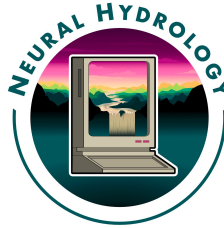
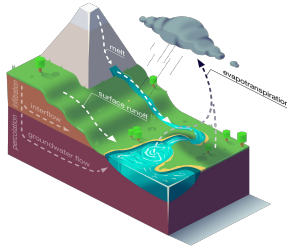


# Recent Advances in Deep Learning and its Potential Benefits for Hydrological Forecasting



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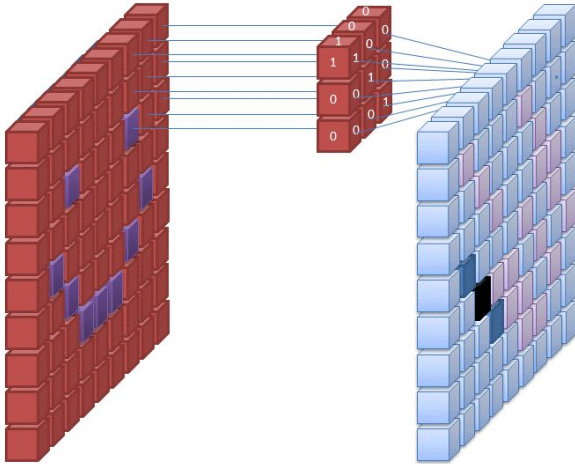
Sepp  
Hochreiter



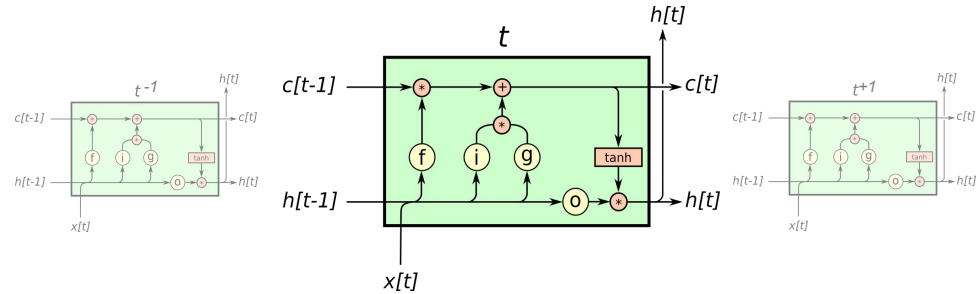
Research blog: [neuralhydrology.github.io](https://neuralhydrology.github.io)

# Machine Learning Tools for Earth Sciences

Spatial: Convolutional Networks



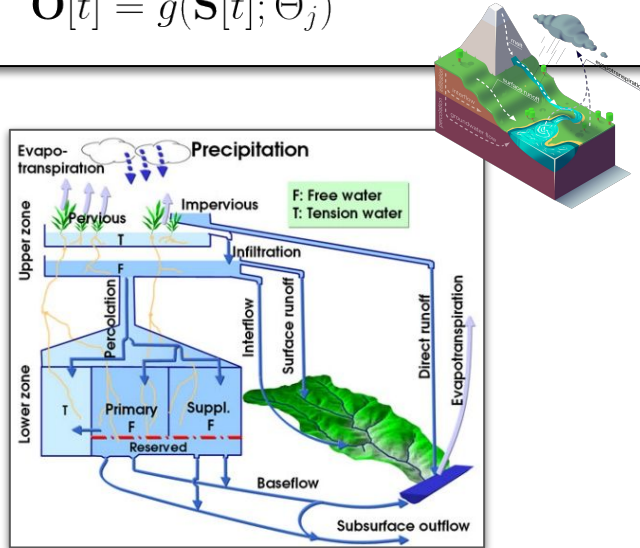
Temporal: Recurrent Networks



# LSTMs are State-Space Models

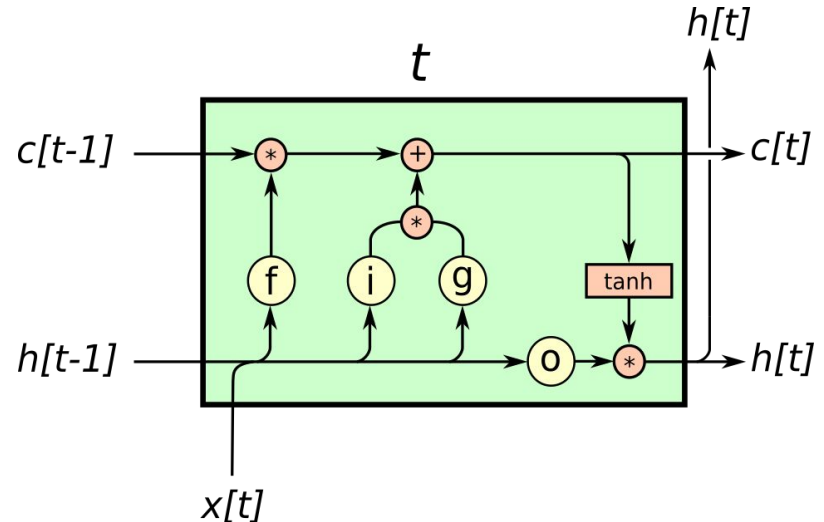
## State-Space model:

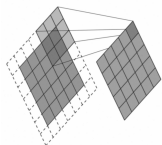
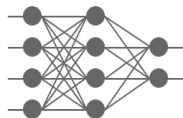
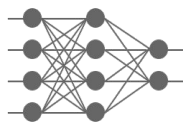
$$S[t] = f(I[t], S[t-1]; \Theta_i)$$
$$O[t] = g(S[t]; \Theta_j)$$



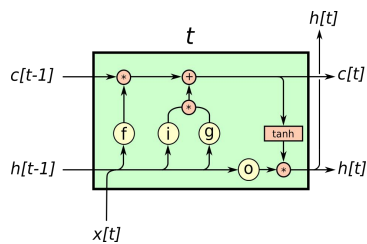
## LSTM model:

$$\{c[t], h[t]\} = f(x[t], c[t-1], h[t-1]; \theta_i)$$
$$\hat{y}[t] = g(h[t]; \theta_j)$$

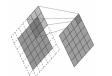




# LSTM



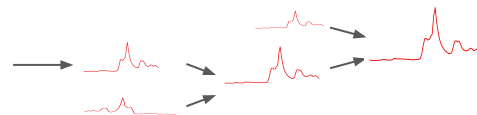
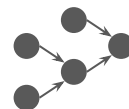
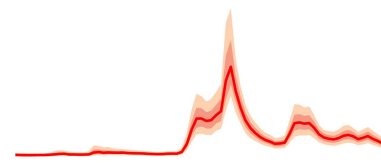
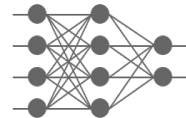
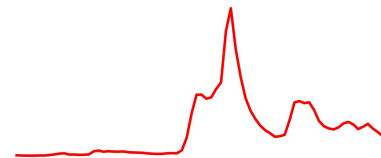
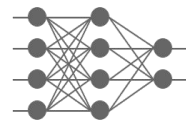
: Fully-connected NN



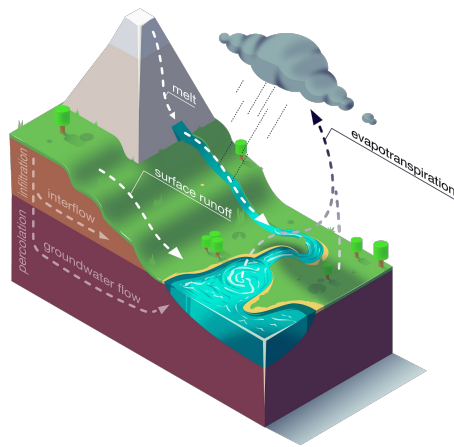
: Convolutional NN



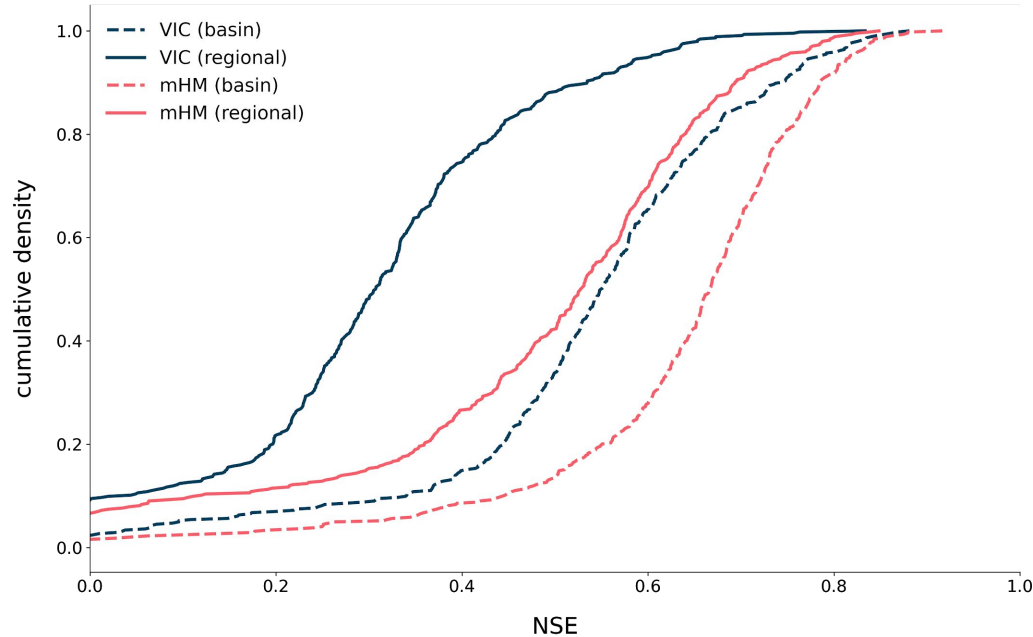
: Graph NN



# Deep Learning for Rainfall-Runoff Modeling

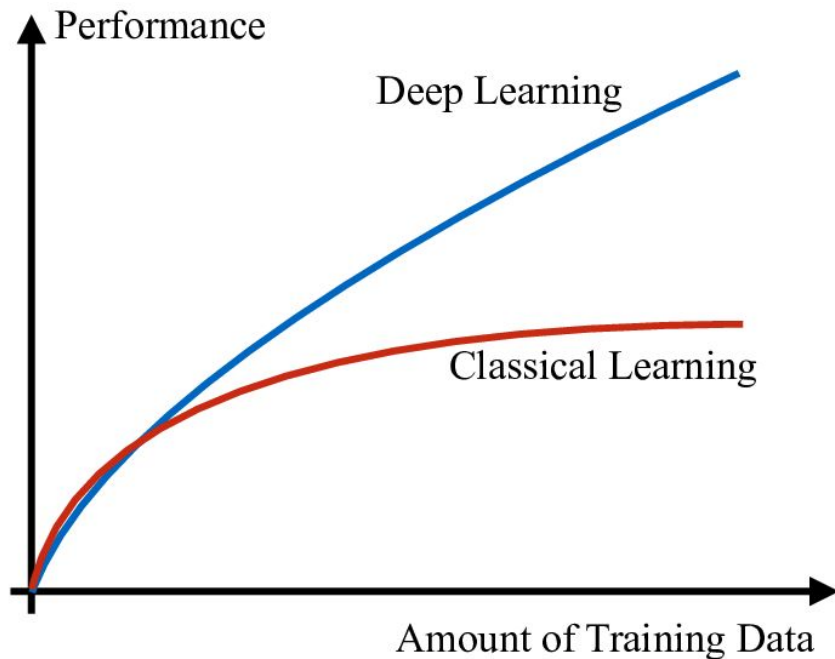


# The state of regional modeling



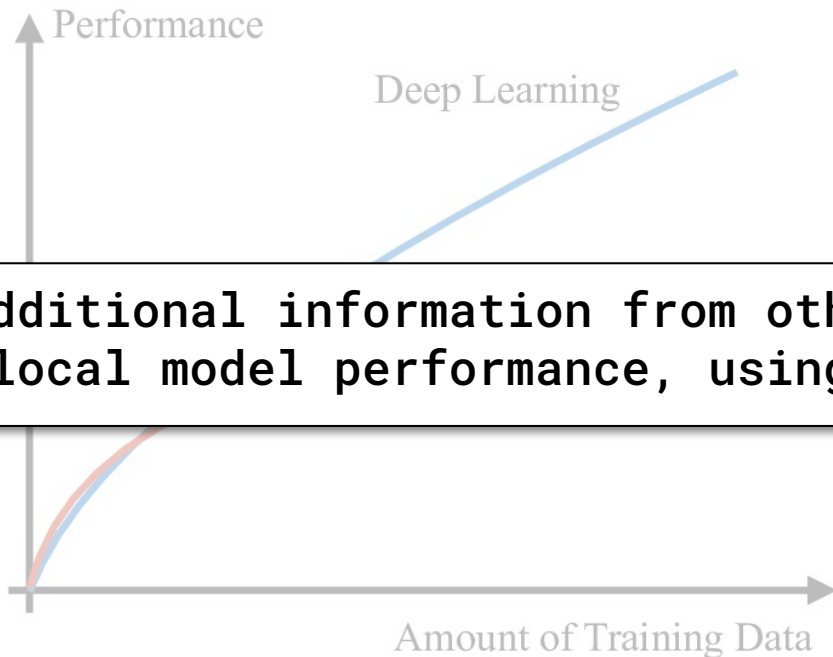
\* empirical CDF of  
model performance  
over > 400 basins

# The Unreasonable Effectiveness of Data



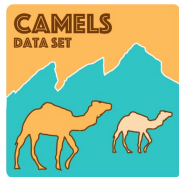
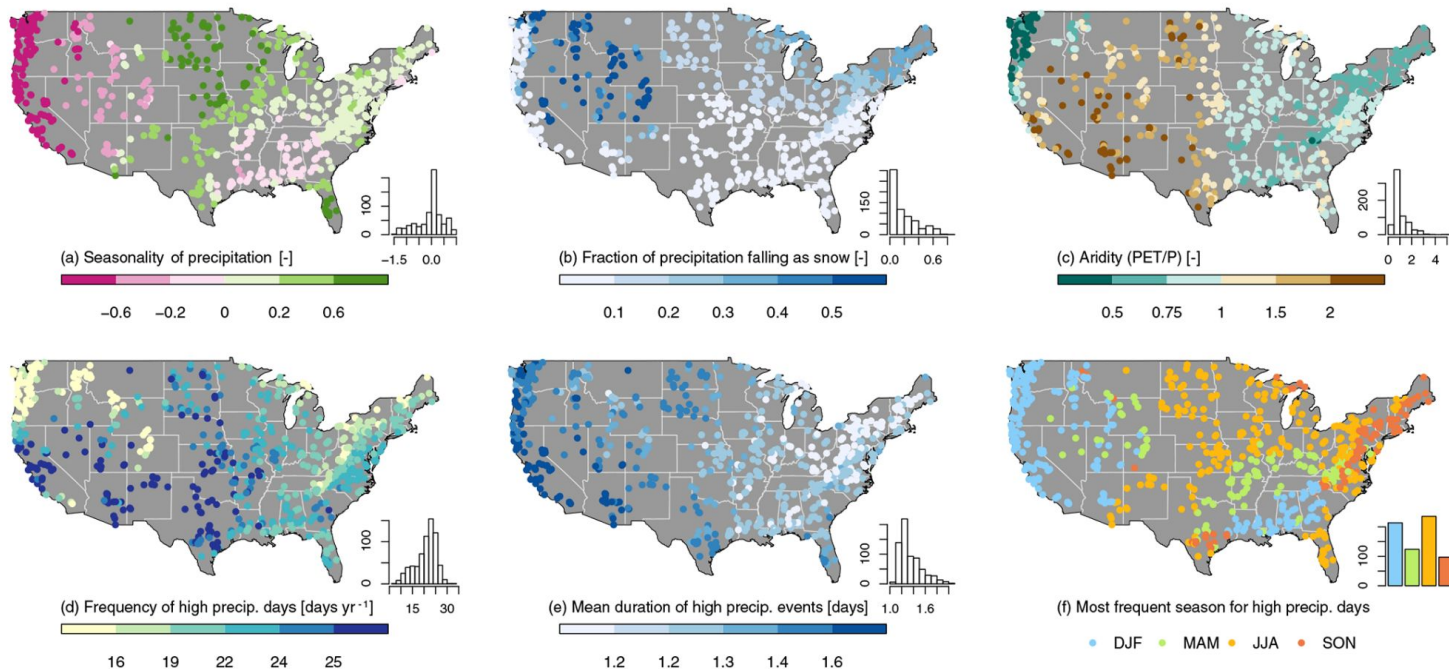


# The Unreasonable Effectiveness of Data



Can we use additional information from other basins to increase local model performance, using DL?

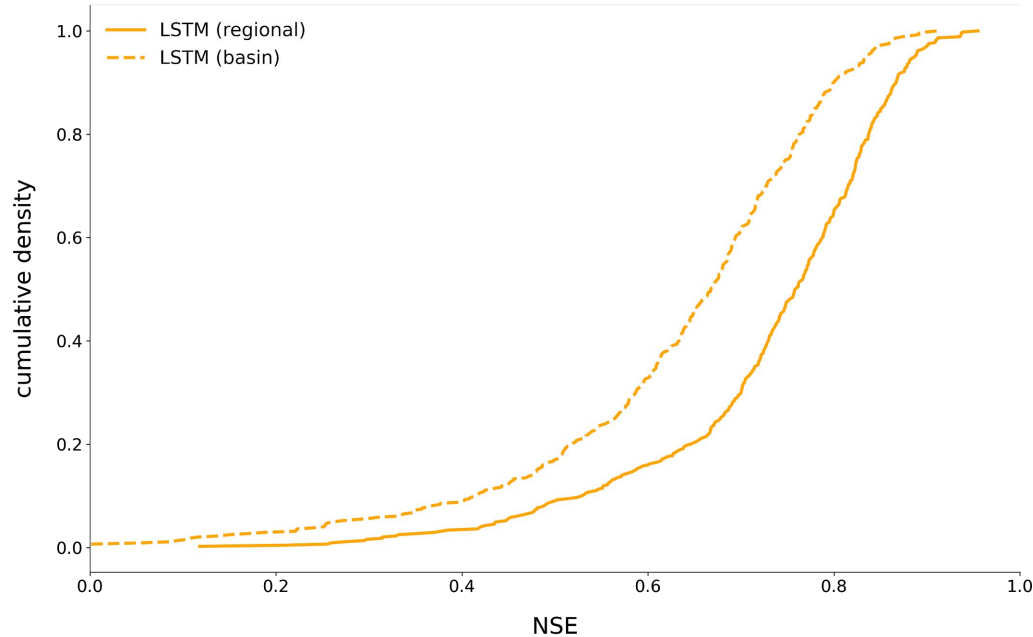
# CAMELS Dataset



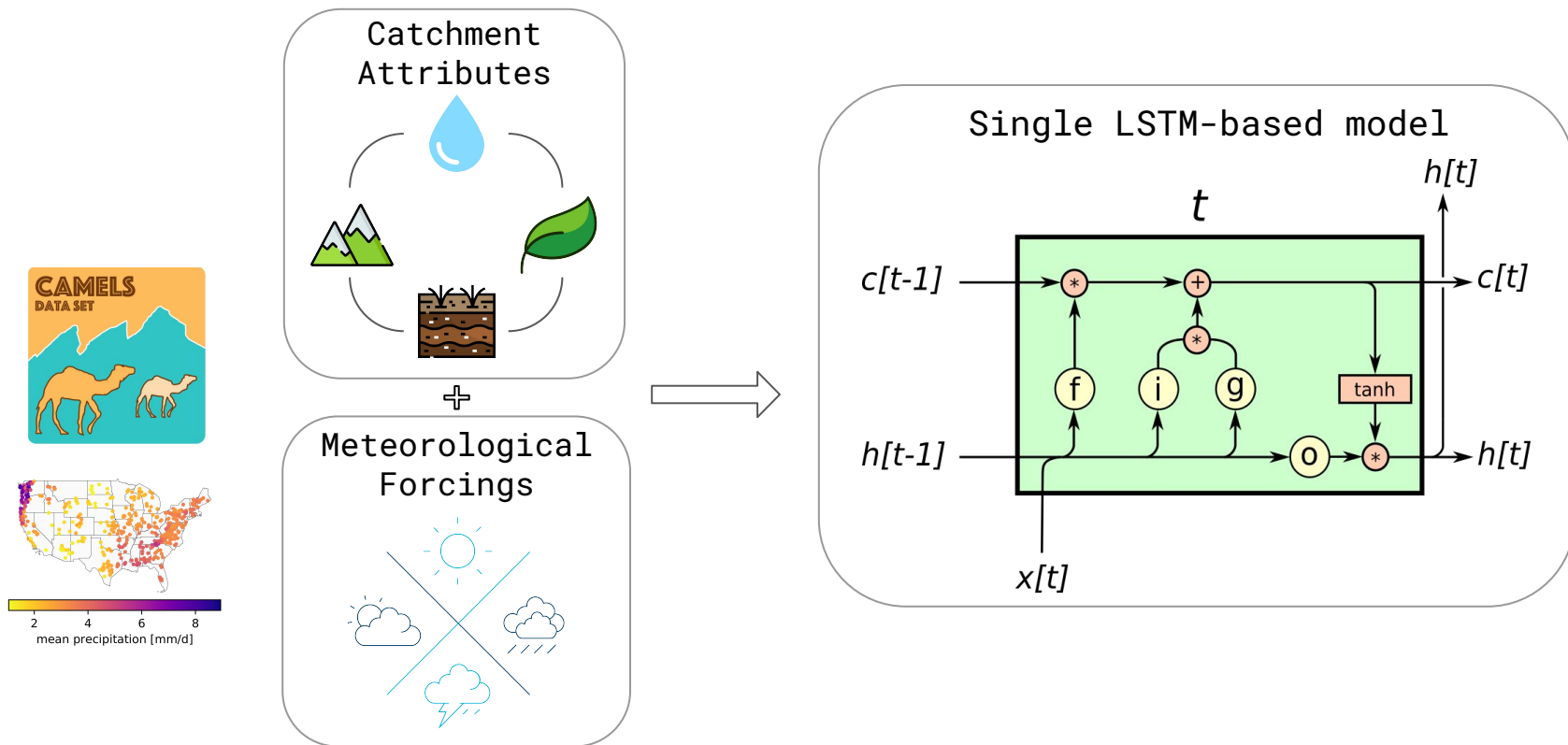
A. Newman, K. Sampson, M.P. Clark, A. Bock, and R.J. Viger, and D. Blodgett, 2014: **A large-sample watershed-scale hydrometeorological dataset for the contiguous USA**. Boulder, CO: UCAR/NCAR.

N. Addor, A. Newman, M. Mizukami, and M. P. Clark, 2017. **Catchment attributes for large-sample studies**. Boulder, CO: UCAR/NCAR.

# The Unreasonable Effectiveness of Data

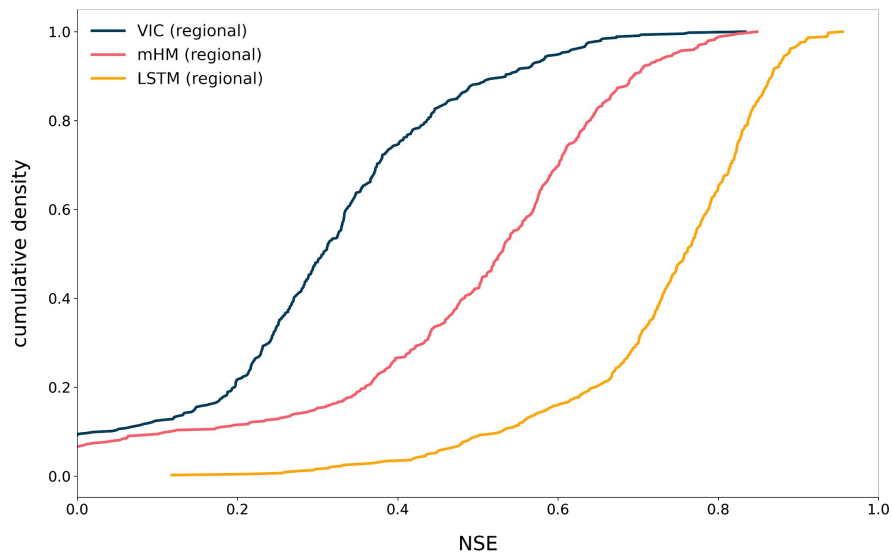


# The experimental setup

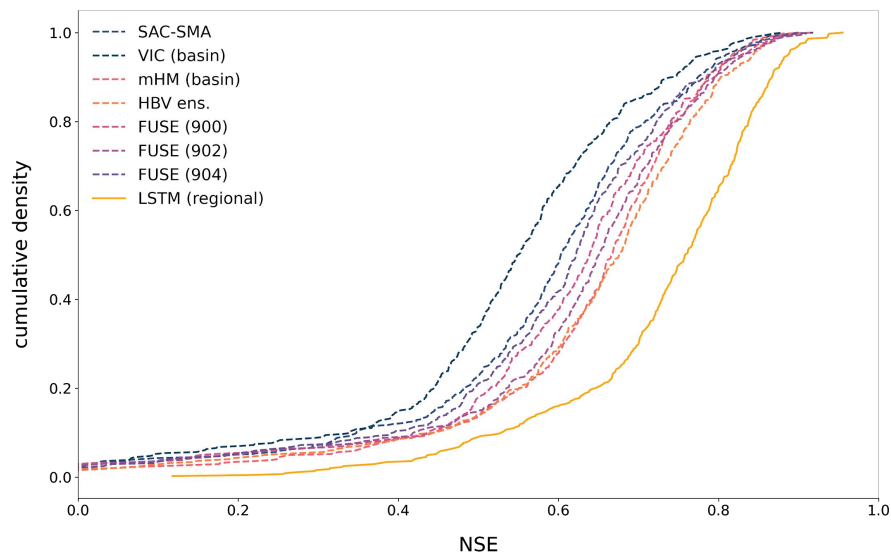


# Benchmarking

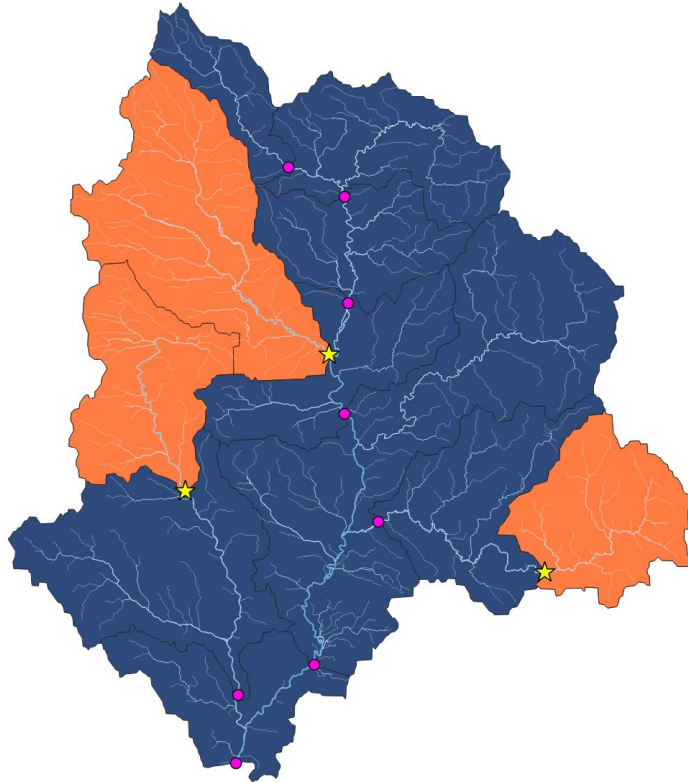
compared to regional model



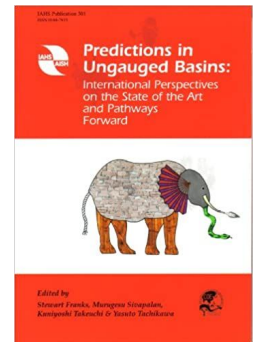
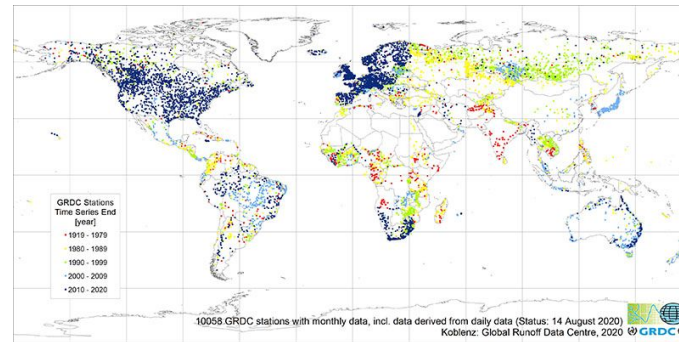
compared to basin-specific models



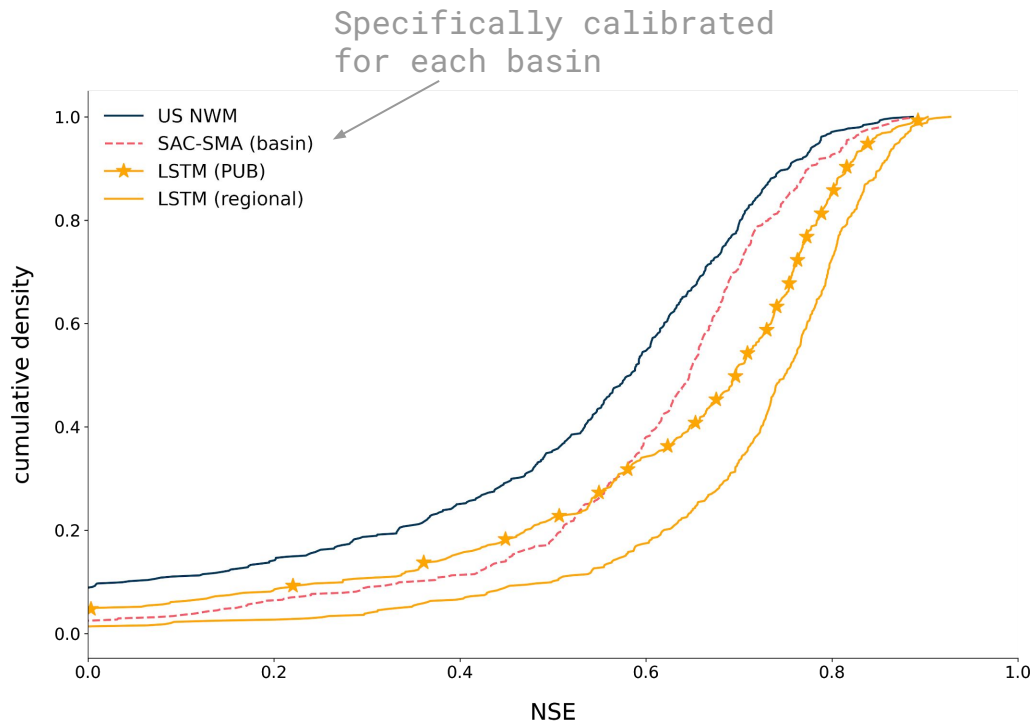
# Testing Generalization



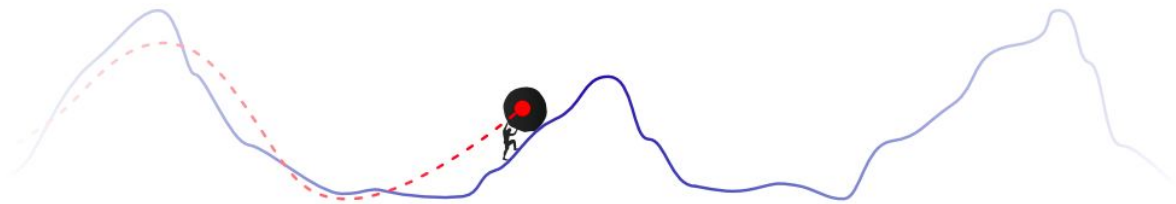
- Streamflow gauge
- ★ Ungauged basin outlet



# Prediction in Ungauged Basin

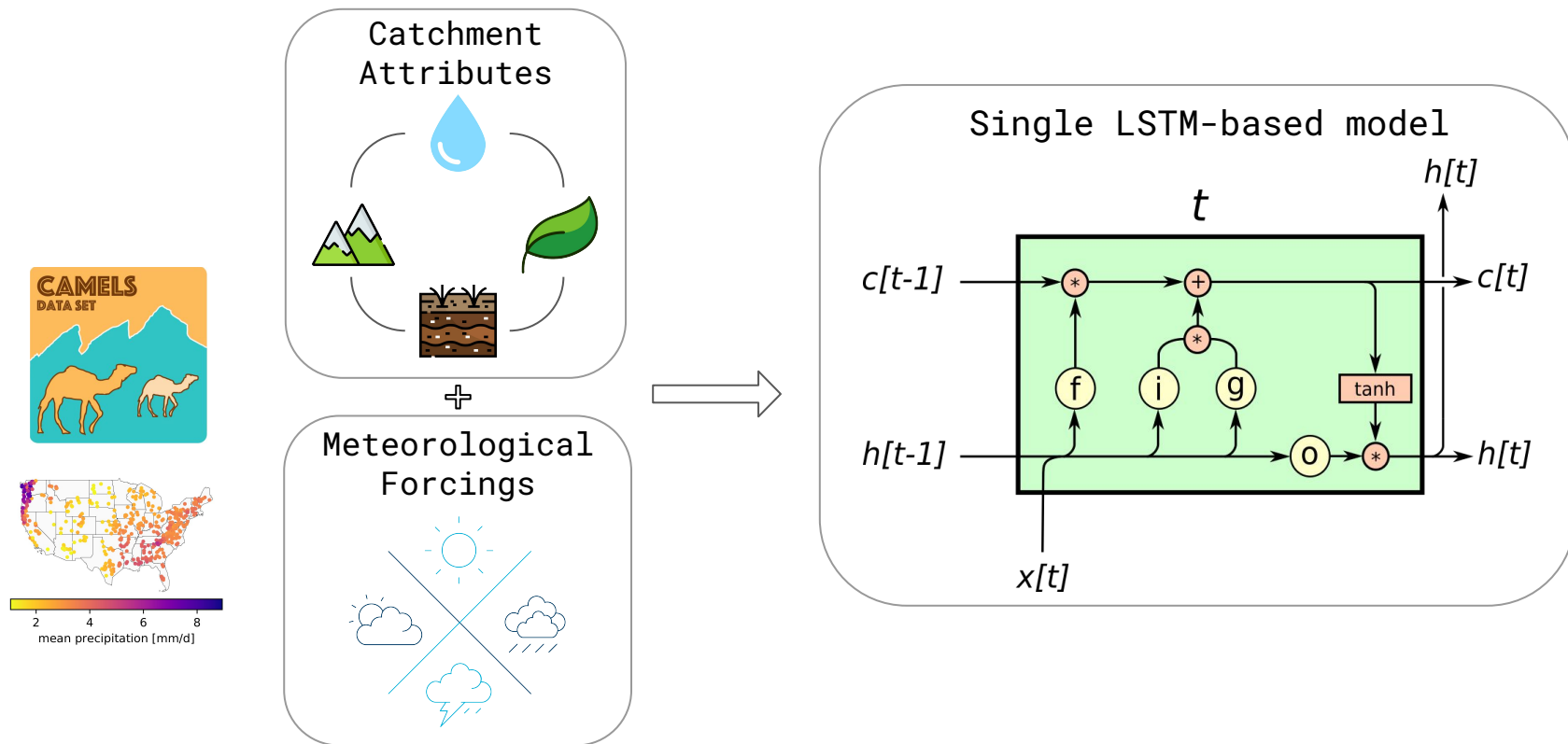


# Model (Setup) Extension

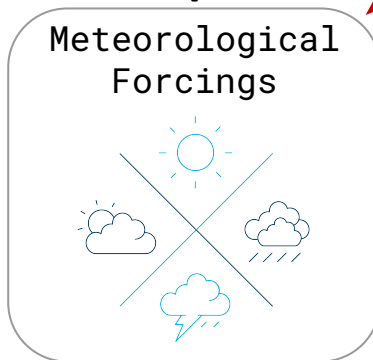
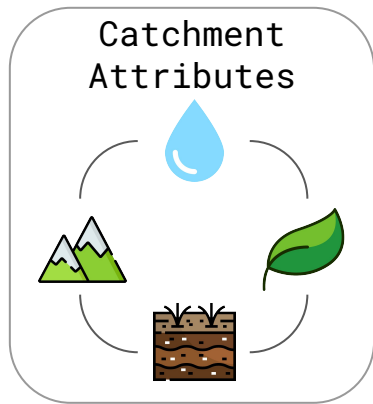
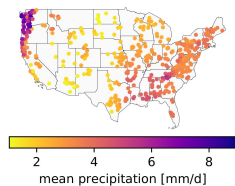
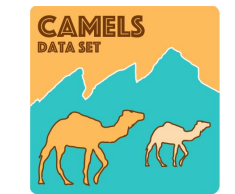




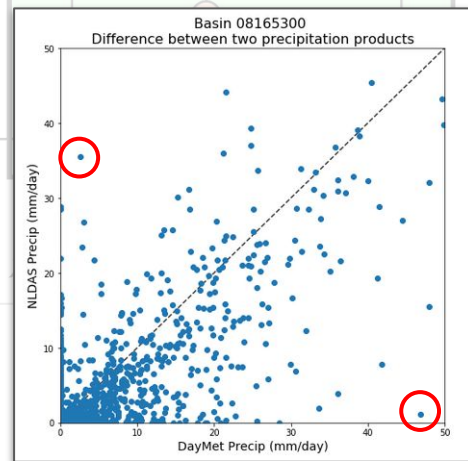
# The Experimental Setup



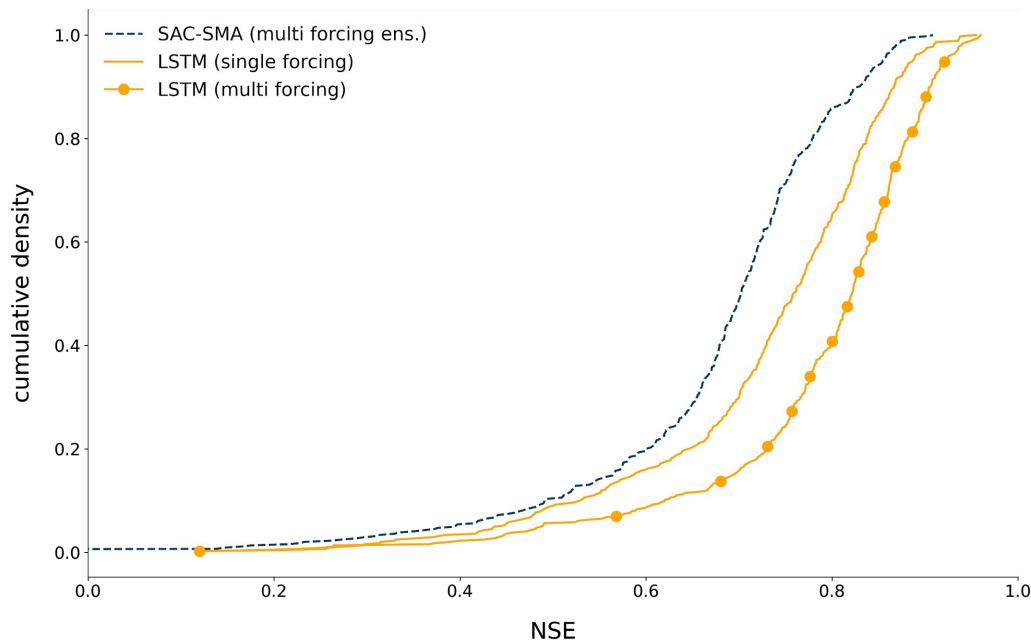
# The Experimental Setup



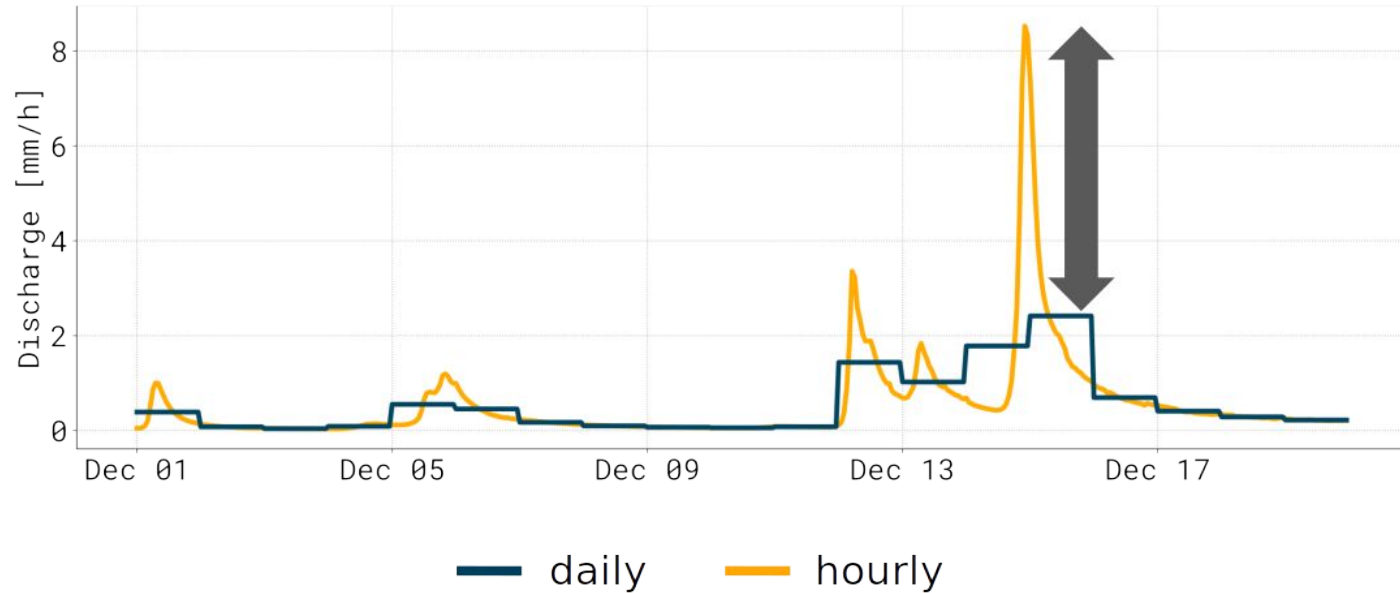
There are  
**no “true” inputs**  
(many different data products exist)



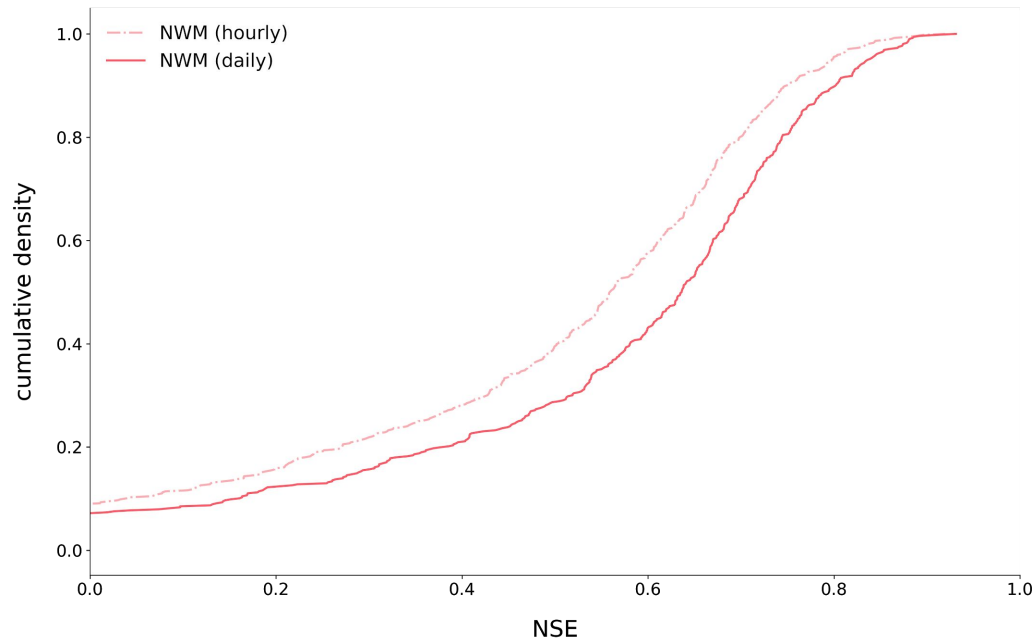
# Leveraging Synergy of Multiple Forcings



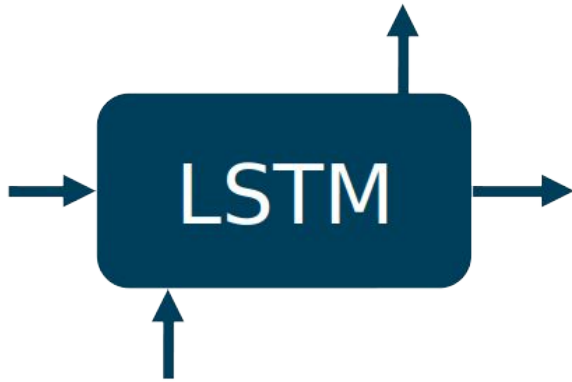
# Higher Temporal Resolutions



# Temporal Frequencies



# Naïve Solution

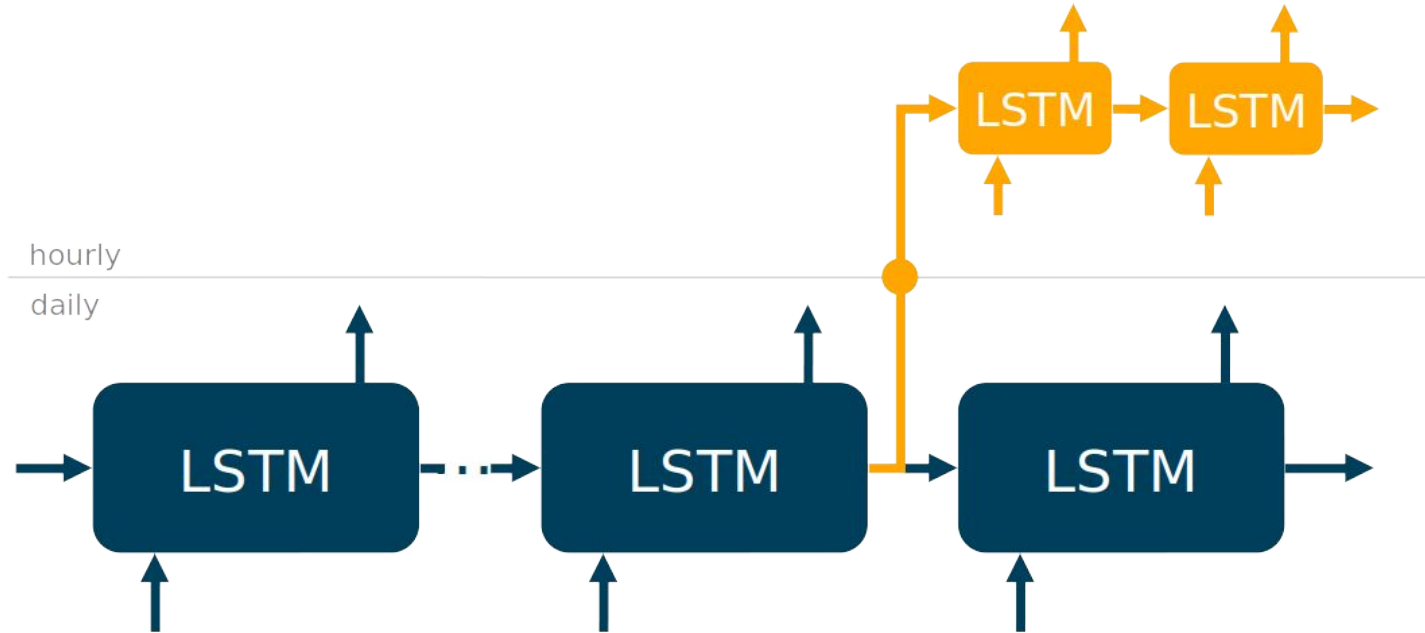


daily

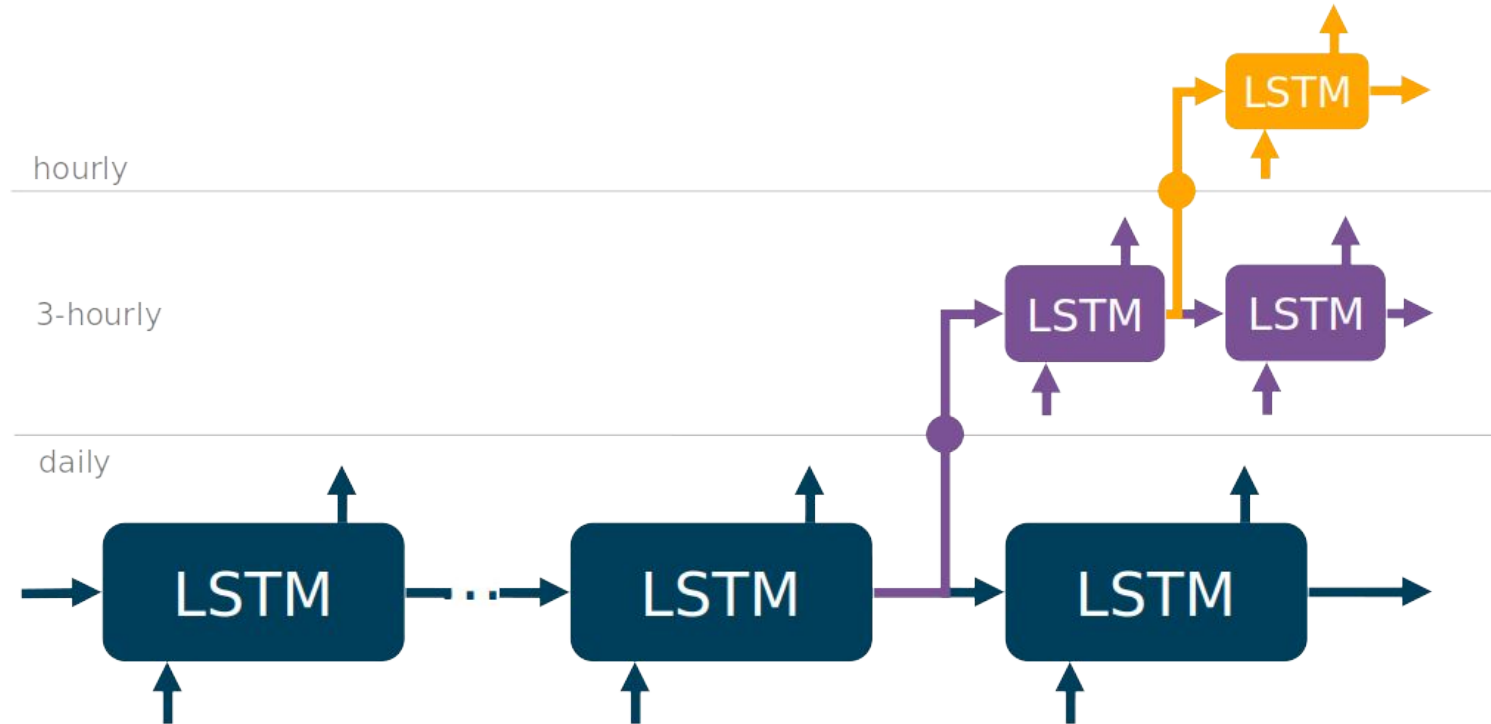


hourly

# Multi-Timescale LSTM

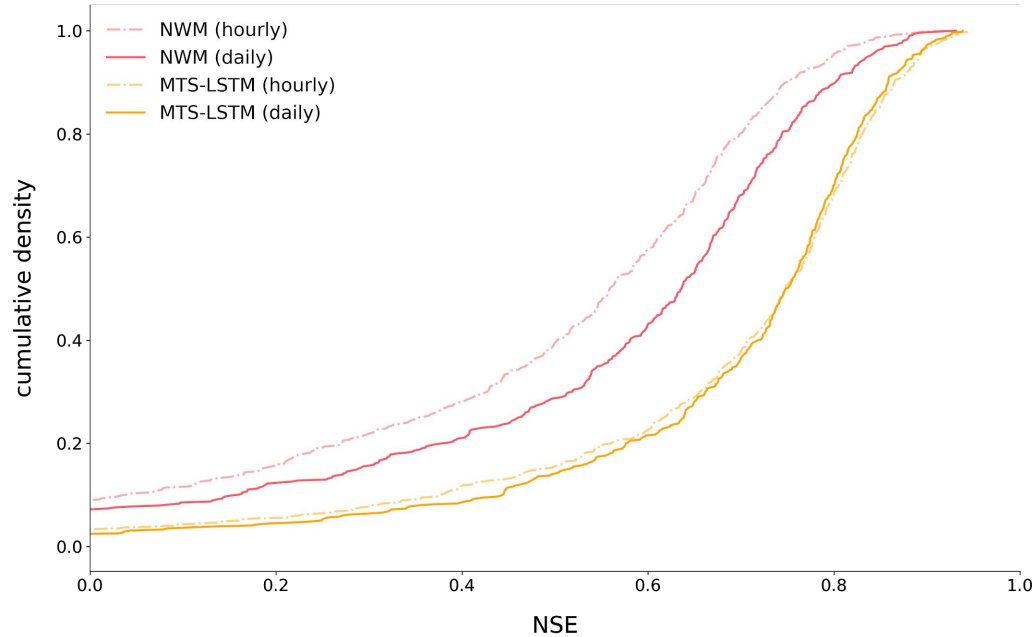


# Multi-Timescale LSTM





# Multi-Timescale LSTM

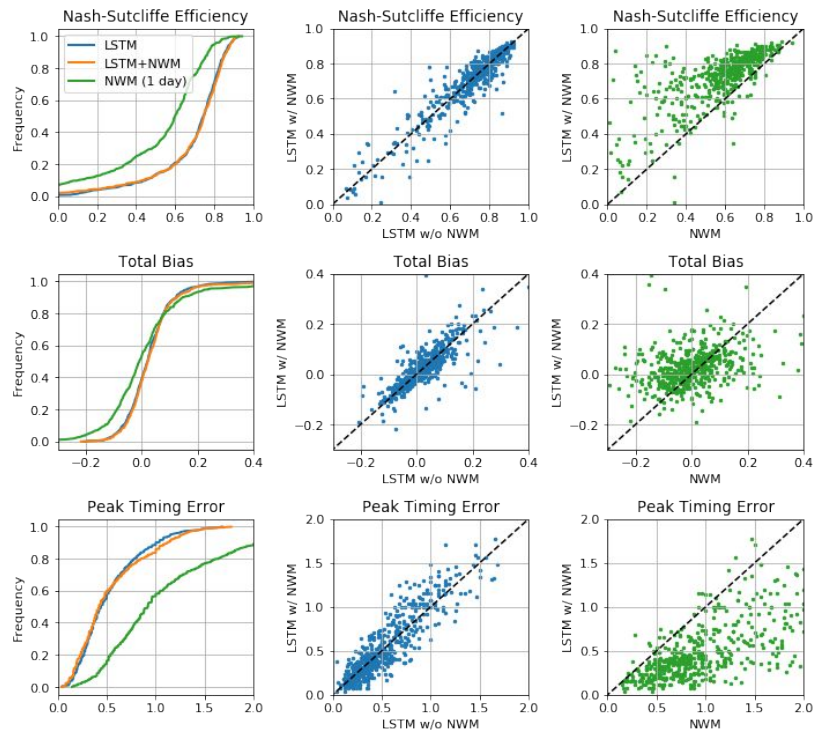
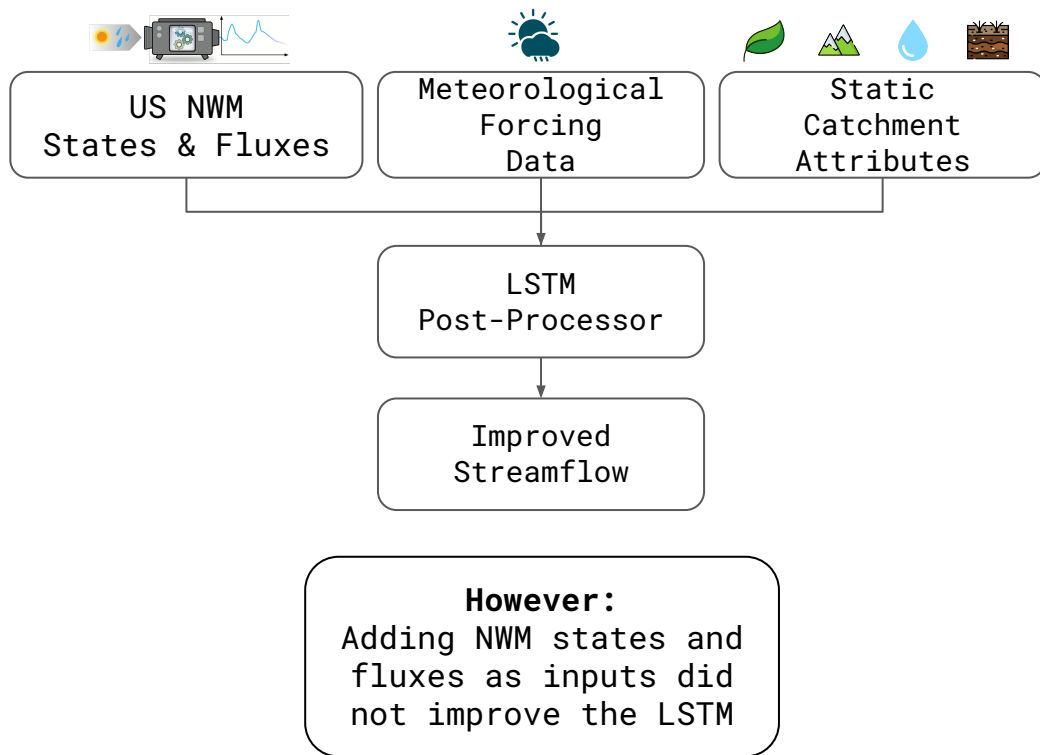


# To Recap

- LSTM-based models are currently the best hydrology models
- Multi-basin training is the way to go
- Generalize to unseen regions and are better than locally calibrated hydrology models
- Leverage synergies from multiple forcing products to increase model performance
- Can provide predictions at multiple time-scales without loss in performance

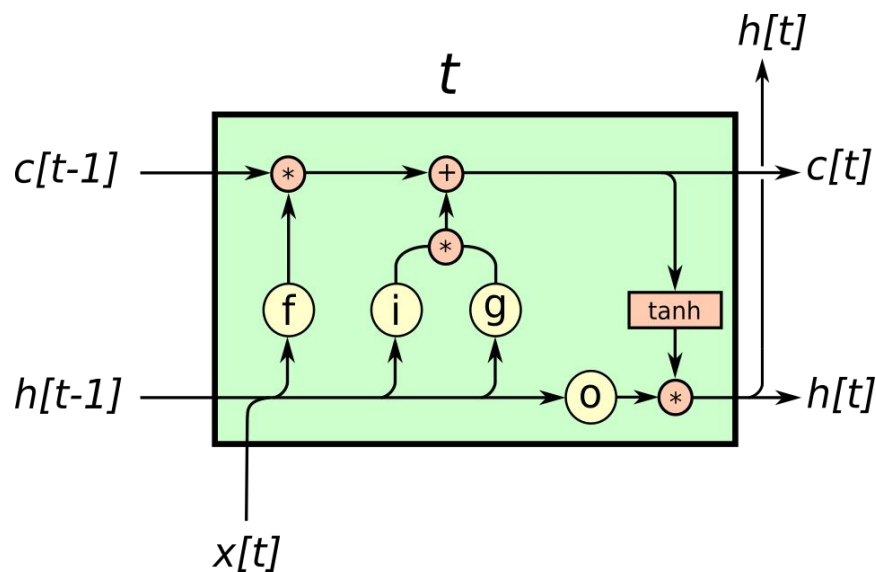
# Physics Integration

# Post-Processing

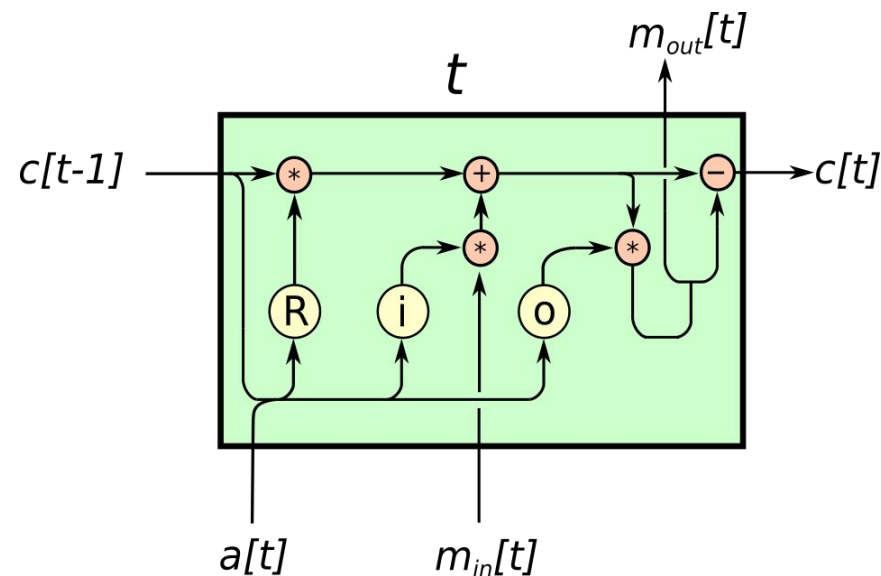


# Mass-Conserving LSTM

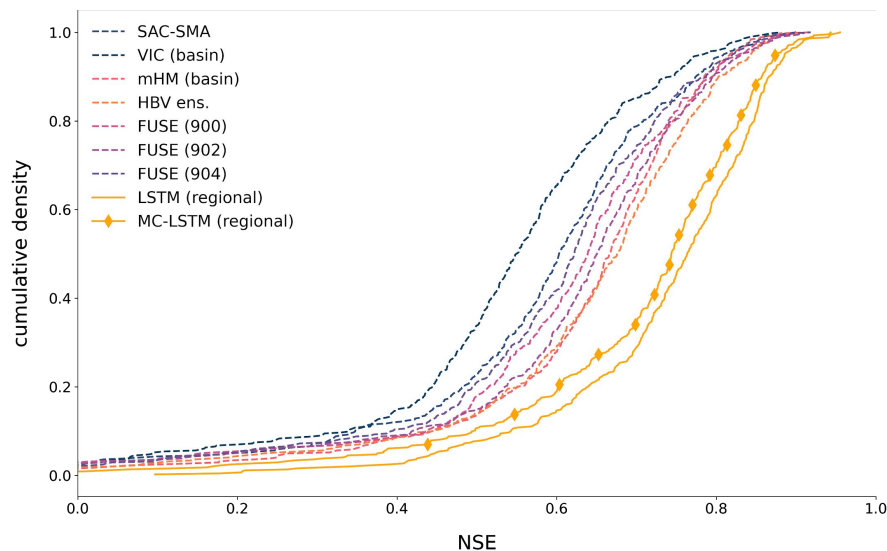
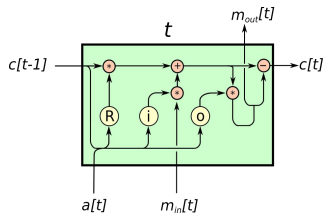
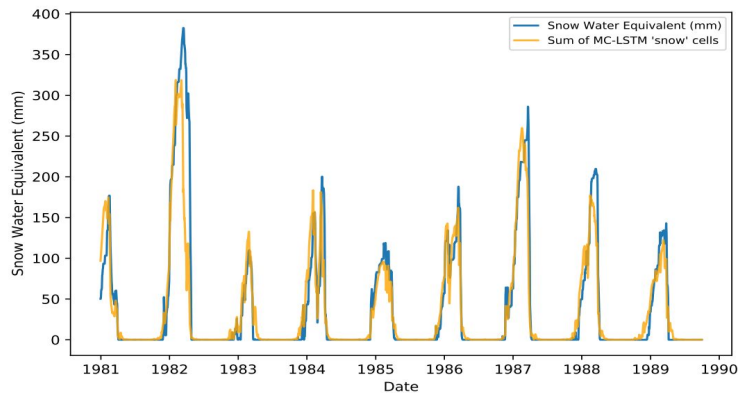
LSTM



MC-LSTM



# Physics into Deep Learning Models



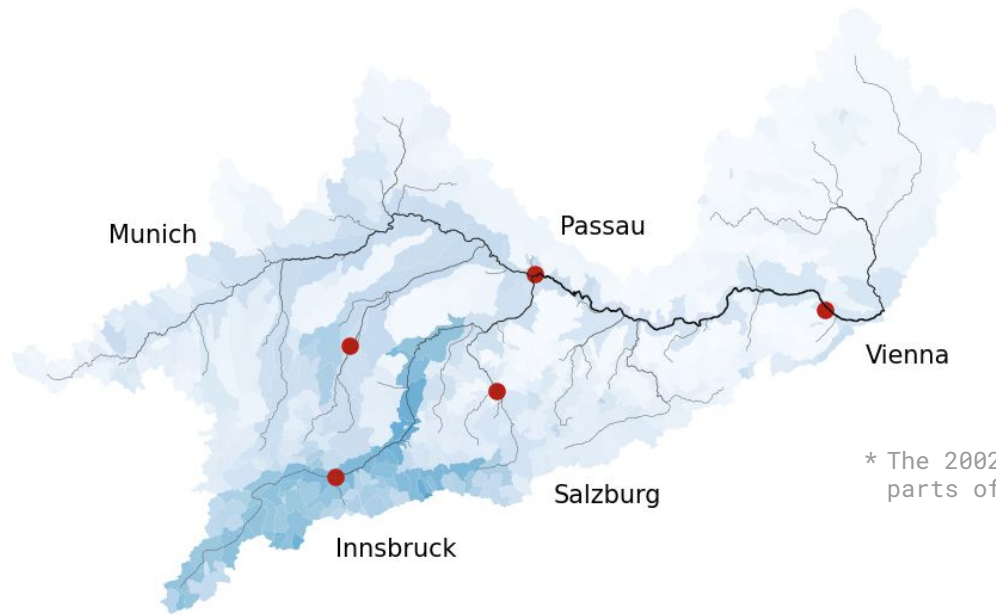




# Looking Forward

# The end

00:00 06 August 2002



\* The 2002 central european flood in parts of the Danube basin



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Research blog: [neuralhydrology.github.io](https://neuralhydrology.github.io)