

## SYNERGIZING MACHINE LEARNING AND SYSTEM DYNAMICS FOR ADAPTIVE WATER MANAGEMENT IN AGRICULTURAL RESERVOIRS

### MISE EN SYNERGIE DE L'APPRENTISSAGE AUTOMATIQUE ET DE LA DYNAMIQUE DES SYSTÈMES POUR UNE GESTION ADAPTATIVE DE L'EAU DANS LES RÉSERVOIRS AGRICOLES

Mi-Hye Yang<sup>1</sup>, and Won-Ho Nam<sup>2</sup>

#### ABSTRACT

The increasing frequency and severity of droughts associated with climate change have intensified the need for prediction-based decision-making in agricultural reservoir management. Although machine learning models effectively capture nonlinear hydrological relationships, their prediction uncertainty often increases during rapid storage fluctuations, limiting operational reliability under drought conditions. This study proposes an integrated modeling framework that combines machine learning-based storage prediction, residual correction, and System Dynamics (SD)-based operational simulation for adaptive drought management in agricultural reservoirs. The framework was developed using dekadal (10-day interval) reservoir storage data. The primary prediction model employed gradient boosting-based ensemble learning to simulate nonlinear storage dynamics, while temporally correlated prediction errors were corrected using a recurrent neural network (RNN)-based auxiliary model trained on lagged residual sequences. The corrected storage trajectories were subsequently coupled with an SD model to evaluate threshold-based operational interventions under drought conditions. Reservoir storage was represented as a state variable, and intervention scenarios were simulated by adjusting storage decline rates through a control coefficient. The proposed framework was applied to the Sinjeong Reservoir in Asan, South Korea. Results showed that the hybrid gradient boosting-LSTM model achieved a prediction RMSE of 7.1%p during the 2024 irrigation season. Under a hypothetical severe drought scenario based on 2021 conditions, SD simulations indicated that interventions initiated during the second dekad of July could reduce end-of-season storage decline by 2.9–25.9 percentage points depending on intervention intensity ( $\alpha = 0.10$ – $0.90$ ). The results demonstrate that early intervention substantially outperforms delayed response, highlighting the potential of integrated machine learning and SD frameworks for adaptive drought operation in aging agricultural reservoir systems.

**Keywords:** Agricultural reservoir management; Hybrid machine learning; System dynamics; Reservoir storage prediction; Adaptive drought operation; Decision support.

#### RÉSUMÉ

L'augmentation de la fréquence et de la gravité des sécheresses associées au changement climatique a renforcé la nécessité d'une prise de décision fondée sur la prévision pour la gestion des réservoirs agricoles. Bien que les modèles d'apprentissage automatique capturent efficacement les relations hydrologiques non linéaires, l'incertitude de leurs prévisions augmente souvent lors de fluctuations rapides du stockage, ce qui limite leur fiabilité opérationnelle en période de sécheresse. Cette étude propose un cadre de modélisation intégré combinant la prévision du stockage fondée sur l'apprentissage automatique, la correction des résidus et une simulation opérationnelle fondée sur la dynamique des systèmes (SD), en vue d'une gestion adaptative de la sécheresse dans les réservoirs

---

1 Ph.D. student, Department of Integrated Systems Engineering, Hankyong National University, Republic of Korea: mihye.yang@hknu.ac.kr

2 Professor, School of Social Safety and Systems Engineering, National Agricultural Water Research Center, Hankyong National University, Republic of Korea: wonho.nam@hknu.ac.kr

agricoles. Le cadre a été élaboré à partir de données de stockage des réservoirs à l'échelle décadaire (intervalle de 10 jours). Le modèle de prévision principal reposait sur un apprentissage d'ensemble par boosting de gradient afin de simuler la dynamique non linéaire du stockage, tandis que les erreurs de prévision corrélées dans le temps ont été corrigées au moyen d'un modèle auxiliaire fondé sur un réseau neuronal récurrent (RNN), entraîné sur des séquences de résidus décalés. Les trajectoires de stockage corrigées ont ensuite été couplées à un modèle SD afin d'évaluer des interventions opérationnelles fondées sur des seuils en conditions de sécheresse. Le stockage du réservoir a été représenté comme une variable d'état, et les scénarios d'intervention ont été simulés en ajustant les taux de diminution du stockage au moyen d'un coefficient de contrôle. Le cadre proposé a été appliqué au réservoir de Sinjeong, à Asan, en Corée du Sud. Les résultats montrent que le modèle hybride de boosting de gradient-LSTM a atteint une RMSE de prévision de 7,1 points de pourcentage pendant la saison d'irrigation 2024. Dans un scénario hypothétique de sécheresse sévère fondé sur les conditions de 2021, les simulations SD indiquent que des interventions amorcées au cours de la deuxième décennie de juillet pourraient réduire la baisse du stockage en fin de saison de 2,9 à 25,9 points de pourcentage, selon l'intensité de l'intervention ( $\alpha = 0,10-0,90$ ). Les résultats démontrent qu'une intervention précoce est nettement plus efficace qu'une réponse tardive, ce qui met en évidence le potentiel des cadres intégrant l'apprentissage automatique et la dynamique des systèmes pour l'exploitation adaptative des réservoirs agricoles vieillissants en période de sécheresse.

**Mots-clés :** Gestion des réservoirs agricoles; Apprentissage automatique hybride; Dynamique des systèmes; Prédiction du stockage des réservoirs; Fonctionnement adaptatif en cas de sécheresse; Aide à la décision.

## INTRODUCTION

Agricultural reservoirs play a critical role in sustaining irrigation water supply and ensuring agricultural productivity under increasingly variable hydroclimatic conditions. In many Asian monsoon regions, including South Korea, agricultural water management systems rely heavily on small- and medium-scale reservoirs constructed primarily during the mid-20th century. However, many of these reservoirs were originally designed under historical climate conditions that differ substantially from present-day hydrological regimes. In South Korea, more than 88% of agricultural reservoirs are over 50 years old, and their operational reliability is increasingly threatened by climate-driven variability in rainfall patterns, rising evaporative demand, and more frequent drought occurrences (KRC, 2025).

Recent drought events have demonstrated that conventional reservoir operation strategies based on fixed storage thresholds and empirical management experience are often insufficient to respond effectively to rapidly evolving water stress conditions. Reservoir storage can decline abruptly during periods of concentrated irrigation demand combined with insufficient rainfall recovery, particularly during the early-to-mid irrigation season. Under such conditions, delayed operational response may lead to severe late-season water shortages, reduced irrigation reliability, and increased vulnerability of agricultural production systems. Consequently, there is growing interest in predictive and adaptive reservoir operation frameworks capable of supporting proactive drought management rather than reactive emergency response.

Machine learning (ML) techniques have recently been widely applied to hydrological forecasting because of their ability to represent nonlinear relationships among climate, hydrological, and operational variables (Maier et al., 2014). In particular, gradient boosting algorithms such as XGBoost and LightGBM have demonstrated strong predictive capability in reservoir inflow forecasting, water level estimation, and storage prediction owing to their robustness and flexibility under complex nonlinear conditions. However, despite their predictive advantages, tree-based ML models possess important limitations when applied to sequential reservoir storage dynamics. Specifically, these models do not explicitly account for temporally correlated residual structures that evolve continuously across consecutive time steps. This limitation becomes particularly critical during rapid storage drawdown periods, when prediction uncertainty may increase substantially and compromise the identification of operational thresholds and appropriate intervention timing.

To overcome these limitations, hybrid modeling approaches that combine machine learning with temporal sequence-learning techniques have received increasing attention. Long Short-Term Memory (LSTM) networks are particularly effective for representing sequential dependencies and temporally correlated patterns in hydrological time series. By learning residual error structures from prior ML predictions, LSTM-based correction models can improve prediction stability under rapidly changing hydrological conditions. Nevertheless, most previous studies have primarily focused on improving forecast accuracy itself, while relatively limited attention has been given to how corrected forecasts can be directly linked to operational drought decision-making processes.

At the same time, System Dynamics (SD) modeling has been widely recognized as a useful framework for representing feedback structures, threshold behavior, and adaptive intervention processes in water resources management systems (Winz et al., 2009). SD approaches are particularly suitable for simulating operational responses under uncertain future conditions because they allow explicit representation of state-dependent intervention rules and management feedback mechanisms. Despite these advantages, the integration of machine learning-based reservoir forecasting with SD-based adaptive drought operation remains largely underexplored in agricultural reservoir management.

Therefore, this study proposes an integrated framework that combines: (1) gradient boosting-based ensemble reservoir storage prediction, (2) LSTM-based residual correction for temporally correlated prediction errors, and (3) SD-based operational intervention simulation for adaptive drought management. The proposed framework aims to bridge the gap between data-driven hydrological forecasting and operational reservoir decision support by linking corrected storage predictions with threshold-based intervention rules.

The framework was applied to the Sinjeong Reservoir in Asan, South Korea, using dekadal storage observations and historical drought characteristics. A severe drought intensification scenario based on the 2021 drought pattern was incorporated to evaluate the operational sensitivity of storage trajectories under different intervention intensities. Through this approach, the study seeks to provide a transferable methodology for integrating ML-based forecasting with adaptive operational decision-making in aging agricultural reservoir systems under increasing drought risk.

## **MATERIALS AND METHODS**

### **Study Area and Historical Drought Characteristics**

The Sinjeong reservoir, located in Eumbong-myeon, Asan-si, Chungcheongnam-do, South Korea, was selected as the case site. Completed in 1960, the reservoir has a total storage capacity of 133.7 thousand m<sup>3</sup> and an effective storage capacity of 132.2 thousand m<sup>3</sup>, serving an irrigated area of 31.0 ha with a watershed area of 80.0 ha. The reservoir is classified as a large-scale facility and is managed by Korea Rural Community Corporation (KRC).

Dekadal (ten-day interval) storage rate data were compiled for the irrigation season (May through September) spanning 1991–2024, yielding 15 dekadal observations per year. Daily precipitation records were obtained from the Cheonan Automated Synoptic Observing System (ASOS) station (Station No. 232, Korea Meteorological Administration), located approximately 27.9 km from the reservoir, and aggregated to the corresponding dekadal intervals. The dataset was split into a training period (1991–2023) and a holdout evaluation year (2024). Historical drought characteristics of the Sinjeong reservoir were analyzed over the training period to provide an empirical basis for scenario construction. Table 1 presents the ten most severe drought years ranked by annual minimum storage rate, and Table 2 presents the ten years ranked by mean dekadal storage change during the late June to late July period.

The late June to late July period (6-3 to 7-3 dekad) was selected as the stress period because it corresponds to the interval of greatest mean seasonal storage recovery under normal climatological conditions (mean  $\Delta S = +1.3$  to  $+8.1\%$  per dekad). Suppression of recovery during this period

therefore produces the most severe downstream storage deficit, making it the most operationally critical window for drought scenario analysis. The most extreme annual drought conditions were recorded in 2001 and 2000, when minimum storage rates fell to 22.4% and 29.8%, respectively (Table 1). However, the selection of the drought intensification scenario was based on period-specific behavior rather than annual minimum storage alone. As shown in Table 2, 2021 recorded the most severe storage depletion during the late June to late July period, with a mean dekadal storage change of -4.64%p, compared to the long-term mean of +5.07%p for the same period. The observed difference of 9.71%p between the mean seasonal trajectory and the 2021 pattern was therefore adopted as the stress factor in the SD simulation framework.

**Table 1.** Historical drought severity and dekadal storage decline characteristics at Sinjeong Reservoir (1991–2023)

| Year | Minimum storage rate (%) | Maximum dekadal storage decline (p) | Mean seasonal storage rate (%) | Mean late-June to late-July storage change (p) |
|------|--------------------------|-------------------------------------|--------------------------------|------------------------------------------------|
| 2021 | 22.4                     | -25.6                               | 59.9                           | -4.64                                          |
| 2000 | 29.8                     | -23.8                               | 57.6                           | +3.80                                          |
| 1997 | 33.4                     | -19.4                               | 61.6                           | +7.10                                          |
| 2007 | 36.0                     | -20.1                               | 54.5                           | +4.75                                          |
| 2012 | 39.0                     | -17.6                               | 71.8                           | +8.74                                          |
| 2008 | 47.0                     | -14.7                               | 64.1                           | +8.00                                          |
| 2022 | 48.5                     | -15.2                               | 75.1                           | +7.33                                          |
| 2015 | 51.9                     | -14.4                               | 68.4                           | +2.84                                          |
| 2014 | 53.8                     | -12.7                               | 76.3                           | +5.27                                          |

### Hybrid Gradient Boosting-Based Reservoir Storage Prediction

The primary reservoir storage prediction framework employed segment-specific machine learning models, with independently optimized algorithms assigned to distinct seasonal periods according to hydrological behavior characteristics observed during the irrigation season. Reservoir storage dynamics in agricultural systems are highly nonstationary because irrigation demand, rainfall recovery, evapotranspiration, and operational release patterns vary substantially throughout the growing season. Consequently, a single unified prediction model may not adequately capture the changing response relationships between meteorological forcing and reservoir storage conditions across all seasonal phases. To address this issue, the irrigation season was divided into four temporal segments, and the most suitable prediction algorithm for each segment was selected through comparative model evaluation. Specifically, LightGBM (Ke et al., 2017) was applied to Segment A (1st–2nd dekads of May), Gradient Boosting to Segment B (3rd dekad of May), Lasso regression to Segment C (1st dekad of June to 1st dekad of July), and XGBoost (Chen and Guestrin, 2016) to Segment D (2nd dekad of July to 3rd dekad of September). These models were selected because preliminary evaluation indicated that different algorithms exhibited varying predictive strengths depending on the seasonal storage response regime. Early irrigation-season segments were characterized by relatively stable storage conditions and gradual depletion, whereas mid-season periods showed rapid drawdown associated with concentrated irrigation demand and insufficient rainfall recovery. Late-season periods exhibited more complex recovery and fluctuation patterns associated with episodic rainfall events and reduced irrigation withdrawals.

Segment-specific input variables were selected using feature importance analysis to reflect temporal differences in storage response dynamics during the irrigation season. Input variables included antecedent storage conditions, cumulative rainfall variables (10-, 20-, and 30-day rainfall totals), rainfall anomalies, storage variability indicators, and reservoir physical characteristics such as effective storage capacity, watershed ratio, and drought frequency. Antecedent storage conditions were included to represent system memory effects, while cumulative rainfall and anomaly variables were

used to capture short- and medium-term hydrometeorological forcing conditions affecting storage variability. Rolling storage prediction was initialized using the observed storage rate during the first dekad of May. Thereafter, predicted storage values were recursively propagated throughout the irrigation season using scenario-based precipitation inputs. At each forecasting step, the predicted storage value from the previous dekad was reused as the initial condition for the subsequent prediction, thereby enabling continuous multi-step simulation of seasonal reservoir storage trajectories. This recursive prediction structure was adopted to emulate operational forecasting conditions in which future observed storage values are unavailable during real-time drought management.

The recursive forecasting framework also enabled direct linkage with subsequent drought intervention simulations under hypothetical drought intensification scenarios. Because operational drought decisions depend not only on current storage conditions but also on anticipated future depletion trajectories, the prediction model was designed to provide continuous seasonal storage evolution rather than isolated single-step forecasts.

### **LSTM-Based Residual Error Correction**

Although the gradient boosting-based prediction models effectively captured nonlinear relationships between hydrometeorological variables and reservoir storage behavior, the tree-based structure does not inherently represent temporal autocorrelation embedded within prediction residuals. This limitation becomes particularly important during periods of rapid storage depletion or abrupt recovery, when prediction errors may propagate sequentially across consecutive forecasting intervals. Under such conditions, even small prediction biases at earlier time steps may accumulate and substantially influence subsequent recursive storage forecasts.

To address this limitation, a residual correction module based on a Long Short-Term Memory (LSTM) network (Hochreiter and Schmidhuber, 1997) was incorporated into the prediction framework. LSTM networks are specifically designed to represent sequential dependencies and long-term temporal correlations in time-series data through gated memory structures. In the present framework, the LSTM model was used not to predict reservoir storage directly, but rather to learn the temporal evolution patterns of prediction residuals generated by the primary gradient boosting models.

The residual series was defined as the difference between observed and model-predicted storage values during the training period. Lagged residual sequences with a window length of four dekads were used as input to the LSTM network, enabling the model to learn sequential error propagation behavior associated with temporally evolving storage dynamics. The LSTM architecture consisted of two recurrent layers with a hidden dimension of 128 and a dropout rate of 0.2 to reduce overfitting risk. Early stopping based on validation RMSE (patience = 20 epochs) was applied during model training to improve generalization performance.

The estimated residual correction term generated by the LSTM model was subsequently added to the primary gradient boosting prediction to produce a refined reservoir storage trajectory. Through this structure, the hybrid framework combined the nonlinear predictive capability of gradient boosting algorithms with the temporal sequence-learning capability of LSTM networks. This hybridization improved prediction stability during dynamically changing hydrological conditions, particularly during rapid drawdown periods when recursive forecasting uncertainty tends to increase.

The residual correction framework was especially important for the subsequent System Dynamics intervention analysis because operational drought decisions are highly sensitive to threshold-crossing timing and storage depletion trajectories. By reducing temporally correlated prediction errors, the corrected storage trajectories provided a more stable basis for evaluating drought intervention timing and operational response intensity under severe drought scenarios.

## System Dynamics-Based Drought Intervention Simulation

To extend the predictive framework toward operational decision support, the corrected storage trajectory was linked to a conceptual SD-based intervention simulation framework implemented using a discrete difference equation:

$$S(t+1) = S(t) + \Delta S(t)$$

where  $S(t)$  denotes the reservoir storage rate at dekad  $t$ , and  $\Delta S(t)$  represents the storage change during the corresponding period.

Under drought intensification scenarios,  $\Delta S(t)$  was modified by applying an additional stress factor during the peak deficit period from late June to late July. The stress factor of 9.7%p per dekad was derived from the observed difference between the mean seasonal storage trajectory and the most severe drought year recorded at the study reservoir (2021).

When the predicted storage rate fell below a predefined critical threshold (52.8%), corresponding to 70% of the mean seasonal storage rate and consistent with the agricultural drought watch level, an operational intervention was triggered. The intervention effect was represented by a control coefficient  $\alpha$  that attenuated the storage decline rate:

$$\Delta S(t)_{\text{intervened}} = \Delta S(t) \times (1 - \alpha), \alpha \in \{0.10, 0.50, 0.90\}$$

The control coefficient  $\alpha$  represents the proportional reduction in net storage loss attributable to operational measures such as irrigation supply curtailment, emergency water allocation adjustment, or demand reduction following drought alert issuance. This formulation is consistent with the tiered drought response protocol used in Korean agricultural water management systems (Mun et al., 2022).

Three intervention intensity levels were evaluated to examine the sensitivity of post-intervention storage trajectories to operational response strength. This simplified SD-based framework enables comparative assessment of storage recovery behavior and intervention effectiveness under severe drought conditions.

## RESULTS AND DISCUSSION

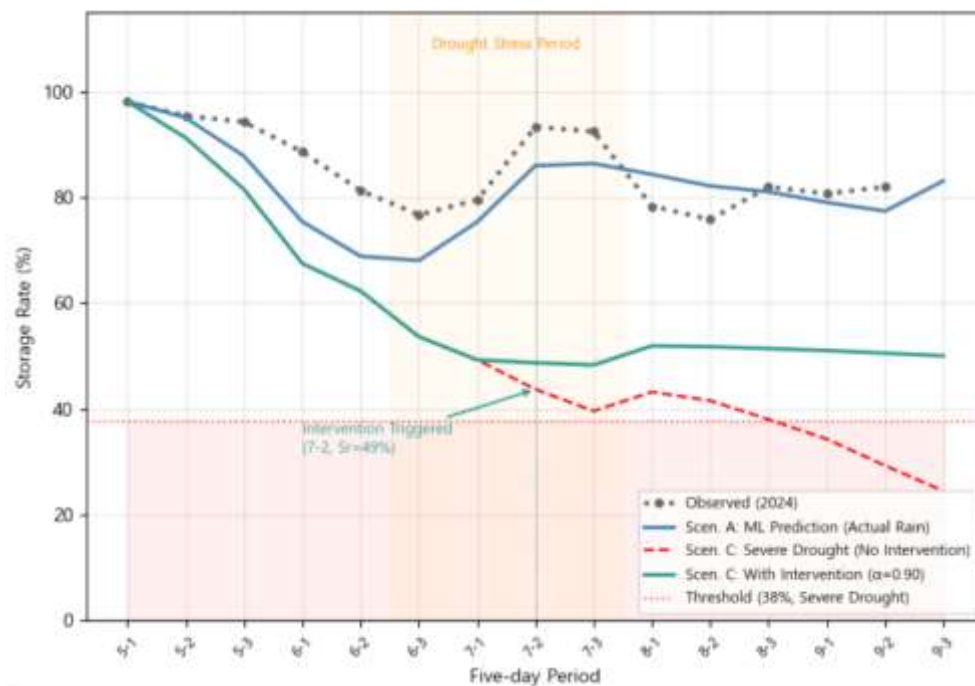
### Prediction Performance of the Hybrid Gradient Boosting–LSTM Model

The hybrid gradient boosting-LSTM model was evaluated against 2024 holdout observations using the actual precipitation record as input. The predicted storage trajectory closely tracked the observed seasonal pattern, capturing the early-season decline from approximately 98% in early May to a minimum near 68% in late June, followed by storage recovery from late July onward. The model achieved an overall RMSE of 7.13%p and MAE of 5.91%p over the 2024 irrigation season (Table 2).

Prediction errors were largest during the early-to-mid irrigation period (5-3 to 6-2, absolute error 8.6–13.2%p), coinciding with the period of rapid storage drawdown driven by peak irrigation demand and below-normal precipitation. Errors decreased substantially from the 1st dekad of July onward, as storage trajectories stabilized following concentrated rainfall inputs. The LSTM residual correction module contributed to reducing temporally persistent prediction biases during the rapid drawdown phase, improving alignment with observed values compared to the gradient boosting-only baseline. Figure 1 (left panel) illustrates the correspondence between the hybrid model prediction and the 2024 observations across the full irrigation season.

**Table 2.** Dekadal reservoir storage prediction performance of the hybrid gradient boosting-LSTM model during the 2024 irrigation season

| Dekadal period | Observed storage (%) | Predicted storage (%) | Prediction error (%p) | Absolute error (%p) |
|----------------|----------------------|-----------------------|-----------------------|---------------------|
| 5-1            | 98.0                 | 98.0                  | 0.00                  | 0.00                |
| 5-2            | 95.3                 | 95.0                  | -0.35                 | 0.35                |
| 5-3            | 94.2                 | 87.7                  | -6.45                 | 6.45                |
| 6-1            | 88.5                 | 75.4                  | -13.17                | 13.17               |
| 6-2            | 81.2                 | 68.8                  | -12.42                | 12.42               |
| 6-3            | 76.7                 | 68.0                  | -8.63                 | 8.63                |
| 7-1            | 79.5                 | 75.3                  | -4.17                 | 4.17                |
| 7-2            | 93.3                 | 85.9                  | -7.31                 | 7.31                |
| 7-3            | 92.4                 | 86.3                  | -6.06                 | 6.06                |
| 8-1            | 78.3                 | 84.3                  | +6.00                 | 6.00                |
| 8-2            | 75.8                 | 82.1                  | +6.33                 | 6.33                |
| 8-3            | 81.9                 | 81.0                  | -0.94                 | 0.94                |
| 9-1            | 80.6                 | 79.0                  | -1.64                 | 1.64                |
| 9-2            | 81.9                 | 77.4                  | -4.57                 | 4.57                |



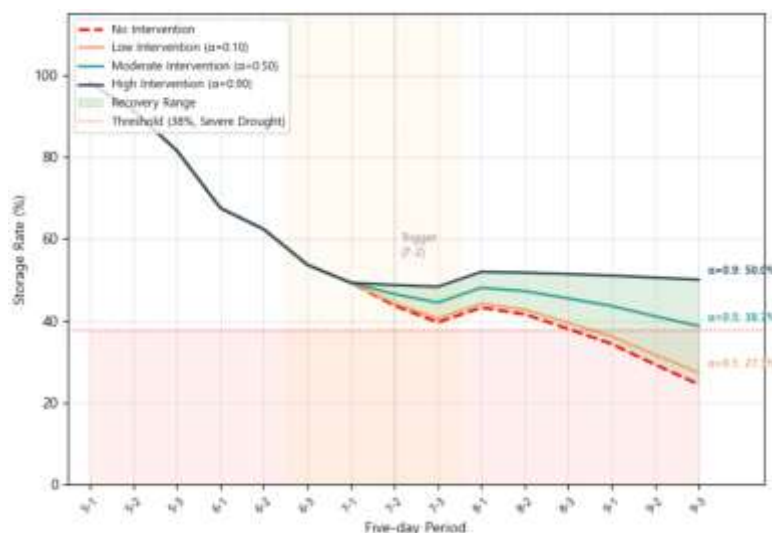
**Figure 1.** Observed and simulated reservoir storage trajectories under actual and severe drought scenarios at the Sinjeong Reservoir. The horizontal dotted line indicates the drought threshold (38%), and the vertical dashed line represents the intervention trigger timing during the second dekad of July.

## Implications for Adaptive Drought Operation in Agricultural Reservoirs

Under the actual precipitation conditions (Scenario A), the predicted storage rate remained above the drought watch threshold 52.8% throughout the irrigation season, indicating that operational intervention was not required. Although below-normal precipitation was observed during the early irrigation period (1st-2nd dekad of June, -19.5 and -33.7 mm below average, respectively), concentrated rainfall in the 1st dekad of July (+231.8 mm above average) facilitated rapid storage recovery, preventing threshold exceedance. Despite below-normal precipitation from early August through early September (-56 to -90 mm per dekad), the storage rate remained above the critical level through the end of the season.

To evaluate the framework under more severe conditions, a drought intensification scenario was constructed based on the most extreme drought year recorded at the study site (2021). The stress period was set from late June to late July, corresponding to the period during which rainfall normally facilitates storage recovery under mean climatological conditions (mean  $\Delta S = +2.4$  to  $+8.1\%$  per dekad). The scenario therefore represents a situation in which the expected summer seasonal rainfall fails to materialize, resulting in continued storage depletion during a period that would otherwise support recovery. An additional decline of  $9.7\%$  per dekad was applied during this period, derived from the observed difference between the mean seasonal storage trajectory and the 2021 drought year.

Without intervention, the simulated storage rate fell below the drought watch threshold (52.8%) at the 2nd dekad of July, reaching a minimum of 23.8% by late September. Upon threshold exceedance, the SD model triggered an operational intervention, attenuating subsequent storage decline according to the specified control coefficient  $\alpha$ . With low intervention intensity ( $\alpha=0.10$ ), the end-of-season storage rate increased from 23.8% to 26.7% (+2.9 percentage points). Moderate intervention ( $\alpha=0.50$ ) yielded a recovery to 38.2% (+14.4 percentage points), while high intervention ( $\alpha=0.90$ ) resulted in 49.7% (+25.9 percentage points) by late September. These results demonstrate a consistent and monotonic relationship between intervention intensity and storage recovery, with outcomes spanning approximately 23 percentage points across the three scenarios. Figure 1 illustrates the sensitivity of post-intervention storage trajectories to intervention intensity. The SD simulations demonstrated clear divergence in storage trajectories following intervention initiation, indicating that stronger intervention intensity substantially mitigated end-of-season storage depletion under severe drought conditions.



**Figure 2.** Simulated reservoir storage trajectories under different intervention intensities ( $\alpha = 0.10$ – $0.90$ ) during a severe drought scenario at the Sinjeong Reservoir. The horizontal dotted line indicates the drought threshold (38%), and the vertical dotted line represents the intervention trigger timing (second dekad of July).

## CONCLUSIONS

This study developed an integrated modeling framework combining gradient boosting-based ensemble prediction, LSTM residual correction, and System Dynamics (SD) simulation for adaptive drought operation of agricultural reservoirs. The proposed framework linked data-driven reservoir storage forecasting with threshold-based operational intervention analysis in a structured and interpretable manner, thereby providing a practical foundation for proactive drought management under increasingly variable hydroclimatic conditions.

Applied to the Sinjeong Reservoir in Asan, South Korea, the hybrid gradient boosting–LSTM model achieved a prediction RMSE of 7.13%p during the 2024 irrigation season. Prediction uncertainty increased during the rapid storage drawdown period (5-3 to 6-2), reflecting the difficulty of representing sequential depletion dynamics using tree-based models alone. This result highlights the importance of explicitly considering temporal error propagation in recursive reservoir forecasting systems, particularly during periods of concentrated irrigation demand and insufficient rainfall recovery. The LSTM residual correction module partially mitigated this limitation by learning temporally correlated error patterns from the residual sequence, thereby improving prediction stability during critical drought periods.

The SD simulation results demonstrated the operational significance of intervention timing and response intensity under severe drought conditions. Under the 2021 analogue drought scenario, reservoir storage declined below the drought watch threshold (52.8%) during the 2nd dekad of July, triggering operational intervention. Depending on intervention intensity ( $\alpha = 0.10\text{--}0.90$ ), end-of-season storage recovery ranged from 2.8 to 25.5 percentage points, demonstrating the substantial influence of supply adjustment decisions on late-season water availability. The simulations further indicated that stronger and earlier intervention consistently outperformed delayed or limited response, emphasizing the importance of proactive rather than reactive drought operation strategies.

The proposed framework also illustrates the potential value of integrating machine learning prediction systems with feedback-driven operational simulation models. While many previous studies have focused primarily on improving forecast accuracy itself, the present study extends the application of ML-based forecasting toward operational drought decision support by explicitly linking predicted storage trajectories with threshold-based intervention mechanisms. This integration enables not only prediction of future reservoir conditions, but also evaluation of alternative management responses under evolving drought stress conditions.

Several limitations should be acknowledged. The SD model employed a simplified storage balance structure and did not explicitly represent inflow processes, seepage losses, irrigation return flow, or spatially distributed water demand. In addition, the drought intensification scenario was constructed from historical observations rather than climate projection ensembles, and the intervention coefficient  $\alpha$  represents a conceptual proxy for operational response intensity rather than a field-calibrated management parameter. Future studies should incorporate physically based inflow modeling, ensemble climate projections, and empirically calibrated intervention functions to improve operational realism and transferability.

Despite these limitations, the proposed approach provides a transferable methodological foundation for integrating ML-based reservoir forecasting with adaptive operational decision support systems. As climate-driven drought risk continues to intensify, the framework developed in this study may contribute to the development of more resilient and adaptive agricultural water management strategies for aging reservoir systems in South Korea and other monsoon-dependent agricultural regions.

## ACKNOWLEDGMENTS

This work was supported by Korea Institute of Planning and Evaluation for Technology in Food, Agriculture, and Forestry (IPET) through Intelligent Agricultural Infra Management for Climate Change

Development Program, funded by Ministry of Agriculture, Food and Rural Affairs (MAFRA) (RS-2025-02219764)

## REFERENCES

- Chen, T. and C. Guestrin. 2016. XGBoost: A scalable tree boosting system. *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*. 785–794.
- Hochreiter, S. and J. Schmidhuber. 1997. Long short-term memory. *Neural Computation* 9(8): 1735–1780.
- Ke, G., Q. Meng, T. Finley, T. Wang, W. Chen, W. Ma, Q. Ye, and T.Y. Liu. 2017. LightGBM: A highly efficient gradient boosting decision tree. *Advances in Neural Information Processing Systems* 30: 3146–3154.
- Korea Rural Community Corporation (KRC). 2025. *Statistical Yearbook of Land and Water Development for Agriculture 2024*. Ministry of Food, Agriculture, Forestry and Fisheries and Korea Rural Community Corporation, Ansan, Korea.
- Maier, H.R., Z. Kapelan, J. Kasprzyk, J. Kollat, L.S. Matott, M.C. Cunha, G.C. Dandy, M.S. Gibbs, E. Keedwell, A. Marchi, A. Ostfeld, D. Savic, D.P. Solomatine, J.A. Vrugt, A.C. Zecchin, B.S. Minsker, E.J. Barbour, G. Kuczera, F. Pasha, A. Castelletti, M. Giuliani, and P.M. Reed. 2014. Evolutionary algorithms and other metaheuristics in water resources: Current status and future directions. *Environmental Modelling and Software* 62: 271–299.
- Mun, Y.S., W.H. Nam, S.B. Woo, H.J. Lee, M.H. Yang, J.S. Lee, and T.H. Ha. 2022. Improvement of drought operation criteria in agricultural reservoirs. *Journal of the Korean Society of Agricultural Engineers* 64(4): 11–20.
- Winz, I., G. Brierley, and S. Trowsdale. 2009. The use of system dynamics simulation in water resources management. *Water Resources Management* 23(7): 1301–1323.