

Response to Reviewer 3 Comments

We sincerely thank the reviewer for the thorough and constructive comments. The suggestions have significantly improved the clarity, rigor, and overall quality of the manuscript. All comments have been carefully addressed, and the manuscript has been revised accordingly. Detailed responses are provided below.

Comments 1: This manuscript proposes an integrated framework combining the Switch Prediction Method (SPM), ensemble rainfall forecasts, and machine learning models (SVM and LSTM) for 72-hour reservoir inflow forecasting during typhoon events. The topic is relevant to reservoir operation and flood management, and the manuscript is generally well organized.

However, the reviewer finds that the inclusion of only two machine learning models does not provide a sufficiently comprehensive evaluation of the proposed framework. Given the significant developments in deep learning and transformer-based forecasting methods in recent years, the authors should better position their work within the current state of the art and clarify the advantages, limitations, and potential competitiveness of the proposed framework relative to more advanced architectures.

Response 1: Thank you for this valuable comment. We agree that transformer-based architectures and other advanced deep learning approaches have shown promising performance in recent hydrological forecasting studies. To address this concern, we have revised the manuscript to better position the proposed framework within the current state-of-the-art.

Specifically, the Introduction has been revised to clarify that the primary objective of this study is not to identify the best-performing forecasting architecture, but rather to evaluate the effectiveness of the proposed Switch Prediction Method (SPM) for improving rainfall forecast inputs and enhancing long lead-time reservoir inflow forecasting. Therefore, two representative machine learning models, namely SVM and LSTM, were selected to represent conventional machine learning and deep learning approaches, respectively.

In addition, Section 2.2.2 has been expanded to explain the rationale behind the selection of these models. By demonstrating the effectiveness of SPM using both SVM and LSTM, the proposed framework can be evaluated independently of a specific prediction architecture, thereby highlighting its applicability across different modeling paradigms and its model-independent benefits.

Furthermore, the Discussion and Future Directions sections have been revised to discuss the limitations of the current study and the potential integration of transformer-based architectures and other advanced deep learning models within the proposed SPM framework. Such investigations may further evaluate the scalability and applicability of the framework under larger datasets and more complex forecasting scenarios.

These revisions better clarify the advantages, limitations, and future competitiveness of the

proposed framework relative to recent forecasting architectures.

Revision location: Introduction; Section 2.2.2; Section 4.4.

Comments 2: Line 121: The study was conducted using only 18 instances of typhoons from one reservoir catchment. Although the forecasts generated were impressive, it is challenging to determine how effective the developed framework would be if applied in a different hydrologic environment. It is essential for the authors to highlight the shortcomings of the available data and present more supportive evidence if possible.

Response 2: Thank you for this important comment. We acknowledge that the study was conducted using 18 typhoon events from a single reservoir watershed, which may limit the generalizability of the proposed framework to other hydrological environments.

The study area was selected because the operational ensemble rainfall forecast products required for this research were only available for the ShihMen Reservoir watershed. These forecasting datasets were obtained through a dedicated research collaboration and provided a valuable opportunity to evaluate the proposed framework using real-world operational forecast products. However, the availability of these datasets also constrained the present study to a single watershed and limited the possibility of conducting a broader cross-basin evaluation.

To address this concern, we have expanded the discussion of research limitations in Section 4.4. The revised manuscript now explicitly states that only 18 typhoon events were available for model development and evaluation, which may not fully represent the range of hydrometeorological variability encountered in different climatic and watershed settings. We also acknowledge that the use of a single reservoir watershed limits the ability to assess the framework under diverse hydrological conditions.

Furthermore, future research directions have been expanded to emphasize the need for validation across multiple basins with different climatic, topographic, and hydrological characteristics. Such investigations will be essential for evaluating the robustness and broader applicability of the proposed framework under different hydrological environments.

We believe these revisions provide a clearer discussion of the limitations associated with the available dataset and better define the scope of the current study.

Revision location: Section 4.4 (Research limitations and future directions).

Comments 3: Lines 263-267: Describe the use of grid search for parameter optimization. However, the manuscript does not provide sufficient details regarding the search ranges, validation procedure, or total number of parameter combinations evaluated. Without such information, the study is difficult to reproduce. The reviewer recommends expanding the methodological description.

Response 3: Thank you for this valuable suggestion. We agree that additional information regarding the parameter optimization process is necessary to improve the reproducibility of the study.

To address this concern, we have substantially expanded the description of the grid-search procedure in Section 3.1. The revised manuscript now provides a detailed explanation of how both model inputs and hyperparameters were optimized. Specifically, we clarify that the lag lengths of rainfall (L_R) and reservoir inflow (L_Q) were jointly optimized with the machine learning hyperparameters using a systematic grid-search procedure.

In addition, Table 4 has been revised to explicitly present both the hyperparameter search ranges and the resulting optimal hyperparameter settings for the SVM and LSTM models. The search ranges considered for kernel functions, Gamma, Cost, Epsilon, hidden-layer structures, activation functions, optimizers, batch sizes, dropout rates, and training epochs are now provided. We also clarify that model performance for each candidate parameter combination was evaluated using a validation subset extracted from the training dataset, and the parameter set yielding the lowest validation error was selected. Once the optimal parameter combination was identified, it was fixed and subsequently applied during the testing phase.

These revisions improve the transparency, reproducibility, and clarity of the parameter optimization procedure.

Revision location: Section 3.1 and Table 4.