Dear Editor,

Thank you for the opportunity to revise our manuscript for a final editorial assessment. We have carefully considered the reviewer's remaining concerns, which we believe mainly stem from an incomplete understanding of the inflow data, model design, and scope of our experiments. We have therefore provided additional evidence, conducted a new benchmark experiment, and made further clarifications. Our responses focus on four main points:

Potential information leakage. The reviewer's argument confuses a mathematical relationship with the recoverability of observed release. Reconstructed net inflow alone cannot determine observed release without the observed storage increment, which is not provided to the model but instead simulated internally (**Response #1**). Our new benchmark experiment further demonstrates that the same net inflow can lead to substantially different storage simulation performance (**Response #4**).

The ResOpsUS dataset. A closer examination reveals that many of these records are themselves derived from observed storage changes and releases through water-balance calculation, as documented by USACE and USBR. Our direct comparison of 175 reservoirs further shows high agreement between ResOpsUS inflows and the reconstructed net inflows used in our study. Indeed, water-balance-derived net inflow has been widely used in previous reservoir-operation modeling studies. Thus, the ResOpsUS dataset does not provide the independent forcing assumed by the reviewer. (**Response #3**)

Scope of model transferability. Our experiments assess transferability to unseen reservoirs without site-specific training, under prescribed historical net-inflow forcing. We have explicitly clarified this scope, changed the term "under data scarcity" in the title to "without site-specific training", and revised the relevant statements throughout the manuscript (**Response #2**). Evaluation under independently simulated hydrological forcing remains a direction for future research.

Contribution of physics encoding. The reviewer incorrectly assumes that physical constraints should reduce release accuracy in exchange for improved storage simulation. In fact, previous hydrological studies have demonstrated that incorporating physical knowledge can improve predictive accuracy and spatial generalization. Our new benchmark results are consistent with these findings, showing improvements in both release and storage simulation (**Responses #4 and #5**).

We believe that our additional analyses and clarifications have adequately

addressed the reviewer's remaining concerns and further strengthened the manuscript. We hope that the revised manuscript can now be considered favorably for publication.

Thank you for your time and consideration.

Sincerely,

Yi Zheng, on behalf of all authors

Response to Reviewer #4's comments

I thank the authors for the detailed response as they have correctly addressed most of my comments (i.e., Eqs S8, normalization, storage feedback). However, my primary concern about the use of the net inflows remains in this revised version.

The mechanism I intended to raise is separate from the one analyzed in Text S4. In addition to entering the mass balance, $Inet,t$ is supplied to the network as a dynamic input (Table 1, which should list 'Net Inflows' rather than 'Inflows'). I know the authors claim that PLSTM is not tied to net inflows, but I return to this point later in my review.

Since $Inet,t=(St+1obs-Stobs)+Rtobs$, the observed release at the same timestep is recoverable from that input up to the storage increment, and a model trained to minimize release loss has a direct incentive to recover it. Small release errors then imply small storage errors through the authors' own Eq. (S20). Text S4 concerns the storage-error propagation but does not address what the network can learn from its inputs.

I accept that net inflow is not a requirement of the framework in principle. My concern is that, in the experiments reported, it plausibly accounts for a substantial share of the performance, and this has not been tested. I agree that one hydrological model could supply time series of net inflows. However, hydrology models that can predict net inflow are uncommon, and difficult to calibrate given the lack of observations of the additional components involved (e.g., reservoir evaporation, losses, unaccounted withdrawals from the reservoirs and so on).

The authors' statement that their observation-closed residual net inflows can be replaced by a host model waves away from the difficulty the framework is meant to address. An observation-closed residual is not the same quantity as a net inflow supplied either by a host model or an offline model: it has its own error structure and

does not contain the observed release as a component.

The authors referred to their previous works to support their current approach, in particular Yu et al. (2025). I have read Yu et al. (2025) and found the context of this study to be very different. Because that model is not constrained to close the mass balance across the watershed, the simulated inflows are free to adjust to whatever the reservoir module needs in order to reproduce the observed releases. Note also that simulated storage does not enter the loss function in Yu et al. (2025). The cited work therefore does not demonstrate that the present framework performs comparably when driven by an independently derived inflow. Obtaining a net inflows time series offline (i.e., produced by a hydrology model calibrated or trained independently of the reservoir module) is likely even harder, since a model calibrated in that way has no observed release series to constrain it.

Response #1:

First, the reviewer's concern about information leakage appears to confuse the mathematical relationship between net inflow and observed release, $R_t^{obs} = I_{net,t}^{rec} - (S_{t+1}^{obs} - S_t^{obs})$, with the ability of the model to recover observed release. Reconstructed net inflow alone cannot determine observed release without the observed storage increment, which is not provided to PLSTM-Reg but is instead simulated internally by the model. A related point was also discussed by Ford and Sankarasubramanian (2023, Sect. 2.2.1).

Fundamentally, PLSTM-Reg learns reservoir operation behavior by predicting release based on reservoir inflow, other water gains and losses, and internally simulated storage states, rather than simply recovering observed release from reconstructed net inflow. The resulting storage is then updated through the embedded water balance, consistent with the sequence of reservoir operation decisions.

Regarding the distinction between net inflow and river inflow, reconstructed net inflow includes river inflow together with other reservoir water gains and losses, such as precipitation, evaporation, and seepage. Under normal conditions, these additional water gains and losses are often assumed to be small relative to river inflow and are therefore neglected in many previous studies (Hou et al., 2022; Liu et al., 2016; Salwey et al., 2024; Song et al., 2022; Xu et al., 2015). Water-balance-derived inflow is also commonly used by reservoir operating agencies, as further explained in **Response #3**.

More importantly, previous studies have shown that LSTM-based models can accurately predict reservoir release using independently derived inflow (Gangrade et al., 2022; He et al., 2026; Longyang and Zeng, 2023; Yu et al., 2025; Zhang et al.,

2018). The greater challenge is long-term storage simulation, where even small release errors can accumulate over time and lead to large storage errors. This is why our previous response focused on storage-error propagation in Text S4. Our new benchmark experiment further supports this point: the standard LSTM achieves reasonably good release accuracy but performs poorly in storage simulation, while PLSTM-Reg performs well in both (see **Response #4**).

Finally, regarding Yu et al. (2025), the reviewer overlooks its separately trained experiments (P-LSTM^0(AK + DJK); Fig. 3d), in which PLSTM achieved NSE values of 0.75 and 0.67 for the two study reservoirs using independently simulated hydrological inflow (Table S4), without adjusting the watershed model to reproduce reservoir releases. Using observed inflow further increased the NSE values to 0.81 and 0.75, respectively.

We have added further clarification in **Section 4.2** regarding the use of reconstructed historical net inflow in the present study. The revised text (**lines 509–517**) reads:

"*In the present large-sample experiments, we used reconstructed historical net inflow (Chen et al., 2025; Section 2.1) to provide consistent water-balance forcing and isolate the evaluation of reservoir-operation modeling from uncertainties in inflow measurement or simulation. This net inflow does not mathematically constrain simulated storage to follow observations; storage errors still accumulate from release errors (see Supplementary Text S4 for details). The PLSTM-Reg architecture does not require reconstructed net inflow as input. When coupled with large-scale hydrological models, PLSTM-Reg can use simulated reservoir inflow, with other water gains and losses accounted for where necessary. Further evaluation under independently simulated hydrological forcing would help quantify its performance in such applications.*"

We have also expanded Section 2.1 to provide additional evidence for the common use of water-balance-derived inflow in previous reservoir studies and by reservoir operating agencies (see **Response #3**).

The revised scoping of "data scarcity" is inappropriate given the importance it takes in this research: the title itself suggests the model is designed to tackle data-scarce region. However, training a model using net inflows derived from historical operations as input does not qualify as such. I asked the authors to confirm explicitly how net inflow was obtained for the held-out reservoirs in Experiments III and IV. The response defines data scarcity as the absence of operational records rather than of forcing, but $Inet$ at a held-out reservoir is computed from that reservoir's own observed storage and release, the records stipulated to be unavailable. The forcing is a

function of the withheld data. In my view, this dependence likely explains a large part of the report out-of-sample performance. Again, the authors pushed back claiming that using hydrology model simulating net inflows could be used, and I agree with this statement, with the caveat I mentioned above. Net inflows models are difficult to calibrate and validate, and their simulation is not the same as an observation closed residual. If the authors are convinced that hydrology simulations of net inflows would provide similar performance, I certainly encourage them to demonstrate this claim.

Response #2:

The reviewer does not clearly distinguish between spatial hold-out validation and the availability of hydrological forcing in practical applications. In Experiments III to V, the held-out reservoirs were excluded from regional-model training to assess transferability to unseen reservoirs without site-specific training. Reconstructed historical net inflow was used in all experiments to provide consistent hydrological forcing and avoid introducing additional uncertainties from hydrological simulations, particularly in evaluating long-term storage simulation. In practical applications, inflow can be supplied by hydrological models, as discussed in **Response #1**. The use of reconstructed net inflow therefore does not invalidate the spatial hold-out experiments. The reviewer's concern about its potential influence on model performance is also addressed in **Responses #1 and #4**.

To better reflect the scope of our experiments and avoid ambiguity about data scarcity, we have revised the title and relevant statements in the manuscript.

First, the revised **title** reads: "*PLSTM-Reg v1.0: A regional physics-encoded LSTM model for simulating reservoir operations without site-specific training*".

In the last paragraph of the **Introduction** (**lines 94–96**), we revised the study objective as follows: "*This study aims to leverage knowledge learned across many reservoirs to improve reservoir-operation simulation and its transferability to unseen reservoirs without site-specific model training.*"

In **Table 1**, we retained "Inflow" as the general input variable and added the following note: "*In all five experiments, inflow refers to reconstructed historical net inflow (Chen et al., 2025; Section 2.1).*"

Finally, in the **Conclusions** (**lines 551–555**), we revised the interpretation of the spatial generalization results as follows: "*This result indicates that …, providing a more reliable basis for reservoir-operation simulation at unseen reservoirs without site-specific model training.*"

In a new paragraph in Section 4.2, the authors mentioned that "In the present large

sample experiments, we used the net inflow provided by Chen et al. (2025) because consistent long-term inflow records are unavailable across the evaluated reservoirs." This is not accurate. The ResOpsUS dataset provides such a dataset (Steyaert al. 2022). In ResOpsUS dataset, 241, 158, 94 and 48 reservoirs have respectively at least 10, 20, 30 or 50 years of continuous time series of inflows, outflow and storage. Note that ResOpsUS was used by Chen et al. (2025), in addition to Li et al. (2024), to create the net inflows dataset used in this study. Chen et al. (2025) selected reservoirs with at least 25 years of data, which leaves over 120 reservoirs with continuous inflows, outflows and storage.

Steyaert, J.C., Condon, L.E., W.D. Turner, S., Voisin, N., 2022. ResOpsUS, a dataset of historical reservoir operations in the contiguous United States. Sci. Data 9. https://doi.org/10.1038/s41597-022-01134-7

Li, D., Chen, Y., Lyu, L., & Cai, X. (2024). Uncovering historical reservoir operation rules and patterns: Insights from 452 large reservoirs in the contiguous United States. Water Resources Research, 60(8), e2023WR036686. https://doi.org/10.1029/2023WR036686

Something the authors fail to discuss in their manuscript is that using net inflows input other than the observed-closed residual used in this study is likely to yield significantly lower performance than advertised here. This is a very important issue this revision has not addressed. Along those lines, I find it very misleading that all elements in the abstract, discussion and conclusion sections gloss over the difficulty at i) obtaining net inflows that are not derived from operational records and ii) applying PLSTM with forcings that do not embed the target variables.

Response #3:

The reviewer suggests that ResOpsUS provides independent inflow records suitable for the requested validation. However, this overlooks how reservoir inflow records are commonly generated. Official documentation from the U.S. Army Corps of Engineers (USACE) and the U.S. Bureau of Reclamation (USBR) confirms that many agency-reported inflows are calculated from observed storage changes and releases through water balance, rather than independently measured (USACE, 2015, 2017a, b, 2023; USBR, 2001, 2020, 2026).

We also directly compared the original inflow records in ResOpsUS with the reconstructed net inflows used in our study for 175 overlapping reservoirs. The two datasets show high agreement (see Fig. R1 below), with median NSE value of 0.99. Together with the agency documentation, this strongly suggests that many ResOpsUS inflow records are themselves water-balance-derived and therefore do not provide the

independent hydrological forcing assumed by the reviewer.

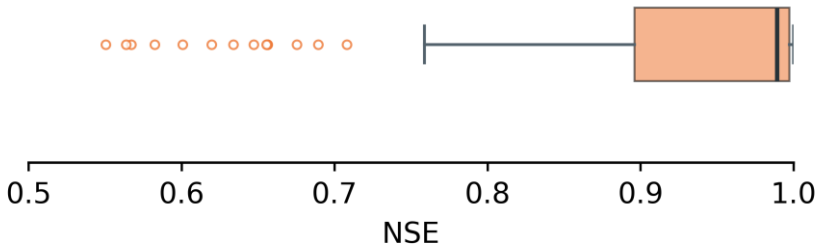


Figure R1. Boxplot of NSE comparing net inflows calculated from storage changes and releases with inflows reported in ResOpsUS for 175 reservoirs. The box spans the 25th–75th percentiles, and the line inside indicates the median. Whiskers extend to the most extreme values within 1.5 times the interquartile range of the box; circles indicate values beyond the whiskers. Nearly 75% of the reservoirs have NSE values above 0.9. NSE values below 0.5 (8.6% of reservoirs) fall outside the displayed range.

Moreover, reconstructing net inflow from observed storage changes and releases is a common practice in reservoir-operation modeling (Ford and Sankarasubramanian, 2023; Li et al., 2024; Liu and He, 2023; Sadki et al., 2023), although net inflow is referred to as "inflow" in some of these studies. Thus, our use of reconstructed net inflow is consistent with established research practice.

We have expanded Section 2.1 to clarify the source and nature of the inflow data and to provide supporting references. The revised text (**lines 116–126**) reads: "*Chen et al. (2025) provide reconstructed net inflow from observed storage and release through water balance, which approximates actual inflow when other water gains and losses are small. This approach is widely used in reservoir-operation studies (Ford and Sankarasubramanian, 2023; Li et al., 2024; Sadki et al., 2023; Zheng et al., 2025) and by reservoir operating agencies. Official documentation from the U.S. Army Corps of Engineers (USACE) and the U.S. Bureau of Reclamation (USBR) describes the calculation of reservoir inflow from storage changes and releases, with additional corrections where appropriate (USACE, 2015, 2017a, b, 2023, 2024, 2025; USBR, 2001, 2020, 2026). ResOpsUS (Steyaert et al., 2022) compiles inflow records largely from these agencies, many of which are therefore not independent of observed reservoir operations. We used the reconstructed net inflow from Chen et al. (2025) to provide consistent water-balance forcing for evaluating reservoir-operation models, particularly for long-term storage simulation.*"

Last, regarding the Figure R1: what I asked for was a baseline in which the physical

knowledge layer is disconnected: a standard LSTM taking the same input as PLSTM (i.e., net inflow and the meteorological forcings as inputs) and predicting release only, with no storage input and no storage correction during the run. Storage is then reconstructed offline by integrating the water balance from the simulated release series. The description given for LSTM-AR does not allow me to determine how close it is to this. It is not stated whether net inflow was retained as an input, whether the storage supplied during training was observed or simulated, or whether any bound was applied to storage at inference. These details determine what the comparison shows, and I would ask that they be specified.

Response #4:

We have conducted a new benchmark experiment following the reviewer's requested configuration. A standard LSTM was trained to predict release using the same reconstructed net inflow, meteorological inputs, and static reservoir attributes as PLSTM-Reg, without storage input, storage feedback, or physical constraints. Storage was then calculated offline through the water balance using predicted release and reconstructed net inflow, starting from observed initial storage, without any clipping or correction. The same initial storage was used for PLSTM-Reg. Both models were evaluated on the same 256 held-out reservoirs using five-fold spatial cross-validation.

The standard LSTM achieved a median release KGE of 0.69, compared with 0.73 for PLSTM-Reg. However, its median storage KGE was -4.83, compared with 0.60 for PLSTM-Reg (see Fig. R2 below). The median absolute release PBIAS was also substantially higher (5.77% versus 0.19%), contributing to cumulative storage errors. These results demonstrate that using the same reconstructed net inflow does not guarantee accurate storage simulation and highlight the benefits of the physics-encoded framework.

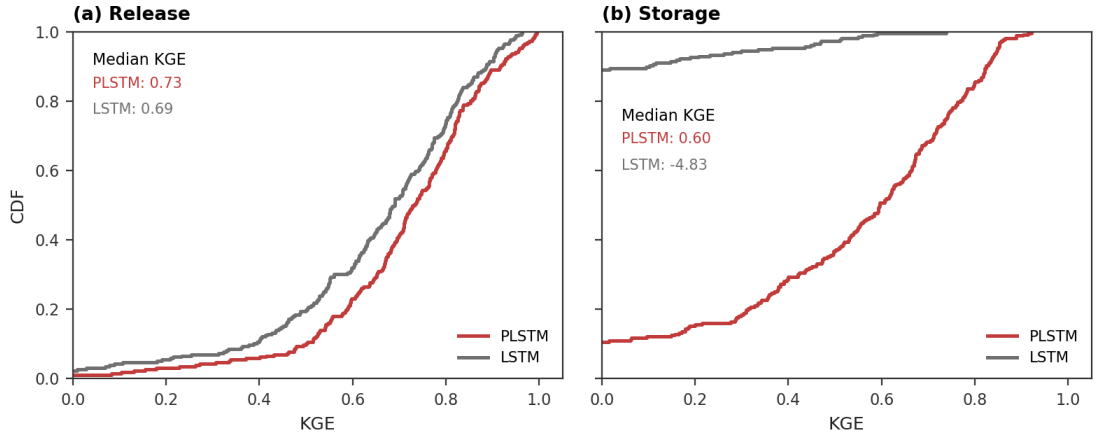


Figure R2. Comparison of PLSTM and a standard release-only LSTM baseline in the five-fold spatial cross-validation experiment. Cumulative distribution functions (CDFs)

show KGE for (a) release and (b) storage across the 256 held-out reservoirs. For visualization clarity, the horizontal axis is limited to KGE values between 0 and 1.

Setting that aside, the result itself is surprising. In PLSTM, the clamp in Eq. (S10) forces release to be recomputed through Eq. (S11) whenever the candidate storage would leave the physical bounds, so the emitted release is the one mass balance requires rather than the one the network would otherwise produce. A model carrying that correction should be *less* accurate on release than one optimizing release without it, and the expected signature of the physics encoding is therefore a modest loss in release accuracy purchasing a substantial gain in storage. Figure R1 instead shows PLSTM identical release medians, or even better, with a distribution that appears somewhat better across much of the range; and significantly better on storage. The physical knowledge layer appears to cost nothing anywhere, which is not what the mechanism predicts. I would ask the authors to explain what release accuracy the physical constraint costs in their framework, and why Fig. R1 does not show it.

Response #5:

The reviewer's assumption that physical constraints must reduce release accuracy to improve storage simulation is not necessarily valid, particularly in spatial generalization experiments. Previous hydrological studies have shown that incorporating physical knowledge can improve predictive accuracy and generalization to unseen locations (Feng et al., 2023, 2024; Mangukiya and Sharma, 2025; Song et al., 2026). More directly, Zheng et al. (2022) reported improved release prediction accuracy using a physics-guided reservoir LSTM compared with a conventional LSTM. These findings show that physical consistency and predictive accuracy are not necessarily competing objectives.

In PLSTM-Reg, physical constraints adjust release only when the candidate storage falls below zero or exceeds reservoir capacity (Eqs. S10–S11). Such corrections do not necessarily reduce release accuracy, as unconstrained release predictions may deviate further from observations. The constraints also prevent physically infeasible storage states from affecting subsequent predictions through recurrent feedback. Moreover, they are incorporated into end-to-end training rather than applied as post-processing, allowing the network to learn under these constraints. Therefore, improved physical consistency does not necessarily come at the expense of release accuracy.

To provide additional research context, we added the following sentence to the Introduction (**lines 79-81**): "*Previous research has also shown that incorporating*

physical constraints into reservoir LSTM models can improve release prediction accuracy (Zheng et al., 2022)."

To conclude, I find the framework novel and the regional learning approach genuinely promising, and I hope the authors continue in this direction. As presented, however, the manuscript does not meet the challenge named in its own title. The forcing contains the target variables, which a trained network can readily decode; the difficulty of obtaining a net inflow series without operational records is not acknowledged; and the claimed applicability to data-scarce reservoirs therefore rests on data those reservoirs would not have. Since resolving this requires re-running the central experiments with an independently derived inflow, the outcome of which would determine the paper's principal conclusions, I do not think it can be settled within the scope of a revision, and I recommend rejection. I would encourage the authors to resubmit once those experiments are complete: the ResOpsUS records identified above appear to make them feasible with the existing reservoir sample.

Response #6:

We appreciate the reviewer's recognition of the novelty and potential of our framework. However, we believe that the recommendation for rejection rests on several questionable assumptions about information leakage, the nature of the ResOpsUS inflow records, and the purpose of spatial hold-out validation. As demonstrated in our **Responses #1 to #5**, these assumptions do not justify dismissing the validity of our experiments or the contributions of the proposed framework.

Our additional benchmark experiment provides further evidence of the benefits of PLSTM-Reg, while our revisions clarify the experimental scope and the interpretation of model transferability. Evaluating the framework under independently simulated hydrological forcing is a valuable direction for future research (**Response #1**), but it is not a prerequisite for establishing the contributions demonstrated in the present study.

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