Diagnostic assessment of reservoir release policies using LSTM across the continental U.S.

Matthew Chen1, Jonathan D. Herman2

1 Department of Civil & Environmental Engineering, University of California, Davis

2 Department of Civil & Environmental Engineering, University of California, Davis

**Abstract**  
The influence of reservoirs on the water cycle introduces significant uncertainty for hydrologic prediction. The representation of reservoirs in hydrologic models ideally must be accurate, interpretable, and transferable across sites. Recent studies have highlighted the potential for data-driven methods, including long short-term memory (LSTM) networks, to accurately capture reservoir releases. However, the performance of LSTM models of reservoir releases has not yet been diagnosed on a large-sample dataset to understand their ability to generalize, and whether their accuracy is physically justified. This study evaluates the ability of LSTMs to represent reservoir release policies across the continental U.S., leveraging the recently developed ResOpsUS dataset. In particular, we focus on five key challenges to the development and application of LSTMs for this purpose: architecture selection, mass conservation, analysis of cell states, large-sample training, and nonstationarity in time.

We find that ...

Summary…

# Introduction

Reservoirs are critical infrastructure that balance human and environmental needs such as flood control (Boulange et al., 2021), water supply (Biemans et al., 2011), hydroelectricity, and environmental flows (Adams et al., 2017; Yin et al., 2014). However, because reservoir releases are managed to consider complex tradeoffs between multiple competing operating objectives, they are fundamentally dependent on human decisions and cannot be modeled as a physical hydrologic process (Longyang & Zeng, 2023; Yang et al., 2016). The role of reservoirs in altering surface flows is widely recognized (Nilsson et al., 2005; Zhou et al., 2016), and human intervention in the water cycle introduces significant uncertainty for hydrologic prediction (Thompson et al., 2013). Further, reservoirs are often represented simplistically in hydrologic models, which may not be able to capture realistic operating rules (Pokhrel et al., 2016). For example, Dang et al., (2020) found that the misrepresentation of dams results in erroneous parameterizations of hydrologic models. Further, Hodgkins et al., (2024) found that when reservoir storage was neglected in national-scale hydrologic models, their errors increase nonlinearly with reservoir storage.

The ideal approach to represent reservoir releases in hydrologic models would be to incorporate the control policies directly as they are defined by operating agencies. The desired storage-release-time of year relationships are traditionally defined by rule curves (Choi et al., 2020; Lund & Guzman, 1999). However, these rule curves are not always well-documented, and do not generalize across basins. It is also widely recognized that true release decisions, which require undocumented operator judgement to adapt to current conditions, constraints, and competing objectives, often deviate from these rules (Oliveira & Loucks, 1997). Given these challenges, alternative models of reservoir release policies have been developed in main categories: generic control policies, optimization methods, and data-driven policies. Generic control policies have low data requirements and are highly transferable, but may not accurately reproduce observed flows at fine temporal resolutions (Haddeland et al., 2006; Hanasaki et al., 2006). On the other hand, optimization methods seek to find optimal releases based on one or more operating objectives (Turner & Galelli, 2016). These methods can provide valuable decision support, although in simulation the predefined objectives and simplifying assumptions often fail to capture the complexity of real-world operating conditions (Giuliani et al., 2021). Finally, data driven methods infer operating policies directly from historical inflow, storage, and release records, such as calibrating the parameters of a generic policy or other functional form against observed data (Tefs et al., 2021; Turner et al., 2020; Yassin et al., 2019; Zhao et al., 2016). For example, Turner et al., (2020) found that such data driven policies are more accurate than generic policies where key parameters are set uniformly across reservoirs.

Within this category of data-driven control policies, several recent studies have highlighted the potential for fully empirical machine learning methods to accurately capture reservoir releases and outperform other data-driven methods (Coerver et al., 2018; Dong et al., 2023; Ehsani et al., 2016; Gangrade et al., 2022; Longyang & Zeng, 2023; Yang et al., 2016). Data-driven methods are supported by recent unprecedented high resolution reservoir datasets on a national scale (Hou et al., 2022; Steyaert et al., 2022), providing an opportunity to develop and analyze data driven reservoir models on large samples, much like the CAMELS dataset has done for rainfall-runoff modeling (cite). In particular, the widespread success of LSTMs in rainfall-runoff modeling (cite) holds promise for modeling reservoir releases: a model with explicit accumulation of one observable state should be able to capture release decisions, provided that the inputs align with relevant decision-making processes.

While LSTMs have been applied to models of reservoir releases, their performance has not been diagnosed on a large-sample dataset to understand their ability to generalize, and whether their accuracy is physically justified. This includes several steps with direct parallels in rainfall-runoff modeling: architecture selection (cite), analysis of cell states (cite), conservation of mass (cite), and large-sample pooled training (Kratzert et al., 2024). Training a data driven model on a standardized large sample of reservoirs captures a diverse range of operating conditions and strategies, and potentially enables the extrapolation of policies to data-scarce regions (Turner et al., 2021). However, it is not clear whether reservoir release policies, once trained, can generalize across basins in the same way as physical hydrologic processes. Further, the accuracy may depend on reservoir storage and other climate factors (cite). Finally, modeling reservoir releases raises the additional challenge of nonstationarity, as the operator preferences and the structure of the policy itself may change during the record (cite).

P6: This study contributes … incl research questions

# Methods

## Long Short-Term Memory Networks

Here we give a brief introduction to the Long Short-Term Memory (LSTM) architecture (Hochreiter & Schmidhuber, 1997). The LSTM model addresses the problem of unstable gradients in training recurrent neural networks by conserving long term information using memory cells managed by several gating mechanisms, which control the flow of information through element-wise matrix multiplication with gate values ranging between 0 and 1. These allow the model to learn temporal relationships and long-term dependencies. Further, the ability of the LSTM to dynamically accumulate information makes it a well-suited candidate to model dynamical systems (Jordan et al., 2021; Kratzert et al., 2019; Yu Wang, 2017) such as reservoir control. In a LSTM, every timestep has a hidden state and a memory cell state The cell states store and maintain long term information, where the information from the cell state can be released into the hidden state where it can be used for prediction. This flow of information is managed by the output gate. As new inputs arrive, the model can also save and remove information from the cell state, which are managed by the input gate and forget gate, respectively. For example, in the reservoir control problem, storage states can be modeled by memory cells, where mass accumulation is managed by the input and forget gates, and release decisions can then be modeled based on the accumulated storage and day of the year, as managed by the output gate. Note that a LSTM architecture does not conserve mass unless explicitly tailored to do so.

The gate values at each timestep depend on the previous hidden state and the new input while the sigmoid function enforces that the gates values are between 0 and 1. The forget gate, , parameterized by the weight matrices , , and , controls what information is perpetuated versus forgotten from the previous cell state (Eq. 1).

Meanwhile, the input gate, , controls the information flow from the new input into the cell state. This gate is parameterized by the weight matrices , , and (Eq. 2).

Finally, the output gate, controls information flow from the cell state to the hidden state to make a prediction at the current timestep. This gate is parameterized by the weight matrices , , and (Eq. 3).

After the gate values are computed, a candidate cell state update is computed from the previous hidden state and data input from the current timestep using a *tanh* activation function (Eq. 4).

The cell state is then updated based on the values of the forget and input gates (Eq. 5).

Finally, the hidden state is computed based on the value of the output gate, which is used to derive the final prediction (Eq. 6).

In Figure 1, the operations from Equations 1-6 are presented as a computational graph.

A diagram of a computer

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Figure . The LSTM architecture represented as a computational graph.

## Data Processing

Reservoir inflow, storage, and release data are drawn from two sources: ResOpsUS (Steyaert et al., 2022), which covers the majority of large reservoirs in the continental U.S. over the period 1980-2020 on a daily timestep; and longer records from the U.S. Bureau of Reclamation RISE system (1940s-present) to support more detailed modeling of specific reservoirs in the Western U.S. We filter the ResOpsUS data to only the reservoirs with records that are at least 90% complete record over 1980-2020, which leaves 119 reservoirs including 4 additional reservoirs from the U.S. Bureau of Reclamation (see Figure 2 map). In general, the reservoir data record including inflow and release timeseries are split into training, validation, and testing portions. The training portion, representing the first 60% of the available timeseries, is used directly for model training, i.e. optimizing model parameters to improve fit. The validation portion, representing the next 20% of the available record, is used for hyperparameter tuning, model selection, and early stopping. Early stopping is a technique that prevents overfitting by interrupting the training process based on the validation data as a proxy for out-of-sample performance (Li et al., 2019). The validation set provides some measure of out-of-sample performance, especially if the validation set is not overutilized in the modeling process (i.e. overfitting to validation or “data leaking”). Finally, the testing portion, representing the last 20% of the available data record, is used solely for the estimation of out-of-sample performance. The testing data is untouched throughout the model building process; however, it is also the furthest away from the training set in time. This may be a challenge if the reservoir operating policy has shifted in the meantime, a challenge we investigate later in the study.

A map of the united states

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Figure . Map of 119 study sites across the continental US. Reservoirs from the U.S. Bureau of Reclamation are highlighted in red, otherwise data is from the ResOpsUS dataset.

Prior to modeling, the data is linearly transformed to be zero mean and unit standard deviation, based on statistics from the training set. In early experiments, data normalization (scaling between 0 and 1) was also tested but provided little benefit over standardization. Additionally, while the majority of records are verified to be complete, missing values are imputed using the training mean. We also split the data into batches of 3 years (the batch sequence length was chosen between 0.5 and 5 years in preliminary testing). Using longer sequences allow the model to capture longer term dependencies but may incur difficulty training due to the vanishing or exploding gradients problem in the training process. That is, gradient magnitudes may become exponentially large or small over many steps of backpropagation through time.

## Model Selection and Hyperparameter Tuning

Model selection experiments are conducted on an individual reservoir (Shasta Reservoir, California) to compare model architectures, select optimal hyperparameters, and compare LSTM performance against other machine learning benchmarks. Shasta reservoir was chosen for its long data history and its representative degree of regulation (discussed in Section XX). It is computationally infeasible to tune hyperparameters using grid search for all 119 reservoirs in the dataset individually, so the model and hyperparameters selection done here are generally considered used throughout the study. While we recognize that optimal hyperparameters for Shasta Reservoir may not be optimal for a different reservoir, tuning to a specific reservoir will provide a general idea for the size of model necessary to capture reservoir operations. That is, we assume that reservoir operating policies across the continental US are somewhat similar in terms of their complexity, even if their operating purposes and typical release patterns differ.

Four main LSTM architectures along with several other machine learning benchmarks are considered (Figure 3) . Since we are interested in the ability of the LSTM to learn to conserve mass and learn reservoir storages implicitly in its cell states, the modeling task is to predict reservoir releases based only on two inputs, the inflow and the day of the year. By doing so, we assume that storage is primarily driven by inflow and outflow, and that this dominates other external effects such as evaporation and seepage. Model 1 is a standard LSTM model where data is first processed by an LSTM and then by a single layer feed-forward neural network to provide additional non-linear flexibility in learning the operating policy. Model 2 is similar to Model 1, but adopts an autoregressive structure in which the previous output is concatenated as an additional input for the current prediction.

For Model 3 and Model 4, we propose two alternative architectures that conserve mass and accumulate implied storage states internally. These models are inspired by the mass-conserving LSTM (MC-LSTM), which is a modified LSTM architecture where its memory states are true mass accumulators (Hoedt et al., 2021). Specifically, Model 3 explicitly models the mass balance for implied storages as an additional internal state and concatenates them as input so that we do not need to rely on the LSTM gating mechanisms to learn to conserve mass. Model 4 is similar to Model 3; except we discard the LSTM gating mechanisms entirely which results in a model resembling a mass-accumulating recurrent neural network (RNN). However, Model 4 is unable to capture longer-range dependencies through learned cell states beyond storage, unlike in Model 3. Since mass balance can be expressed explicitly for the reservoir control problem, these models require an order of magnitude less computational complexity compared to the MC-LSTM. All four models are trained using the square error loss function.

For hyperparameter tuning, we tune the model architecture details using exhaustive grid search. Specifically, we select the model with the optimal validation loss over a predefined grid of hyperparameters, averaging over 5 different random seeds to account for stochasticity in the optimization algorithm. We tune the number of LSTM layers (1 or 2), the size of the LSTM hidden layer (between 5 and 50), the hidden size of the feed-forward network (between 5 and 50), and the dropout regularization probability (0.3, 0.5, or 0.7). The LSTM experiments were conducted in the Pytorch deep learning library (Paszke et al., 2019). In training, model parameters were optimized using the Adam algorithm, a first-order stochastic gradient descent algorithm with momentum and strong empirical performance (Kingma & Ba, 2015).

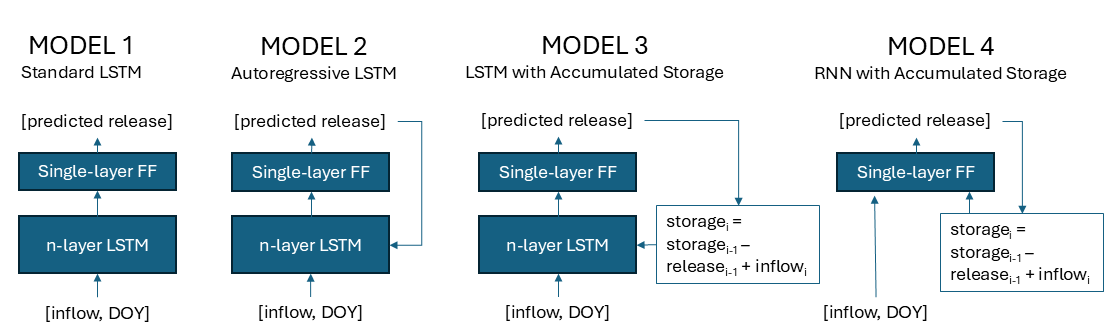


Figure 3. LSTM model architectures. “FF”: feed-forward neural network; “DOY”: day of the year.

## Machine Learning Benchmarks

As benchmarks for the LSTM model, we consider autoregressive linear and random forest models with 5 lags. Specifically, we model reservoir releases as a function of the current day of the year and inflow, as well as the previous 5 inflow values. We also consider benchmarks where the current observed storage is another data input, since the linear and random forest models cannot learn to preserve information over time unlike the LSTM architecture (these are denoted linear-S and random forest-S, respectively). This modeling problem is represented by Equation 7, where is the predicted target release at time , and are the inflow, storage, and day of year features, respectively.

These benchmark models, trained with square-error loss, are implemented in the open-source *scikit-learn* library (Pedregosa et al., 2011).

Since we are interested in the LSTM learning storage information implicitly, it is useful to also add a benchmark where observed storage is explicitly provided to the LSTM model. As such we also compare a version of Model 1 (denoted as Model 1-S) that is provided inflow, storage and the day of the year rather only inflow and day of the year.

## Model Diagnostics

Beyond model selection, we aim to diagnose the behavior of LSTM reservoir models, including assessing their physical interpretability, analyzing performance in large samples, and testing if learned policies are generalizable in space and time.

### Analysis of Cell States

We investigate whether a LSTM model of reservoir releases can learn storage representations in its memory cell states without being given storage data explicitly, with a larger goal to determine if such a model is physically interpretable. This is inspired by the success of LSTM in capturing hydrologic states such as snowpack in its memory cells without requiring snowpack data (Kratzert, Herrnegger, et al., 2019). Similar to Kratzert et al., (2019), we study the correlation coefficients between the memory cell states compared to observed storage, and visualize the timeseries of memory states with stronger relationships. The purpose of this analysis is to uncover if the LSTM manages to learn storage information (therefore conserving mass) in an interpretable way; the ideal would be a model that aligns with physical understanding of reservoir storage and release decisions.

Further analysis of the cell states is by applying dimensionality reduction, specifically Principal Components Analysis (PCA). PCA seeks to take linear combinations of the cell states into uncorrelated components that maximize the variances of the individual components. The goal is to study how the LSTM internal states interact with and respond to the input inflow and the output release, to interpret how decisions are made internally.

### Large Sample Individual Training

Next, we ask the question of how well the LSTM model and the benchmarks perform when trained individually to a large sample of reservoirs across the continental United States. Beyond understanding performance in a large sample, these results support analyses that explain conditions of where and how the models perform well. We use inflow and release records from the ResOps dataset (Steyaert et al., 2022), and filter for reservoirs where the record is at least 90% complete. For each reservoir selected, we conduct data processing as before, selecting 60% of the available record for training, 20% for validation, and the last 20% for testing.

### Model Performance vs. Degree of Regulation

Research has shown that LSTM runoff models perform worse on managed basins, particularly those with higher degrees of regulation (Ouyang et al., 2021). Consequently, we hypothesize that this result extends to reservoir models directly, i.e. higher degrees of regulation in a reservoir adversely affects performance. Specifically, we compare performance from the large sample of individually trained reservoirs against the ratio of mean inflow to maximum storage (a proxy for capacity), which represents (inversely) the degree of regulation. We then compute Pearson’s correlation coefficient between the LSTM performance and the degree of regulation. Statistical inference is done using randomization testing and Monte Carlo resampling, i.e. via permutation test, to determine the p-value against the null hypothesis of no correlation.

### Model Performance Over Time

While overfitting can lead to a downward shift between training set and out-of-sample performance, reservoir policies themselves may also change over time. Any difference between the out-of-sample and test distributions may cause a declining trend in performance. To understand this problem, we first train a new “initial” LSTM model for several example reservoirs with different degrees of regulation based on the first 30 years and validate on the next 10 years, and then analyze performance on rolling and sliding 20-year windows to capture how performance changes over time. Notably, this experiment is challenged by limited record lengths: the length of the initial training window is chosen so that the model can learn a reasonable representation of the operating policy while the moving window size is chosen to balance signal and noise. For this reason, we select four example reservoirs for this analysis with longer records available from the U.S. Bureau of Reclamation (Shasta, Trinity, Folsom, and New Melones, all in California). We also analyze the entire prediction timeseries for the select reservoirs with different degrees of regulation and plot predicted releases against observed releases for the entire record length. The goal is to further understand the influence of the degree of regulation, as well as to gain insight into the prediction behavior of the LSTM model.

### Large Sample Pooled Training

Finally, we test a top-down modeling approach, that is, learning a general model by training on all available data. To access the ability of a simultaneously trained LSTM reservoir policy to generalize, we randomly select 80% of ResOps reservoirs (where at least 80% of the data record is complete), pool and train on them simultaneously, and test out-of-sample performance using the remaining 20% of reservoirs. This is not to be confused with data splitting in time, where we train, validate, and test on the same reservoir. Here, out-of-sample testing is done on held out reservoirs, not held out time.

We also compare the test performance after fine-tuning the pooled model on individual reservoirs. Finetuning in this context refers to calibrating a pre-trained model to a specific reservoir by running additional training iterations from data unique to the reservoir of interest. This is related to the concept of transfer learning in the machine learning literature in which a pre-trained model trained on a large dataset can be adapted to improve performance for a potentially different task on a smaller dataset (Tan et al., 2018). The idea of “knowledge transfer” has shown to be successful in a variety of domains including image recognition (Iorga & Neagoe, 2019) and natural language processing (Ruder et al., 2019). In this case, we can train and validate (on a 75% training and 25% validation split, respectively) using 5-30 year subsets of the complete data record for the held-out reservoirs as the finetuning data, and finally test using the last 20% of the complete record so that results between finetuning, individual training, and the pooled training model are comparable. Note that validation scores here are not directly comparable since they vary in length depending on the amount of fine-tuning data used.

# Results

## Model Selection and Comparison to Benchmarks

Table 1 summarizes performance results for Models 1-4 trained on Shasta Reservoir, as well as its linear and random forest benchmarks, and models where storage is explicitly provided.

Table 1. Train, validation, and test scores for Models 1-4 and benchmark models. Models with observed storage as input are denoted with -S.

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From a model selection perspective and to prevent data leakage, we are interested in comparing validation scores so that the test data is completely withheld from the model building process; the test data can later be used for further analysis of model behavior (such as the behavior of cell states) and provide a final estimate for out-of-sample performance. Between Models 1-4, Model 1 (validation ) and Model 2 (validation ) both perform reasonably well and are essentially identical, however, we select Model 1 as the main LSTM architecture of interest going forward since Model 1 is more parsimonious and efficient to train. After running the hyperparameter tuning process with exhaustive grid search, we find the following optimal configuration for Model 1: 1 LSTM layer, 30 LSTM hidden units, 15 feed-forward hidden units, and a dropout probability of 0.3. Figure 4 provides a visualization of the hyperparameter tuning results. Note that smaller architectures, particularly with 5 LSTM or feed-forward hidden units, and higher dropout (0.7) are associated with higher validation error; tuning results are more uniform beyond these cases.

A diagram of a network

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Figure . Hyperparameter tuning of Model 1 on Shasta Reservoir

In validation, Model 1 out-performs the linear-S (validation ) and random forest-S (validation ) benchmark models, even though these benchmarks have observed storage as an input, and is nearly tied in performance with the rule based model. This highlights the advantage of LSTM to learn non-stationarities, long-term dependencies and non-linear temporal relationships compared to other machine learning architectures. However, Model 1 underperforms itself when observed storage is provided (Model 1-S, validation ). This shows that even if Model 1 learns to maintain internal information about storage over time, this information can be used suboptimally. This could be the case even when some information about storage is directly available. For example, Model 3 (validation ), which is a modified variant of Model 1 that maintains its own mass balance as an additional input, have implied storages that matches observed storages reasonably well, yet validation performance is lower than Model 1 where there is no explicit mass balance (See Supplemental Figure S1).

However, (validation ), which also maintains mass balance as input similar to Model 3, (implied storages for Model 4 also match observed storages reasonably well). This may be because and is therefore more parsimonious. Specifically, after tuning, Model 4 has roughly 40% fewer parameters than Model 1. This result highlights the potential for physics-informed machine learning to promote model parsimony and interpretability (De La Fuente et al., 2024), in this case by enforcing mass balance manually rather than relying on the LSTM to learn it.

Across all machine learning models, we observe severe declines in performance in the test period compared to the validation or training periods. For example, Models 1, 2, and 4 each show declines of 0.26 in between the validation and testing periods. This could be due to either poor generalization, policy changes over time, or a combination (this is further discussed in Section 3.5). Interestingly, some storage-driven machine learning models including Model 3, Model 1-S, and Random Forest-S have much lower declines in and perform better in the test period. The models that base release decisions directly on storage demonstrate improved long-term generalizability and robustness under future distributional shifts. In fact, the model with the least overfitting (and the best performance under the test data) is the physically driven rule-based model. Beyond simply access to storage state information, the rule based model makes decisions in a realistic manner (for example, hedging for water supply).

## Inspection of Cell States and Observed Storage

In this section, we compare the memory cell states of Model 1 trained on Shasta reservoir with observed storages to see if the model learns physically interpretable states internally. In the test data, six different cell states (XX %) have correlation coefficients with observed storage that are greater than or equal to in absolute value to 0.40, an arbitrarily chosen threshold, with values of 0.52, 0.50, 0.48, 0.46, 0.43, and -0.45, respectively. These states are scaled and plotted against observed storage for the testing dataset in Figure 5. We observe that in many cases, the memory cell states contain information about the seasonality of storages, but are only weakly correlated to the values of storages themselves. It is possible that storage values are represented through complex interactions of multiple different states, though unfortunately such a situation would not be directly interpretable. These results are consistent with the previous finding that performance is lower when storage is withheld from the LSTM (Table 1). Similar results are found for the cell states of Models 3 and 4 (Supplemental Figure XX).

A screenshot of a graph

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Figure . Comparison of cell states with high correlation (|| > 0.4) to observed storage.

While the cell states in Figure 5 are correlated with observed storage to varying degrees, they are also correlated with each other. We can also visualize the cell states by dimensionally reducing them using principal components analysis (PCA). Comparing the first three principal components of cell states to modeled predictions and inflow (Figure 6), we find that the cell states learn to decompose and store information about the magnitude and timing of release predictions, annual seasonal patterns, and the timing and magnitude of inflow peaks. Specifically, the peak behavior of the first principal component aligns with peak release predictions. The second principal component, while also influenced by outflow peaks occasionally, appears to focus more on annual seasonal patterns. Finally, the peak behavior of the third principal component aligns with inflow peaks. These factors are consistent with physical understanding of how reservoir release decisions are made, however, it is still unclear how storages are incorporated into release decisions, if at all.

A graph of different components

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Figure . First three principal components of LSTM cell states against inflow and predicted releases. The Pearson’s correlation coefficients between the selected principal component and observed inflow, observed storage, and predicted outflow are shown in the legend.

## Performance for Many Reservoirs

We extend our results to evaluate Model 1 performance when fitted individually to large sample of ResOps reservoirs (). Figure 7 shows the distribution of scores across the training, validation, and test sets. We find that in both validation and testing, Model 1 (validation median = 0.618) performs similarly to a random forest with observed storage (validation median = 0.612), while both significantly outperform the linear models (validation median = 0.376). Model 1-S, with observed storage inputs, has the highest performance (validation median = 0.712). These aggregate results are consistent with the model selection findings for Shasta reservoir, though the ranking may be different for individual reservoirs. We also observe large spreads of scores for each model, with high and low extreme values across reservoirs. For example, the interquartile range for Model 1 in validation is 0.357 with a maximum score of 0.978 and a minimum score of -1.656.

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Figure . Distribution of scores for Model 1 and selected benchmarks for n=116 reservoirs. Models with observed storage as input are denoted with -S.

Figure 8 shows with respect to geographic location, and we find no apparent spatial patterns. Climate and hydrologic factors alone do not appear to be a strong indicator of model performance.

A map of the united states

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Figure . Map of train, validation, and test scores for individually trained LSTMs

## Degree of Regulation and Model Performance

A lower degree of regulation may indicate shorter lag times between inflow and release, i.e., release predictions are more directly sensitive to inflow, leading to better model accuracy. Since we previously found large variances in performance across a large sample of reservoirs (Figure 7), this investigation helps explain why some reservoirs perform better than others. Figure 9 shows these results, plotting performances against the log ratio between mean inflow and max storage (a higher value of this ratio indicates a lower degree of regulation). We find that the Pearson correlation between scores and the degree of regulation to be 0.6, 0.59, and 0.49 for the training, validation, and test scores, respectively. Randomization testing shows that the correlation coefficients are significant at the 0.05 level, rejecting the null hypothesis of no correlation. These results provide strong evidence that model performance is adversely associated with increased degree of regulation more that climate and hydrology (Figure 8).

A graph of a model performance

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Figure . Train, validation, and test plotted against the log mean-inflow-max-storage ratio for individually trained LSTMs.

Four specific sites, Folsom (FOL), Shasta (SHA), Trinity (TRI), and New Melones (NM), are selected from the points in Figure 9 to represent different degrees of regulation, as measured by the log mean-inflow-max-storage ratio. Folsom represents the lowest degree of regulation, while Trinity and New Melones have higher degrees of regulation. Shasta reservoir falls in between. An additional factor in this choice of reservoirs is the availability of longer inflow records from the U.S. Bureau of Reclamation dating back to the construction of the reservoir, providing several additional decades prior to the ResOpsUS dataset. Figure 10 plots the predicted and observed releases for these four selected reservoirs using LSTM Model 1. Both Shasta and Folsom capture peak releases reasonably well, however, Shasta is more prone to false-positive peaks, which can be resolved by inputting observed storage (see Supplementary Materials Figure S2 for Model 1-S timeseries). This suggests that adding observed storage allows the Shasta model to learn better thresholding behavior and improve performance when predicting larger lags between inflow and release. Importantly, the model was unable to learn this optimally on its own. Folsom has a lower degree of regulation making it more sensitive to inflow patterns directly, which corresponds to higher performance. In contrast, New Melones and Trinity reservoirs have much lower performance corresponding to their high degree of regulation. While both learn reasonable seasonal releases, the models have largely ignored peak releases especially for Trinity reservoir. Adding observed storage to the model does not alleviate this behavior, which highlights peak releases that are not solely driven by flood protection. In all, these results complement the finding that the degree of regulation adversely affects model performance.

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Figure . Timeseries plots for predicted and observed releases for Shasta, Folsom, New Melones, and Trinity using Model 1

## Performance Over Time

The drop in performance between the train and test period may be explained partly by changes in the reservoir operating policy during that time. We investigate this question using an “initial model” trained on the first 30 years of record and validated on the next 10 years for the four selected reservoirs with longer records (Folsom, Shasta, New Melones, and Trinity). Figure 11 shows performance in 20-year rolling and sliding windows for these selected reservoirs. The initial model for Folsom shows an initial drop in performance apparent in the rolling windows, but then stabilizes. This behavior is expected with some degree of overfitting. In contrast, performance for Shasta continues to decline and does not stabilize. This is also consistent with declining train, validation, and test for the full Shasta model in Figure 10. In the sliding window plots, there is a clear decrease in slope in the out-of-sample region. This behavior is consistent with changing distributions between testing windows and the initial training window – supporting the hypothesis that changing operating policies are resulting in declining performance, which is further exacerbated by the initial overfitting. The trends for New Melones and Trinity are more difficult to interpret. New Melones has a much shorter record length, so it is difficult to distinguish between overfitting and shifting operating policy. The initial model for Trinity appears to be underfit, with very poor training performance but higher out-of-sample performance.

A graph of different types of windows

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Figure . 20-year rolling and sliding performance for initial models trained for Shasta and Folsom Reservoirs

Shasta, New Melones, and Trinity have higher degrees of regulation and may be more sensitive to changes in policy, while Folsom releases are more sensitive to inflows directly which make them less affected by changes to the operating policy. This conjecture is supported by a weak negative correlation () between the difference in train and test and the log mean-inflow-max-storage ratio. The result is statistically significant (, indicating that a higher degree of regulation corresponds to larger declines between the train and test performance (See Supplemental Figure S3). Overall, we find that declines in performance over time due to policy changes are location specific and related to the degree of regulation of each site. Here, we provide an approach to analyze this problem, provided that there is long enough of a data record to train an initial model and track performance over time meaningfully.

## Pooled Training and Finetuning

After training models to reservoirs individually, we answer the question of whether stronger results can be achieved by training on a pool of reservoirs simultaneously, and if transfer learning or finetuning can be leveraged to further improve performance. Figure 12 compares scores on the last 20% of record for out-of-sample (OOS) reservoirs, comparing individually trained models, the pooled model, as well as finetuning the pooled model with 5-30 years of data. Recall that the training and validation periods for each fine-tuning process do not align, although we can compare performance on the same testing period. The pooled model (median score of 0.343) performs significantly worse than training individually (median score of 0.567). This result confirms that given the feature space, we are unable to find a strong reservoir policy that generalizes across reservoirs. Introducing finetuning improves performance, although it does not improve on the individually trained models. This suggests that finetuning on the pooled model provides little additional knowledge compared to individual training. It may be possible to improve this result by pooling according to other reservoir characteristics, such as the operating purpose or hydrologic region. However, this result suggests that the generalization ability of LSTMs observed in rainfall-runoff modeling may not extend to models of reservoir release policies, as these tend to be location-specific.

A diagram of a graph

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Figure . performance scores on the last 20% of available record for out-of-sample (OOS) reservoirs (n = XX) for individual and pooled Model 1 and finetuning on 5-30 years data

# Discussion and Conclusion

Think about key takeaways from the results figures, and how they fit with prevous literature cited in the introduction.

Some ideas:

* LSTMs show the ability to model reservoir release policies as well or better than other data-driven methods. However, this does not appear to be due to their inherent ability to accumulate storage over time; cell states show only modest correlations with observed storage (and they do not conserve mass).
* The accuracy does not appear to relate to the reservoir location (climate/hydrologic factors). Instead, it is strongly related to the degree of regulation. The models are more accurate for reservoirs with a lower degree of regulation, where the release is more directly related to the inflow and does not depend on longer-timescale accumulation.
* How does accuracy compare to previous studies? At least the ones that report R2 values across many reservoirs. We can say which ones are reporting in-sample vs. out of sample accuracy scores.
* Pooled training does not show an improvement on out-of-sample reservoirs, especially in the absence of fine-tuning. This suggests that the transferability of trained LSTMs for rainfall-runoff modeling may not hold for modeling reservoir release policies.
* The decline in performance between the training and test periods is in part due to overfitting, but may also be influenced by changes in the operating policies over time. This is difficult to resolve because the long data records are needed to support training.
* Fitting operations in multi-reservoir systems, which is the case in some of these larger basins. We assume releases are only based on storage/inflow at each single reservoir.

Possible applications of this approach (or data-driven reservoir models in general): more efficient approximations to embed in hydrologic models? How would this compare to ad hoc models used by agencies? See refs in proposal about diagnostic assessment of national water model (has issues with reservoir representation).

Limitations/future work

# Data Availability Statement

All code corresponding to methods and figure generation can be found in the repository: https://github.com/Matt2371/DL-reservoir-modeling.

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# Supplementary Materials

A group of graphs showing different types of lines

AI-generated content may be incorrect.

Figure S1. Implied storage states plotted against observed storage for Model 3 and 4

A graph of different colored lines

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Figure S2. Timeseries plots for predicted and observed releases for Shasta, Folsom, New Melones, and Trinity using Model 1-S

A graph with red line and blue dots

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Figure S3. Decline in in training and test versus log mean-inflow-max-storage ratio.