui peuvent s'avérer insuffisants pour une détection précoce de la sécheresse et une réponse opérationnelle par étapes. Dans cette étude, un cadre de gestion de la sécheresse fondé sur les données est proposé pour les réservoirs agricoles,

¹ Department of Integrated Systems Engineering, Hankyong National University, Anseong, Republic of Korea

² School of Social Safety and Systems Engineering, National Agricultural Water Research Center, Hankyong National University, Anseong, Republic of Korea

³ Institute of Agricultural Science, Chungnam National University, Daejeon, Republic of Korea

⁴ Rural& Bio-Systems Eng. Dept. Chonnam National University, Gwangju, Korea: ksyoon@jnu.ac.kr

en intégrant une classification statistique des stades de sécheresse à une prévision à court terme du taux de stockage basé sur l'apprentissage automatique. Deux grands réservoirs agricoles situés dans le bassin versant de Yeongsan, le réservoir de Jangseong et celui de Naju, ont été retenus comme études de cas. Tout d'abord, des stades de sécheresse spécifiques à chaque réservoir ont été définis à partir des distributions à long terme des taux de stockage utilisant des seuils basés sur les centiles. Ensuite, un modèle Extreme Gradient Boosting (XGBoost) a été développé pour prédire le taux de stockage des réservoirs à court terme à partir du niveau de stockage antécédent, des précipitations, des précipitations cumulées et de variables saisonnières. Troisièmement, des simulations basées sur des scénarios ont été réalisées en tenant compte de conditions météorologiques représentatives d'une année de sécheresse et pour différents états de stockage initiaux, afin d'évaluer les transitions possibles entre les différents stades de sécheresse. Enfin, les taux de stockage prévus ont été convertis en volumes de stockage et mis en relation avec des estimations de l'approvisionnement en eau agricole disponible. Ce cadre est conçu pour faciliter la mise en place d'alertes de sécheresse interprétables sur le plan opérationnel et d'une gestion adaptative de l'irrigation, en combinant le contexte historique de la sécheresse avec des informations de prévision à court terme. Les résultats indiquent que l'approche proposée peut fournir une base pratique pour le diagnostic de la sécheresse spécifique à chaque réservoir, la planification des mesures d'intervention fondées sur les prévisions et l'évaluation des risques liés à l'approvisionnement dans des conditions marquées par la mousson et des données limitées.

Mots-clés : Réservoir agricole; Gestion de la sécheresse; Taux de stockage; XGBoost; Apprentissage automatique; Corée du Sud; Approvisionnement en eau; Climat de mousson.

1. Introduction

Agricultural reservoirs are essential infrastructure in monsoon Asia, where irrigation reliability depends heavily on seasonal rainfall variability. In South Korea, these reservoirs play a critical role in stabilizing paddy irrigation, sustaining agricultural productivity, and mitigating drought impacts. Because precipitation is concentrated during the summer monsoon and typhoon season, while winter and spring are relatively dry, agricultural water security depends not only on total annual rainfall but also on seasonal distribution and antecedent reservoir storage (Chang, 2004; IPCC, 2021).

Recent hydroclimatic changes have increased the complexity of reservoir management. Droughts in South Korea have become more frequent and prolonged, often progressing from meteorological drought to agricultural and hydrological drought depending on water demand and storage conditions (Bae et al., 2019). Climate change is expected to further intensify rainfall variability and extreme events, reducing the effectiveness of conventional fixed-threshold reservoir operation.

Traditional forecasting approaches, including physically based hydrological models such as Tank and SWAT, provide process-based understanding but require extensive calibration, detailed watershed information, and substantial parameterization, limiting their operational applicability in managed agricultural systems (Beven, 2001; Vörösmarty et al., 2010). Because reservoir storage is influenced not only by inflow but also by irrigation withdrawals and operational rules, data-driven approaches offer a practical alternative.

Machine learning has become increasingly valuable in hydrology for capturing complex nonlinear relationships directly from data (Maier et al., 2010; Shen, 2018; Reichstein et al., 2019). Various models, including neural networks, support vector regression, random forest, recurrent neural networks, and long short-term memory, have been applied to reservoir forecasting (ASCE Task Committee, 2000; Yaseen et al., 2019; Apaydin et al., 2020; Zhu et al., 2020; Ahmed et al., 2022).

Among these, XGBoost has attracted attention for its high predictive accuracy, computational efficiency, and resistance to overfitting (Chen and Guestrin, 2016). Recent studies confirm its applicability in hydrological forecasting and drought assessment (Niazkar et al., 2024; Sen, 2025), although most focus primarily on prediction accuracy rather than operational decision-making.

For drought management, reservoir operators require not only accurate forecasts but also interpretable guidance for staged response. A percentile-based classification framework using long-term reservoir storage distributions provides a statistically robust method for defining drought severity relative to each reservoir's historical variability, rather than applying uniform thresholds. Interpretability remains a challenge in machine learning adoption, but XGBoost partially addresses this through Gain-based feature importance, which quantifies input variable contributions and improves transparency for operational use without requiring separate explanation tools (Reichstein et al., 2019; Nearing et al., 2021).

The study focuses on Jangseong Reservoir and Naju Reservoir in the Yeongsan River basin, major agricultural irrigation systems in southwestern South Korea. The objectives are to: (1) define reservoir-specific drought stages using long-term storage ratio distributions; (2) develop and evaluate an XGBoost model for short-term storage prediction based on antecedent storage, rainfall, cumulative rainfall, and seasonal variables; (3) analyze drought stage transitions under representative drought meteorological scenarios and varying initial storage conditions; and (4) estimate stage-linked available water supply and discuss implications for adaptive agricultural reservoir management.

2. Materials and Methods

2.1 Overall study framework

The overall workflow is summarized conceptually in Figure 1. First, long-term daily storage ratio data were collected for each reservoir and analyzed statistically to derive drought stage thresholds based on percentile classification. Second, hydro-meteorological and temporal variables were used to train reservoir-specific XGBoost models for short-term prediction of storage ratio. Third, representative drought-year weather conditions and initial storage scenarios were imposed to simulate future storage trajectories and corresponding drought stage evolution. Finally, predicted storage ratios were converted to storage volume through reservoir-specific storage–elevation–capacity relationships, and the resulting volumes were interpreted in terms of potential agricultural water supply availability.

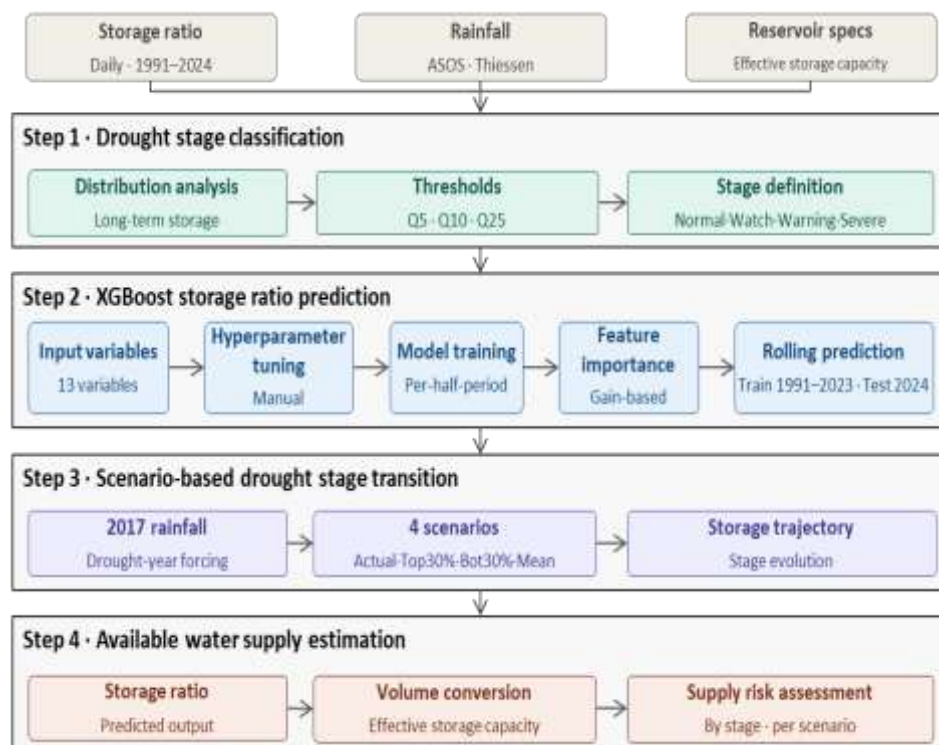


Figure 1. Overall research framework

2.2 Study area

This study focuses on Jangseong Reservoir and Naju Reservoir, two major agricultural reservoirs in the Yeongsan River basin, Jeollanam-do, South Korea. Constructed in 1976 under the Yeongsan River Basin Comprehensive Development Project, both reservoirs play critical roles in regional irrigation water supply. Jangseong Reservoir, located in Jangseong-gun, has a catchment area of 12,280 ha, an effective storage capacity of 96.7 million m³, and an irrigation service area of 11,139 ha. Naju Reservoir, located in Naju-si, has a catchment area of 10,470 ha, an effective storage capacity of 106.5 million m³, and an irrigation service area of 9,267 ha (Bang et al., 2019).

2.3 Data

Daily storage ratio and water level data for Jangseong and Naju Reservoirs were obtained from the Rural Water Resources Integrated Information System (RAWRIS) operated by the Korea Rural Community Corporation (KRC). The analysis covered the period 1991–2024, yielding long-term daily records for both reservoirs after quality control. Catchment rainfall data were obtained from the Korea Meteorological Administration (KMA) Automatic Weather Station network.

For modelling, the daily data were aggregated into five-day intervals to match operational forecasting timescales. Missing values arising during feature engineering, including lagged and rolling aggregate predictors, were removed by listwise deletion. No normalization was performed, as XGBoost is robust to monotonic transformations of predictor variables.

To preserve temporal dependency and emulate real-world forecasting conditions, the dataset was chronologically divided into a training set (1991–2023) and an independent test set (2024). Hyperparameters were selected through comparative evaluation of five manually tuned model configurations, without a separate validation dataset.

2.4 Statistical drought stage classification

A key element of this study was the development of reservoir-specific drought stage classifications based on the long-term distribution of storage ratios. For each reservoir, historical daily storage ratio records were analyzed to derive empirical percentile thresholds, following the distribution-based drought severity framework of the U.S. Drought Monitor (Svoboda et al., 2002). Drought stages were classified as *Caution*, *Alert*, and *Severe* at the 25th, 10th, and 5th percentile thresholds, respectively, while storage conditions above the 25th percentile were categorized as *Normal*.

2.5 XGBoost-based storage ratio prediction

Input variables were selected to capture the primary drivers of short-term reservoir storage variation, including storage persistence, antecedent rainfall conditions, and seasonal hydroclimatic characteristics. The final model incorporated 13 predictors: initial storage ratio for the target five-day period, cumulative rainfall during the target period, mean storage ratio over the preceding month, cumulative rainfall over the preceding 3 and 5 five-day periods, rainy-day counts over the preceding 3 and 5 five-day periods, rainfall standard deviation over the same antecedent periods, terminal storage ratio of the preceding five-day period, mean terminal storage ratio over the preceding three five-day periods, deviation of the current storage ratio from the long-term mean, and an indicator representing concentrated rainfall intensity.

The XGBoost model was trained separately for each five-day period for both reservoirs to account for temporal variability in seasonal storage dynamics. Hyperparameters were determined through manual tuning across multiple experimental configurations, and the final parameter set was selected based on overall RMSE performance. The same optimized hyperparameter configuration was consistently applied to both reservoir models.

2.6 Model performance evaluation

Model performance was assessed using the independent test dataset (2024) based on Root Mean Square Error (RMSE) and Nash–Sutcliffe Efficiency (NSE) (Moriassi et al., 2007). Evaluation was conducted under a rolling prediction framework, where the predicted storage ratio for each five-day period was recursively used as input for the subsequent forecast, thereby simulating operational forecasting conditions. For contextual benchmarking, the resulting RMSE values were interpreted against performance ranges reported in previous reservoir prediction studies.

2.7 Scenario design

Scenario-based simulations were conducted using the meteorological conditions of 2017, a representative severe drought year in South Korea, as the common rainfall forcing across all scenarios. For each reservoir, four initial storage scenarios were defined based on the distribution of storage ratios observed on 1 January over the full study period (1991–2024): (1) the actual initial storage observed in 2017, used as the baseline scenario to reproduce observed drought-season dynamics; (2) the mean initial storage of the upper 30% of years ranked by 1 January storage ratio; (3) the mean initial storage of the lower 30% of years ranked by 1 January storage ratio; and (4) the long-term mean initial storage years ranked by 1 January storage ratio. All scenarios were subjected to the same 2017 rainfall sequence, enabling direct comparison of drought stage transitions attributable solely to differences in antecedent storage conditions.

2.8 Estimation of available agricultural water supply

To enable operational interpretation of model outputs, predicted storage ratios were translated into storage volumes using reservoir-specific storage–elevation–capacity relationships. The estimated storage volumes were then used as indicators of available agricultural water supply under each forecast scenario.

3. Results

3.1 Long-term storage characteristics and drought stage thresholds

The long-term storage ratio records of Jangseong and Naju Reservoirs revealed distinct reservoir-specific distributions and seasonal dynamics. Both reservoirs exhibited clear annual storage cycles, characterized by replenishment during the summer monsoon season and progressive depletion during winter and spring. However, the magnitude and persistence of low-storage conditions differed between the two systems, suggesting that a single uniform threshold would not adequately represent drought risk across both reservoirs.

The percentile-based classification effectively divided the historical storage records into operationally interpretable drought stages. For Jangseong Reservoir, the threshold values for the *Caution*, *Alert*, and *Severe* stages were 52.0% (Q25), 39.1% (Q10), and 32.1% (Q5), respectively. Corresponding thresholds for Naju Reservoir were 45.5% (Q25), 32.7% (Q10), and 26.2% (Q5). The observed minimum storage ratios during the 2017 drought year—30.3% for Jangseong and 21.8% for Naju—fell below the Q5 thresholds in both reservoirs, confirming the severity of the event and supporting the validity of the derived drought-stage classification.

3.2 XGBoost model performance

Model performance was first evaluated using the independent 2024 test dataset. The XGBoost model showed strong predictive accuracy, with an RMSE of 2.45% and NSE of 0.97 for Jangseong Reservoir, and an RMSE of 3.13% and NSE of 0.79 for Naju Reservoir. To examine model performance under extreme drought conditions, the framework was applied to the 2017 drought-year scenario using recursive rolling forecasts, where each predicted storage ratio served as input for the next prediction step. Under this setting, RMSE increased to 7.48% and 6.62% for Jangseong and Naju Reservoirs,

respectively, while NSE declined to 0.40 and 0.54. This reduction in performance is attributable to the cumulative propagation of prediction errors during prolonged dry periods, a common limitation of recursive forecasting frameworks (Fig.1 and Fig.2).

3.3 Scenario-based drought stage transitions

Scenario simulations demonstrated that drought risk was highly sensitive to antecedent storage conditions, even under identical meteorological forcing. Under the representative 2017 drought-year rainfall sequence, reservoirs initialized with higher storage ratios remained within the *Normal* or *Caution* stages for extended periods, whereas those starting from lower storage conditions transitioned more rapidly into the *Alert* or *Severe* stages.

A key finding from the scenario analysis is that drought vulnerability depends not only on meteorological forcing but also critically on initial reservoir storage conditions. Reservoirs entering the irrigation season with relatively low storage may experience substantial drought risk even under rainfall conditions that would be manageable from a higher starting point. Under the lower 30% initial storage scenario, predicted storage ratios for both reservoirs entered the *Caution* stage during portions of the irrigation season. In contrast, the upper 30% and long-term mean initial storage scenarios maintained storage above the *Caution* threshold throughout the season (Fig.1 and Fig.2).

These results highlight the decisive role of initial storage conditions in shaping drought-stage transitions and water supply risk. From an operational perspective, the findings suggest that drought preparedness should begin before severe storage depletion becomes evident, through proactive storage management, early warning systems, and staged response strategies informed by forecasted storage deterioration.

3.4 Estimated available agricultural water supply

Conversion of predicted storage ratios into storage volumes enabled direct interpretation of scenario outcomes in terms of irrigation water availability. Under the lower 30% initial storage scenario, both reservoirs entered the *Caution* stage during parts of the irrigation season, with estimated mean daily available water supplies of approximately 459,000 m³ for Jangseong Reservoir and 526,000 m³ for Naju Reservoir. In contrast, scenarios with higher or average initial storage maintained storage above the *Caution* threshold throughout the season, highlighting the critical influence of initial storage conditions on drought-stage transitions and supply availability.

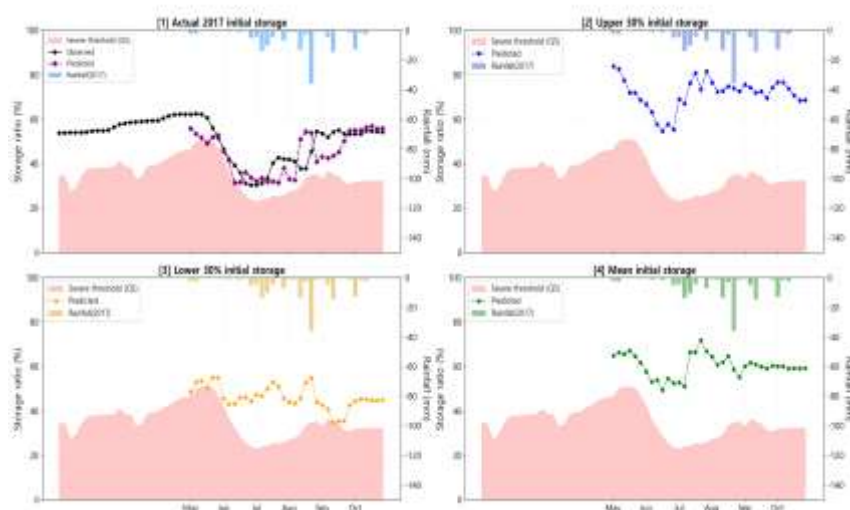


Figure 2. Scenario-based storage ratio prediction – Jangseong Reservoir

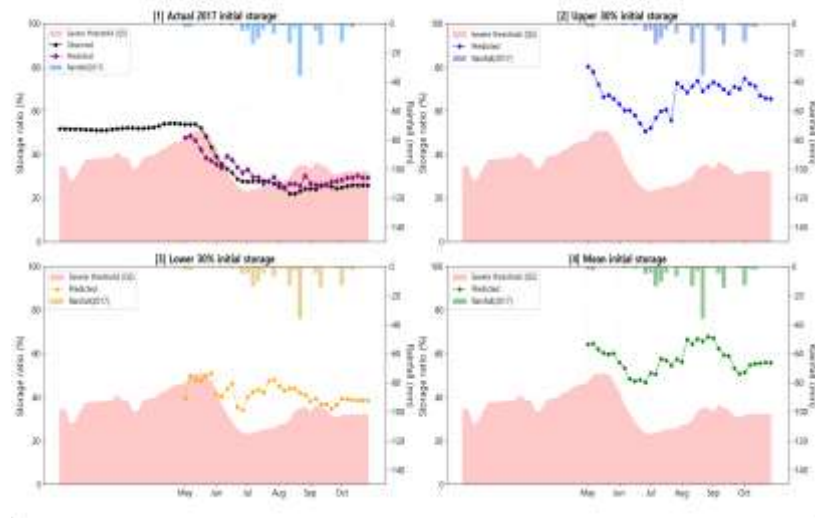


Figure 3. Scenario-based storage ratio prediction – Naju Reservoir

4. Discussion

The proposed framework provides a practical bridge between predictive modelling and operational drought management. Although previous studies have largely emphasized improving forecast accuracy for reservoir inflow or storage, fewer have linked predictive outputs directly to drought warning stages and supply-based decision support. By combining reservoir-specific drought classification with XGBoost forecasting, the framework improves the operational interpretability of predictive information.

This is particularly important in monsoon-dominated systems, where drought risk depends strongly on rainfall timing and antecedent storage conditions. A storage level that appears acceptable in one reservoir may represent substantial drought risk in another, depending on local hydrological behavior. The use of reservoir-specific percentile thresholds therefore provides a more context-sensitive and operationally relevant approach than uniform fixed thresholds.

The strong performance of the XGBoost model aligns with recent findings that tree-based ensemble methods perform well in hydrological forecasting applications (Niazkar et al., 2024). Given the nonlinear interactions among storage persistence, delayed rainfall effects, and seasonal variability, XGBoost offers a suitable and computationally efficient modelling framework for short-term reservoir storage prediction.

5. Conclusions

This study developed a data-driven drought management framework for agricultural reservoirs in monsoon-dominated regions by integrating percentile-based drought stage classification with XGBoost-based short-term storage prediction. Using Jangseong and Naju Reservoirs in South Korea as case studies, the framework converted long-term historical storage records into reservoir-specific drought warning stages and linked machine learning forecasts directly to operational drought assessment.

The results showed that percentile-based drought thresholds provided a practical and interpretable basis for reservoir-specific drought diagnosis, reflecting the unique hydrological characteristics of each system rather than relying on uniform rule-based criteria. The XGBoost model demonstrated strong predictive performance, and feature importance analysis confirmed that initial storage conditions and rainfall variables were the dominant drivers of short-term storage variation, supporting the physical plausibility of the approach. Scenario analysis highlighted that drought vulnerability depends not only on meteorological conditions but also strongly on initial storage conditions. Under identical drought-year rainfall forcing, reservoirs with lower antecedent storage transitioned more rapidly into drought warning

stages and experienced reduced supply availability. This finding suggests that proactive drought preparedness should begin before severe drought conditions emerge, using storage-based early warning and staged response planning.

From an operational perspective, the proposed framework provides practical decision-support information by translating forecasted storage conditions into management-relevant drought stages and estimated supply availability. This improves the usability of predictive modelling for irrigation reservoir operation, particularly in monsoon climates where seasonal rainfall concentration makes timing and antecedent storage critically important.

Overall, the study demonstrates that integrating machine learning prediction with historically grounded drought-stage classification can provide a practical and interpretable framework for adaptive agricultural reservoir drought management under increasing hydroclimatic uncertainty.

References

- Ahmed, A.N., Yafouz, A., Birima, A.H., Kisi, O., Huang, Y.F., Sherif, M., Sefelnasr, A., El Shafie, A. 2022. Water level prediction using various machine learning algorithms: A case study of Durian Tunggal River, Malaysia. *Engineering Applications of Computational Fluid Mechanics*. 16(1): 422–440. <https://doi.org/10.1080/19942060.2021.2019128>.
- Apaydin, H., Feizi, H., Sattari, M.T., Colak, M.S., Shamshirband, S., Chau, K.W. 2020. Comparative analysis of recurrent neural network architectures for reservoir inflow forecasting. *Water*. 12(5):1500. <https://doi.org/10.3390/w12051500>.
- ASCE Task Committee. 2000. Artificial neural networks in hydrology. I: Preliminary concepts. *Journal of Hydrologic Engineering*. 5(2):115–123. [https://doi.org/10.1061/\(ASCE\)1084-0699\(2000\)5:2\(115\)](https://doi.org/10.1061/(ASCE)1084-0699(2000)5:2(115)).
- Bae, H., Ji, H., Lim, Y., Ryu, Y., Kim, M., Kim, B. 2019. Characteristics of drought propagation in South Korea: relationship between meteorological, agricultural, and hydrological droughts. *Natural Hazards*. 99:1–16. <https://doi.org/10.1007/s11069-019-03676-3>.
- Bang, J., Choi, J.Y., Kim, K. 2019. Analysis of water supply system and multi-reservoir water balance of Naju Reservoir. In: *Proceedings of the Korean Society of Agricultural Engineers Annual Conference*. Korean Society of Agricultural Engineers. pp. 34–34.
- Beven, K.J. 2001. *Rainfall-Runoff Modelling: The Primer*. Wiley, Chichester.
- Chang, C.P., 2004. *East Asian Monsoon*. World Scientific series on Asia-Pacific weather and climate: volume 2. Singapore. <https://doi.org/10.1142/5482>.
- Chen, T., Guestrin, C. 2016. XGBoost: A scalable tree boosting system. In: *Proceedings of the 22nd ACM SIGKDD International conference on knowledge discovery and data mining*, San Francisco, CA, USA, pp. 785–794. <https://doi.org/10.1145/2939672.2939785>.
- IPCC, 2021. *Climate Change 2021: The Physical Science Basis*. Working Group I Contribution to the IPCC Sixth Assessment Report.
- Maier, H.R., Jain, A., Dandy, G.C., Sudheer, K.P. 2010. Methods used for the development of neural networks for the prediction of water resource variables in river systems: Current status and future directions. *Environmental Modelling & Software*. 25(8):891–909. <https://doi.org/10.1016/j.envsoft.2010.02.003>.
- Niazkar, M., Menapace, A., Bretan, B., Piraei, R., Jimenez, D., Dhawan, P., Righetti, M. 2024. Applications of XGBoost in water resources engineering: A systematic literature review (Dec 2018–May 2023). *Environmental Modelling & Software*. 174:105971. <https://doi.org/10.1016/j.envsoft.2024.105971>.
- Nearing, G.S., Kratzert, F., Sampson, A.K., Pelissier, C.S., Klotz, D., Frame, J.M., Prieto, C., Gupta, H.V. 2021. What role does hydrological science play in the age of machine learning? *Water Resources Research*. 57: e2020WR028091. <https://doi.org/10.1029/2020WR028091>.
- Moriasi, D.N., Arnold, J.G., Van Liew, M.W., Bingner, R.L., Harmel, R.D., Veith, T.L. 2007. Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. *Transactions of the ASABE*. 50(3):885–900. <https://doi.org/10.13031/2013.23153>.
- Reichstein, M., Camps-Valls, G., Stevens, B., Jung, M., Denzler, J., Carvalhais, N., Prabhat. 2019. Deep learning and process understanding for data-driven Earth system science. *Nature*. 566(7743):195–204. <https://doi.org/10.1038/s41586-019-0912-1>.

- Sen, S.G. 2025 Machine learning-based water level forecast in a dam reservoir: A case study of Karaçomak dam in the Kızılırmak Basin, Türkiye. *Sustainability*. 17:8378. <https://doi.org/10.3390/su1718837>.
- Shen, C., 2018. A transdisciplinary review of deep learning research and its relevance for water resources scientists. *Water Resources Research*. 54(11):8558–8593. <https://doi.org/10.1029/2018WR022643>.
- Svoboda, M., LeComte, D., Hayes, M., Heim, R., Gleason, K., Angel, J., Rippey, B., Tinker, R., Palecki, M., Stooksbury, D., Miskus, D., Stephens, S. 2002. The Drought monitor. *Bulletin of the American Meteorological Society*, 83(8):1181–1190. <https://doi.org/10.1175/1520-0477-83.8.1181>.
- Vörösmarty, C.J., McIntyre, P.B., Gessner, M.O., Dudgeon, D., Prusevich, A., Green, P., Glidden, S., Bunn, S.E., Sullivan, C.A., Liermann, C.R., Davies, P.M. 2010. Global threats to human water security and river biodiversity. *Nature*, 467:555–561. <https://doi.org/10.1038/nature09440>.
- Yaseen, Z.M., Sulaiman, S.O., Deo, R.C., Chau, K.W. 2019. An enhanced extreme learning machine model for river flow forecasting: State-of-the-art, practical applications in water resource engineering area and future research direction. *Journal of Hydrology*. 569:387–408. <https://doi.org/10.1016/j.jhydrol.2018.11.069>.
- Zhu, S., Luo, X., Yuan, X., Xu, Z., 2020. An improved long short-term memory network for streamflow forecasting in the upper Yangtze River. *Stochastic Environmental Research and Risk Assessment*. 34(11):1313–1329. <https://doi.org/10.1007/s00477-020-01766-4>.