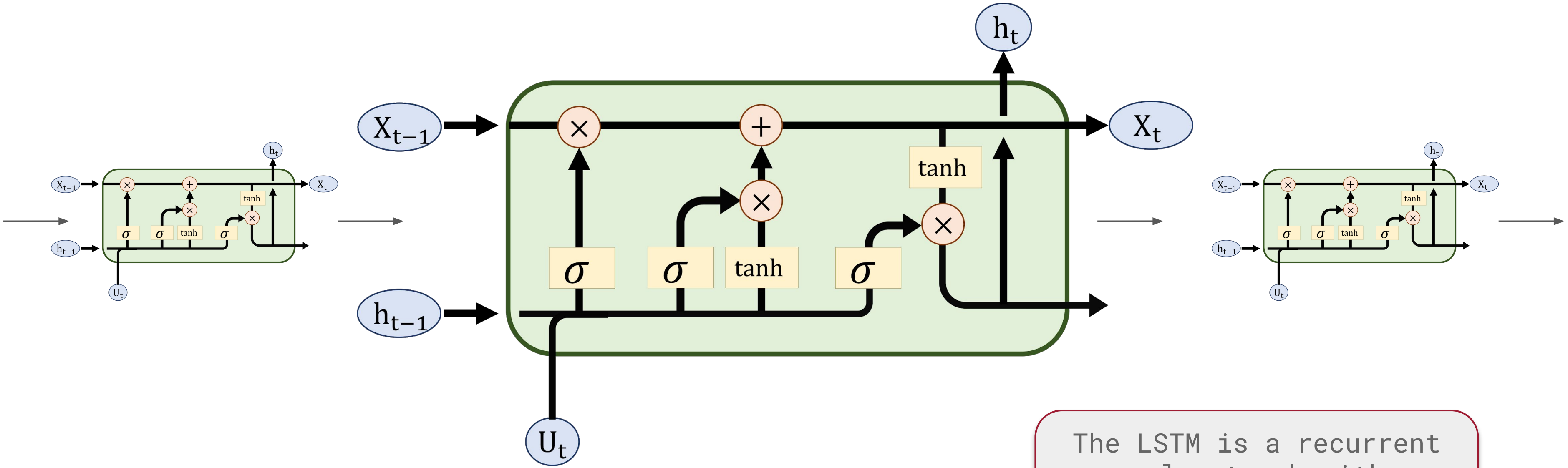
Deep Learning for Rainfall-Runoff Modeling

neuralhydrology.github.io

Grey S. Nearing[1,2], Frederik Kratzert[3], Alden K. Sampson[4], Craig S. Pelissier[5], Daniel Klotz[3], Jonathan M. Frame[2], Cristina Prieto[6], Hoshin V. Gupta[7]

[1]Google Research, [2]University of Alabama, [3]Johannes Kepler University, LIT AI & Machine Learning Laboratory, [4]Upstream Tech, Public Benefit Corporation, [5]NASA Center for Climate Simulation, [6]Instituto de Hidraulica Ambiental de la Universidad de Cantabria, [7]University of Arizona

Long Short Term Memory (LSTM)

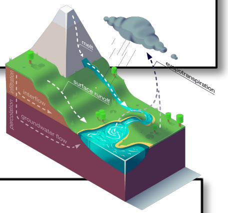


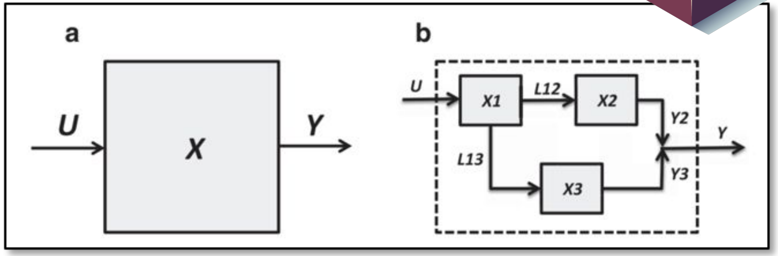
The LSTM is a recurrent neural network with an input-output-state relationship.

LSTMs are State-Space Models

State space model:

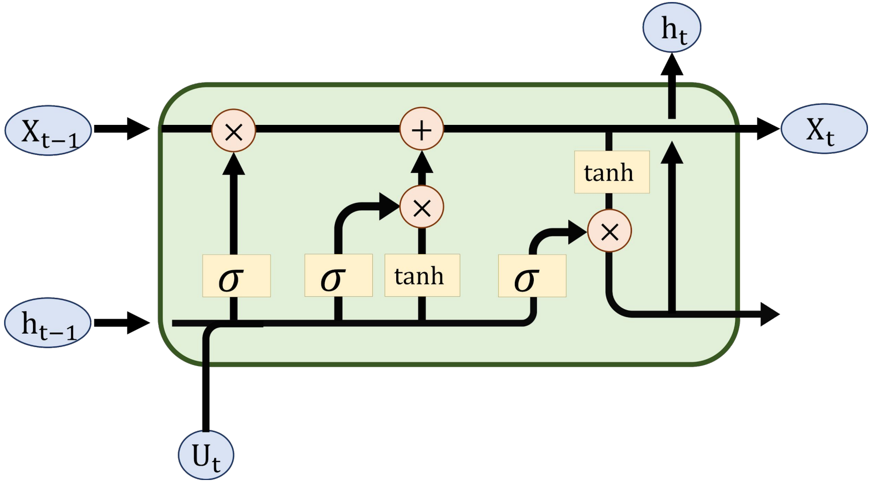
$$\mathbf{S}[t] = f(\mathbf{I}[t], \mathbf{S}[t-1]; \Theta_i)$$
$$\mathbf{O}[t] = g(\mathbf{S}[t]; \Theta_j)$$



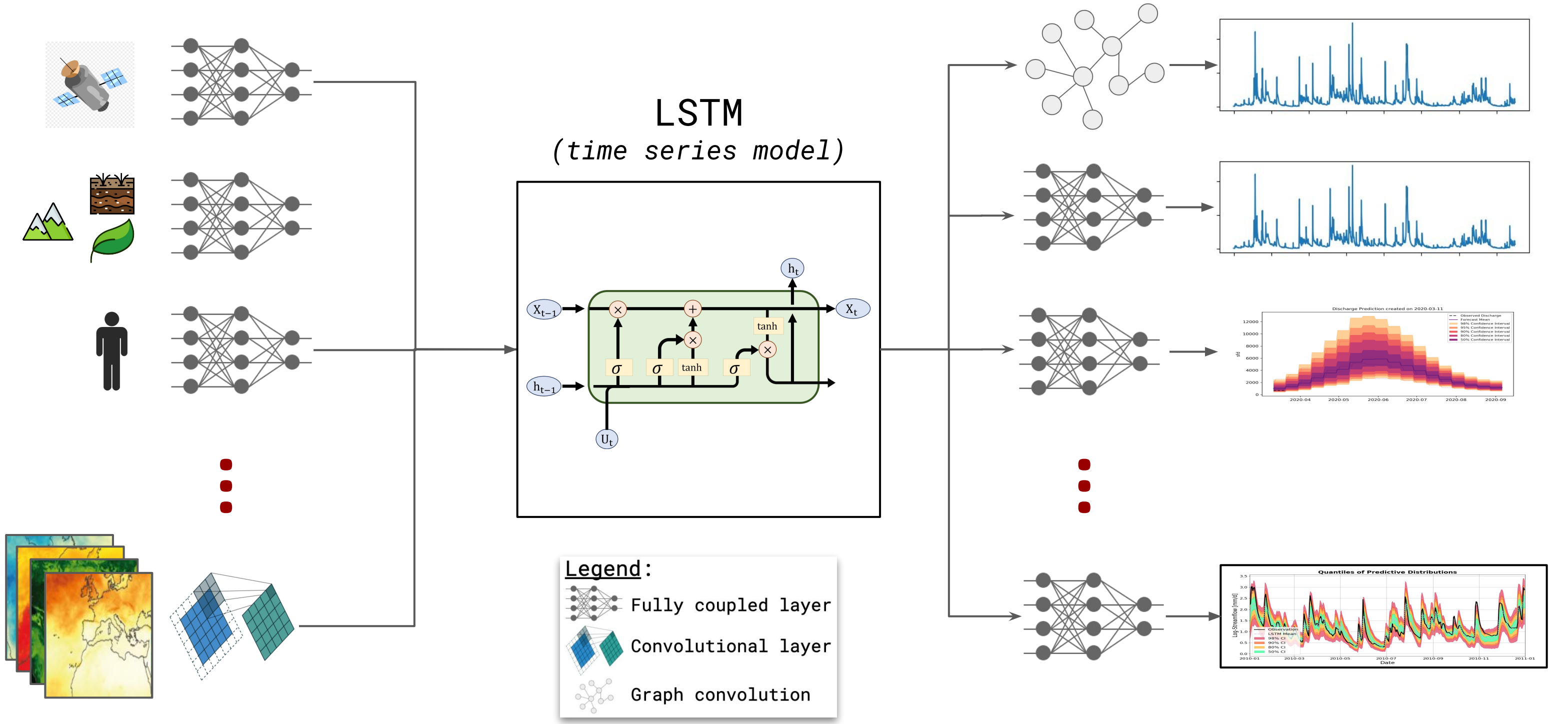


LSTM model:

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



Embedding into Deep Learning Models

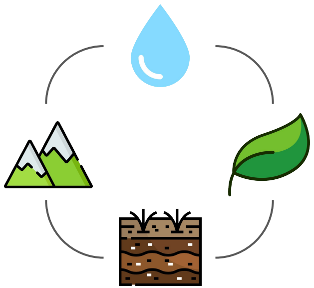


Experimental Setup

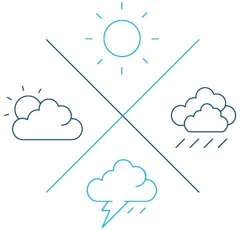
531
Basins

9 Years
Training
Data

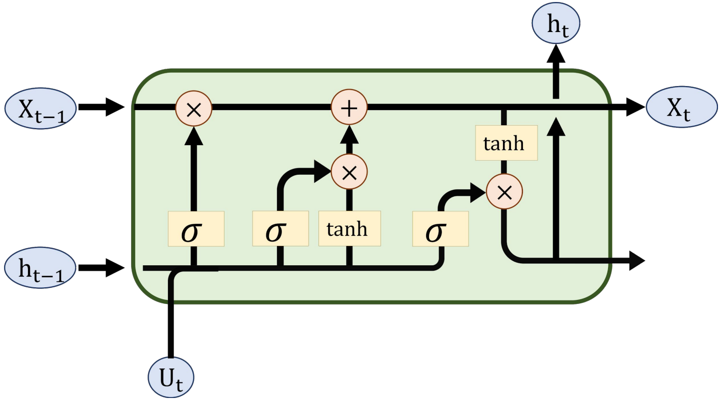
Catchment Attributes



Meteorological Forcings

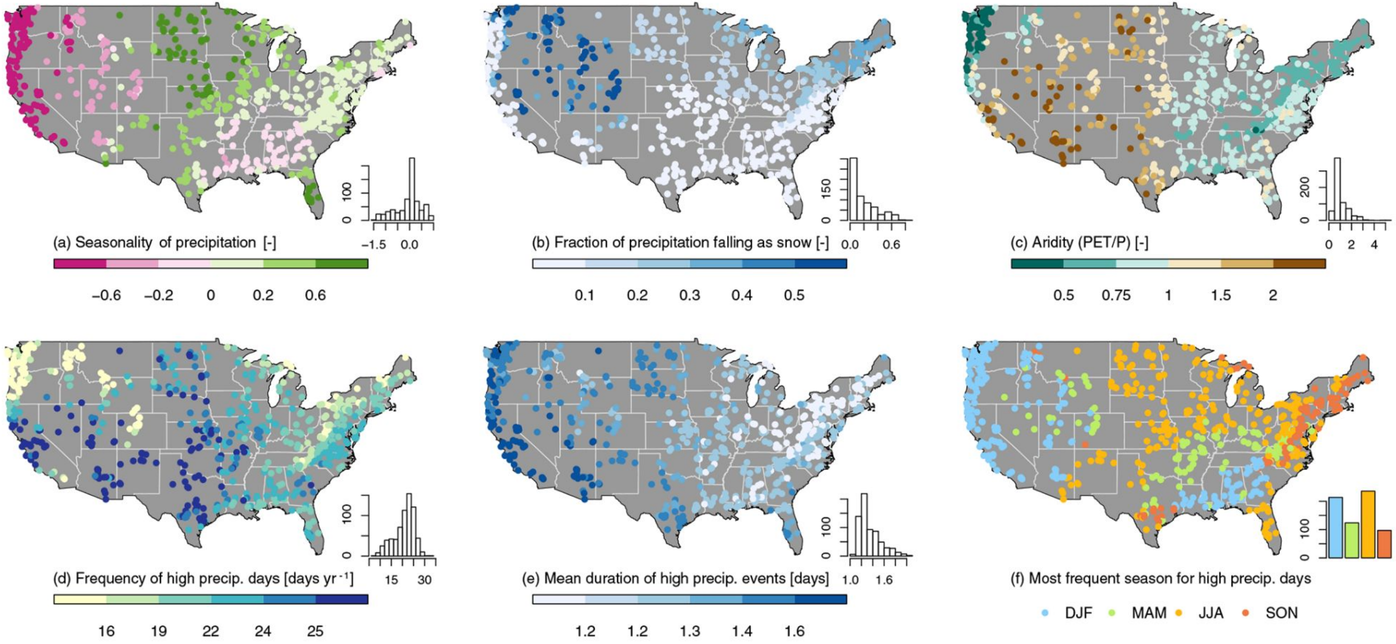


LSTM-based model



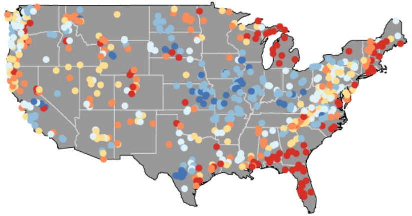
CAMELS Dataset

531 CONUS catchments with diverse climate, ecology, geology.



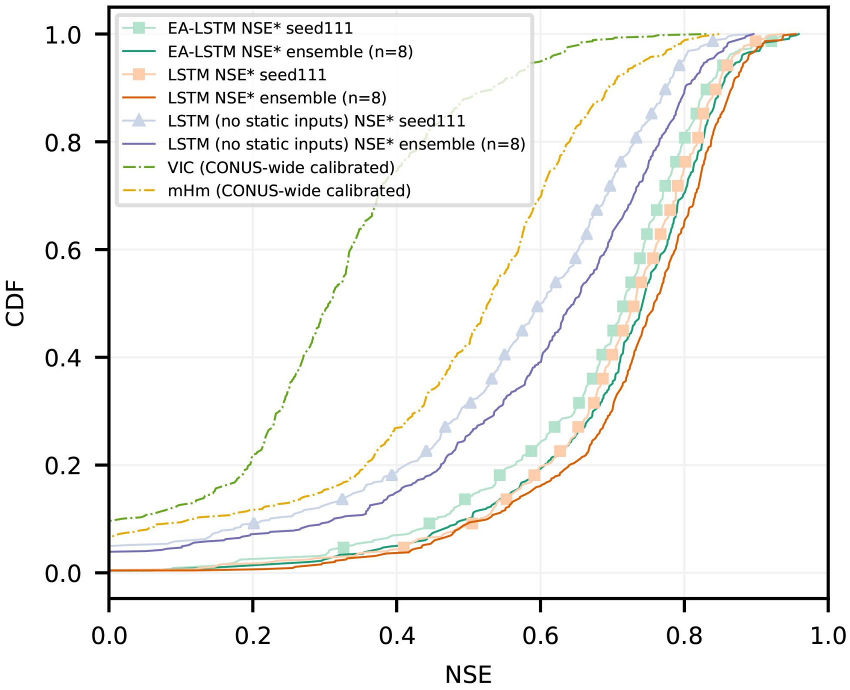
Addor, N., Newman, A.J., Mizukami, N., & Clark, M.P. (2017). The CAMELS data set: catchment attributes and meteorology for large-sample studies. *Hydrology and Earth System Sciences*

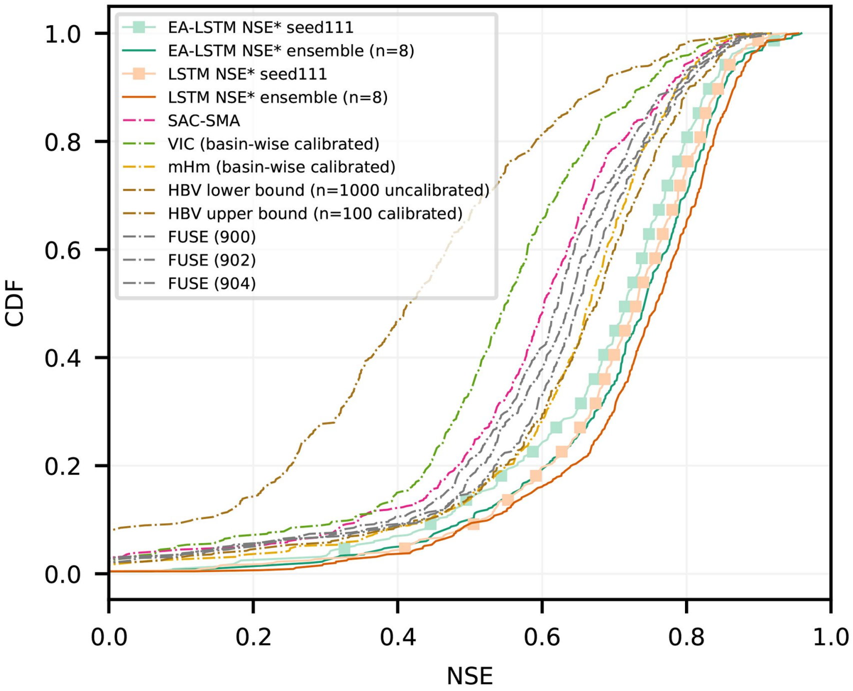
Newman, Andrew, et al. "Development of a large-sample watershed-scale hydrometeorological data set for the contiguous USA: data set characteristics and assessment of regional variability in hydrologic model performance." *Hydrology and Earth System Sciences*



Regional Modeling

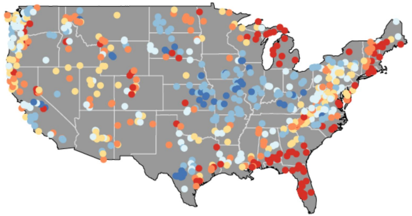
Regional LSTMs are better than catchment-specific hydro models.



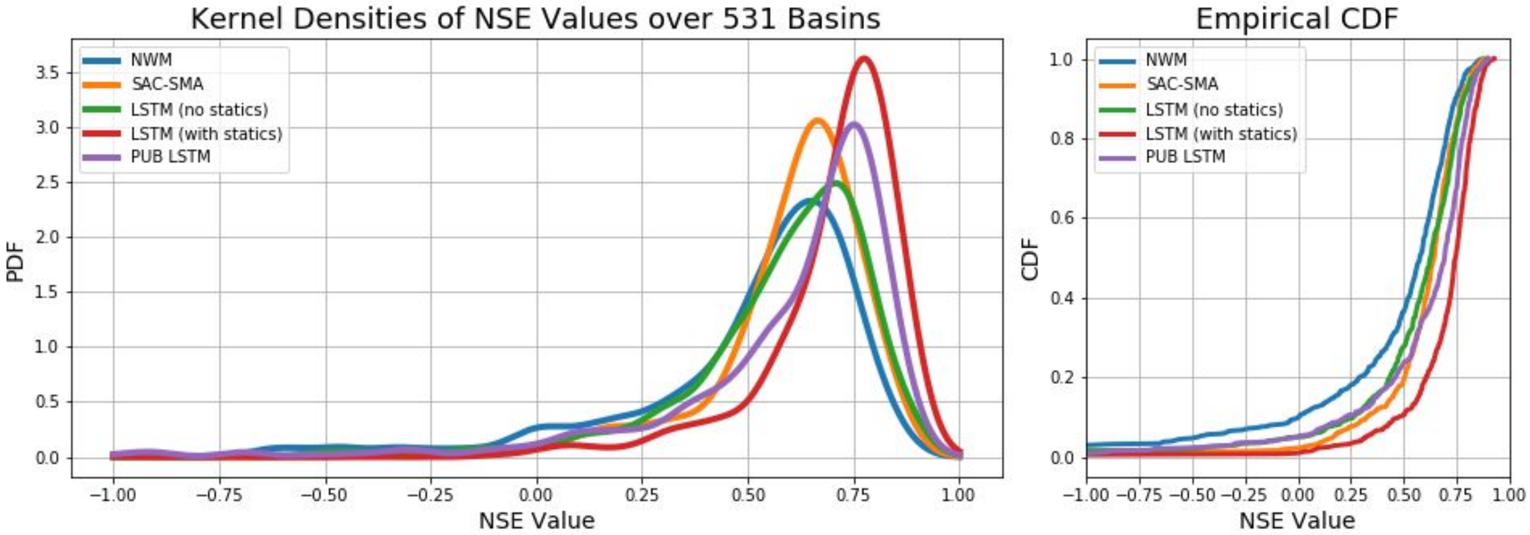


Kratzert, F., Klotz, D., Shalev, G., Klambauer, G., Hochreiter, S., & Nearing, G. (2019). Towards learning universal, regional, and local hydrological behaviors via machine learning applied to large-sample datasets. *Hydrology & Earth System Sciences*, *23*(12).

Prediction in Ungauged Basins

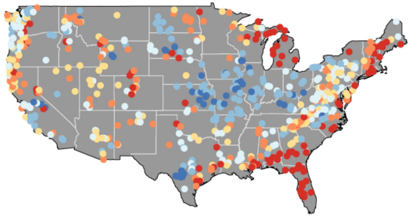


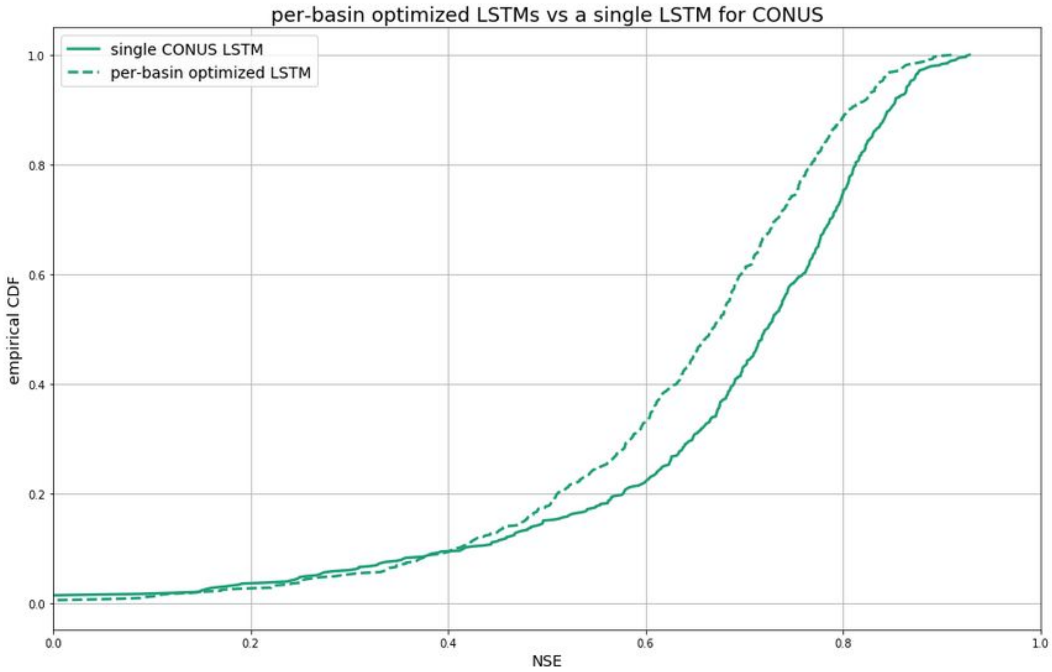
LSTMs are better in ungauged basins than SAC-SMA is in gauged basins.



Kratzert, F., Klotz, D., Herrnegger, M., Sampson, A. K., Hochreiter, S., & Nearing, G. S. (2019). Toward improved predictions in ungauged basins: Exploiting the power of machine learning. *Water Resources Research*, *55*(12), 11344-11354.

Learning a General Model



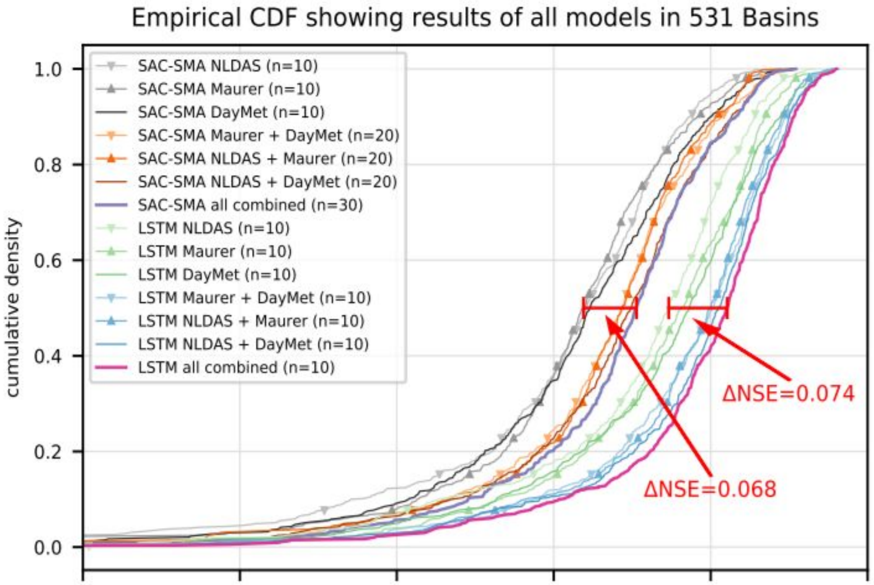


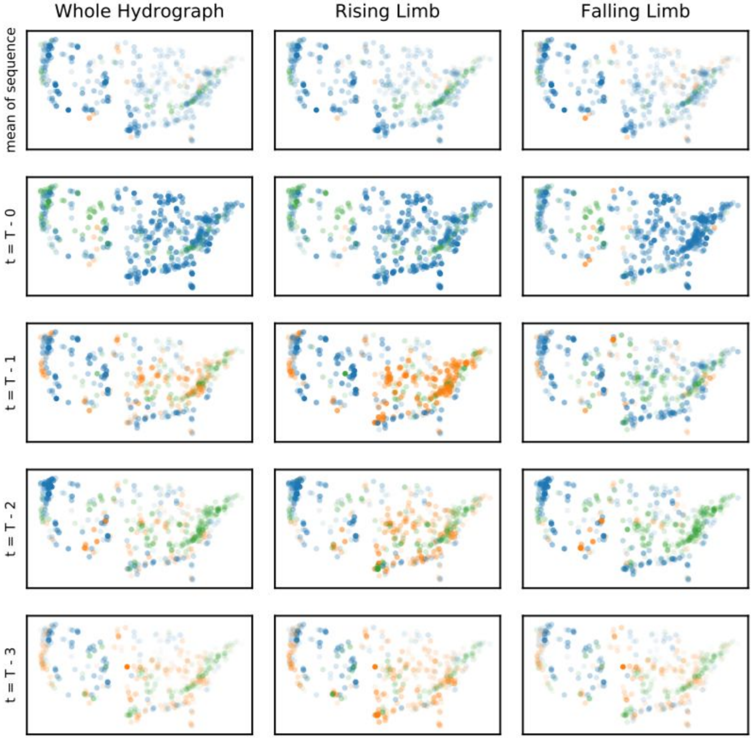
The LSTM is better when trained on multiple catchments than when trained on individual catchments.

Nearing, G., Kratzert, F., Sampson, A. K., Pelissier, C. S., Klotz, D., Frame, J., ... & Gupta, H. (2020). What role does hydrological science play in the age of machine learning?

Certain “hard” tasks are easy with DL

Multiple Forcings w/o Ensembles

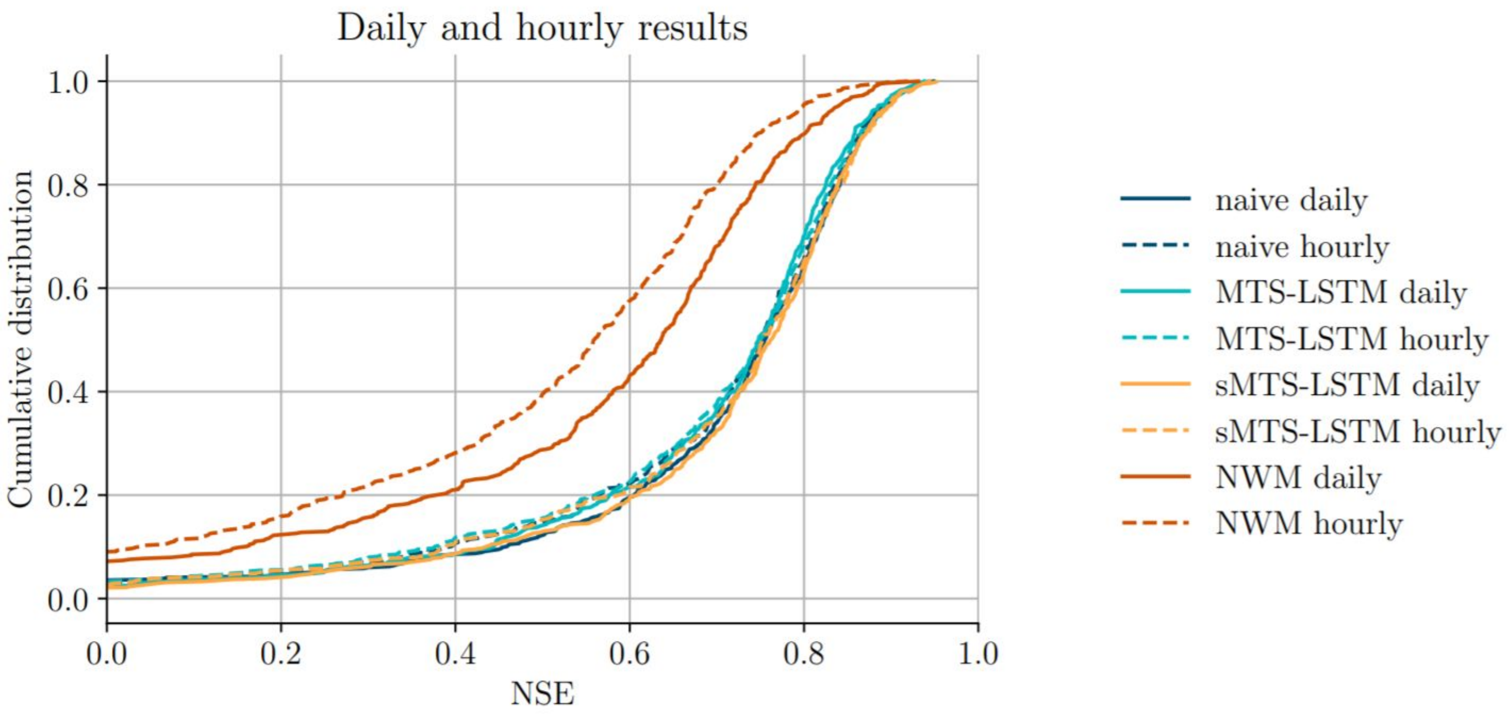




Kratzert, F., Klotz, D., Hochreiter, S., & Nearing, G. S. (2020). A note on leveraging synergy in multiple meteorological datasets with deep learning for rainfall-runoff modeling. *Hydrology and Earth System Sciences Discussions*, 1-26.

Certain “hard” tasks are easy with DL

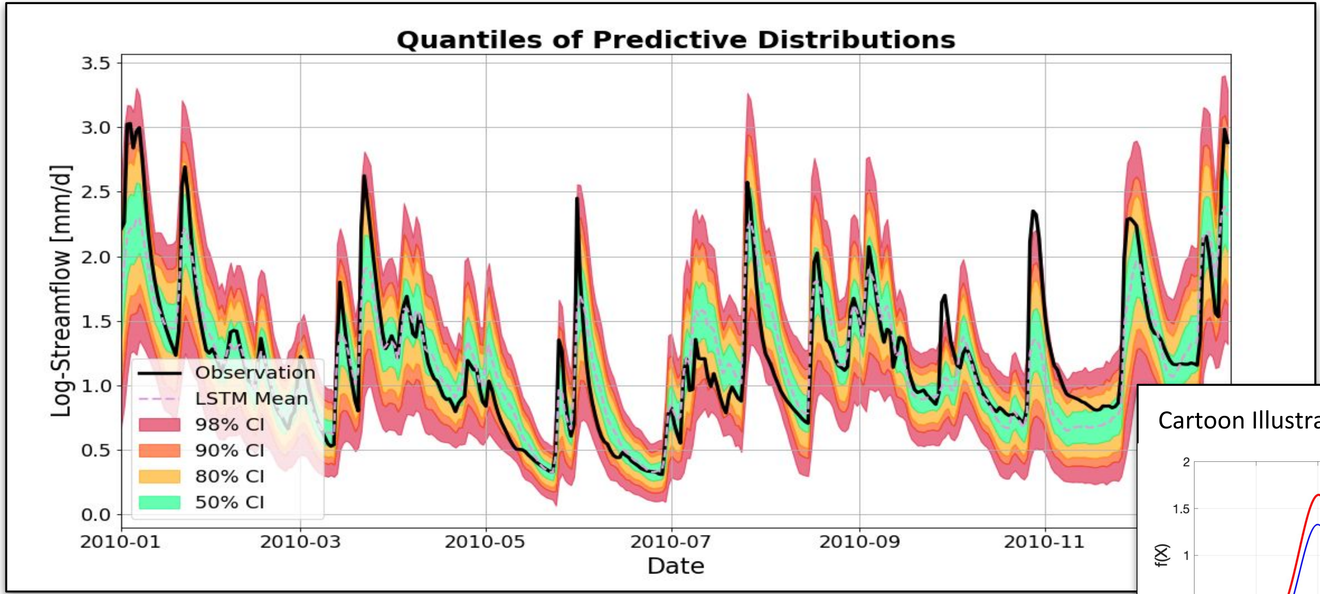
Multiple Time Scales

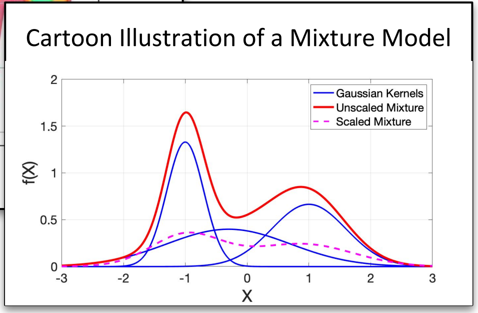


Gauch, M., Kratzert, F., Klotz, D., Nearing, G., Lin, J., & Hochreiter, S. (2020). Rainfall-Runoff Prediction at Multiple Timescales with a Single Long Short-Term Memory Network. *arXiv preprint arXiv:2010.07921*.

Certain “hard” tasks are easy with DL

Estimating Uncertainty



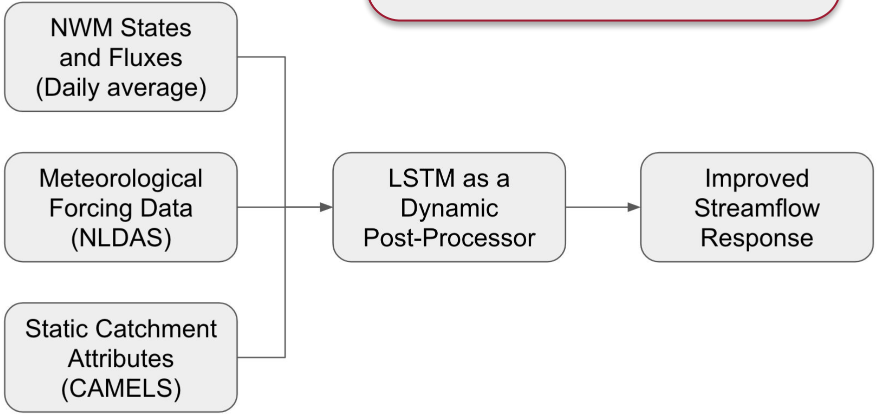


Alden Sampson;
Upstream Tech, PBC

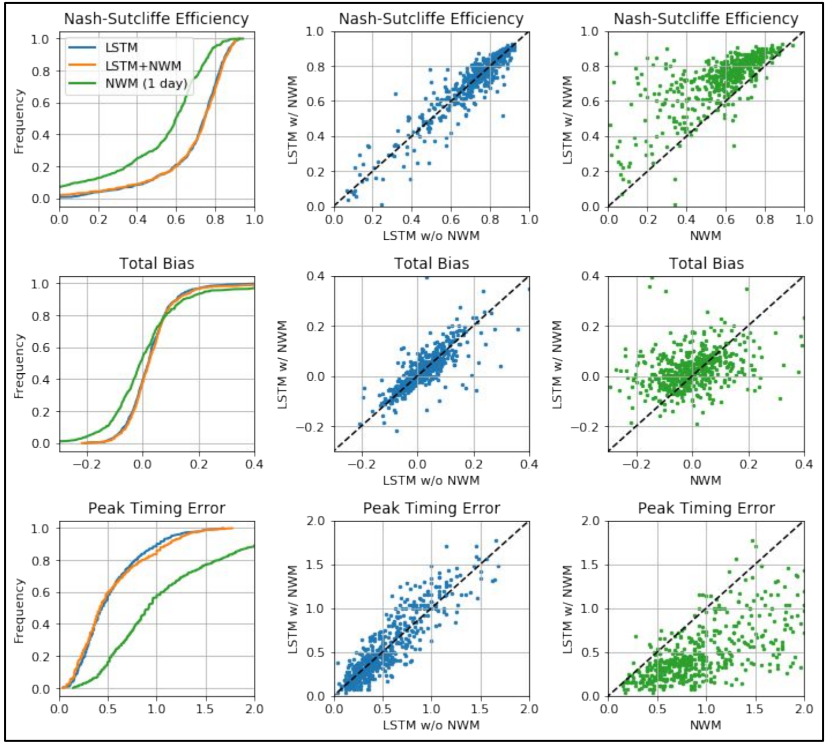
Physics Integration

Post-Processing

Adding NWM states and fluxes as inputs did not improve the LSTM



National Water Model Post-Processing



Frame, J., Nearing, G., Kratzert, F., & Rahman, M. (2020). Post processing the US National Water Model with a Long Short-Term Memory network.

Post-Processing

The LSTM "listens" to the NWM, but there isn't any extra information.

Sensitivity of LSTM to Different Inputs

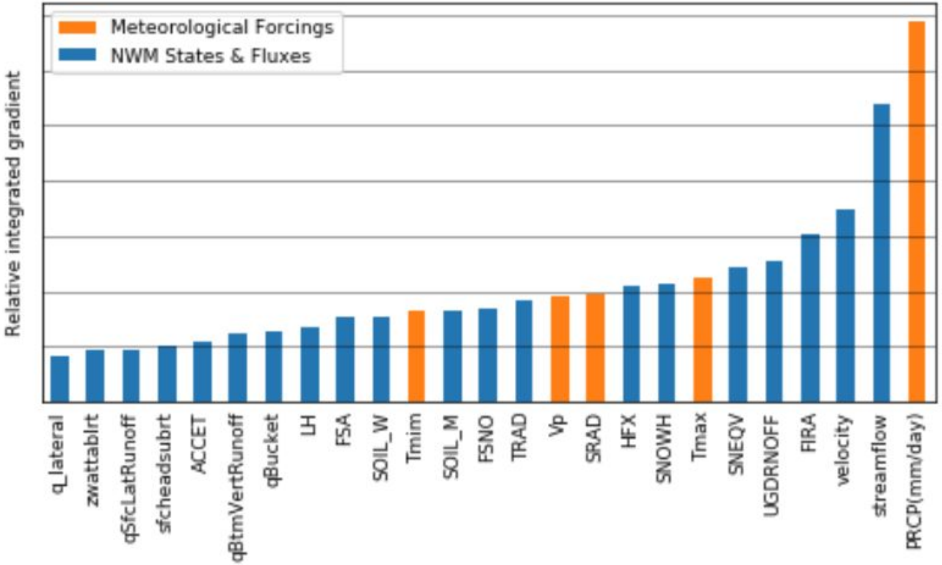
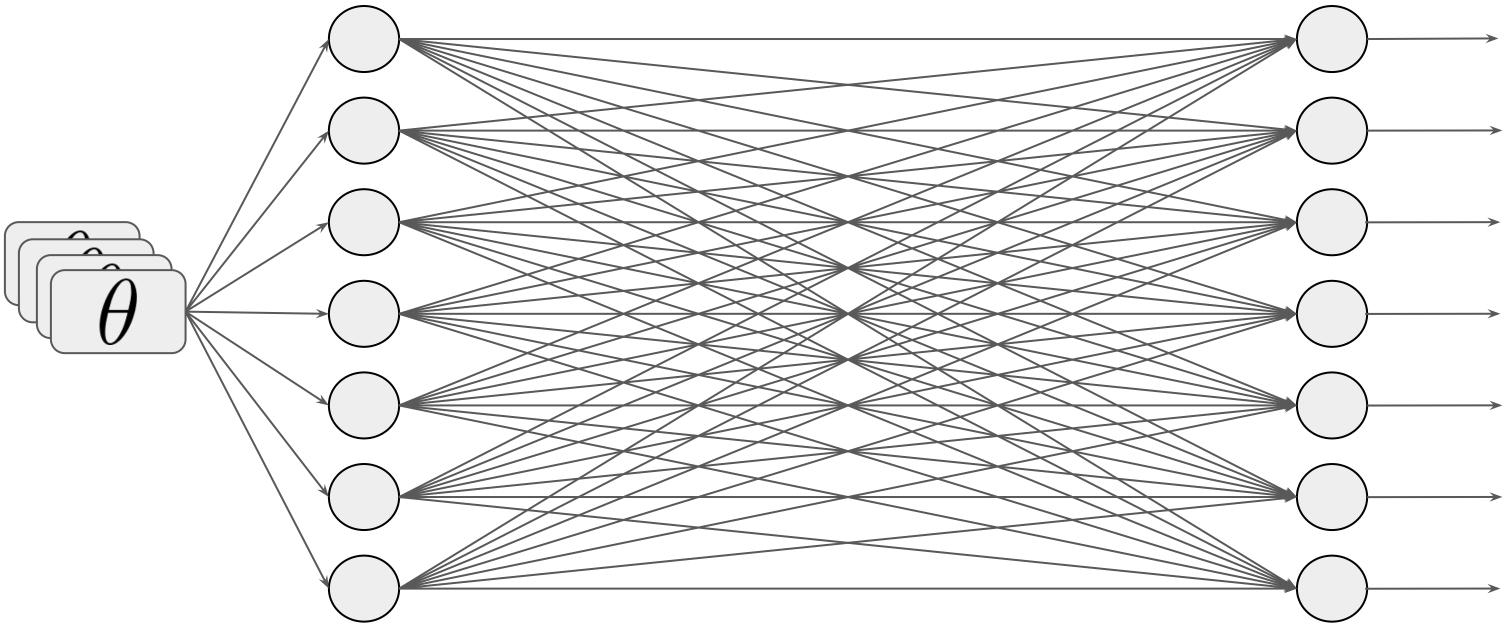


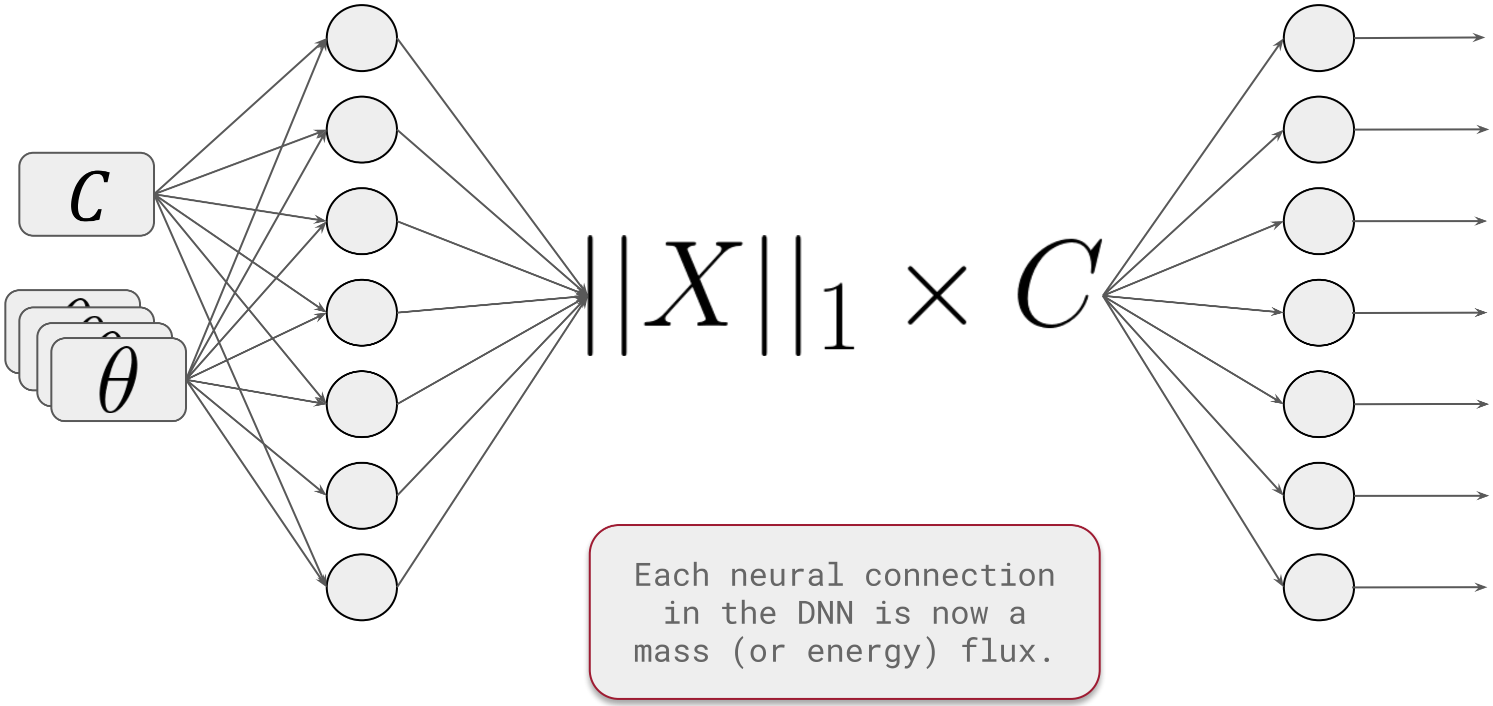
Figure 7. Attributions to the LSTM post-processor predictions. The vertical axis shows the relative magnitude of attribution (importance) for each input, with precipitation (PRCP) as the top contributor and NWM-predicted runoff into channel reach (q_lateral) contributing the least.

Frame, J., Nearing, G., Kratzert, F., & Rahman, M. (2020). Post processing the US National Water Model with a Long Short-Term Memory network.

Physics into Deep Learning Models

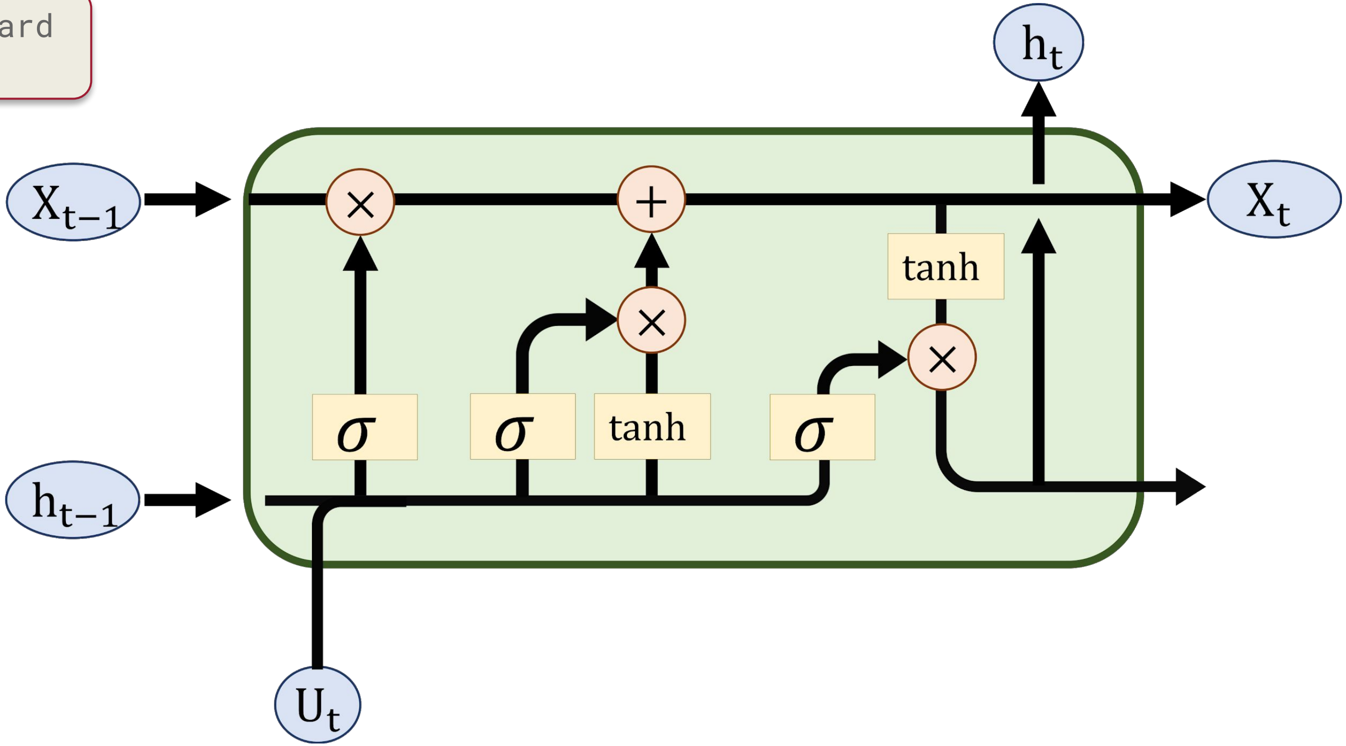


Physics into Deep Learning Models



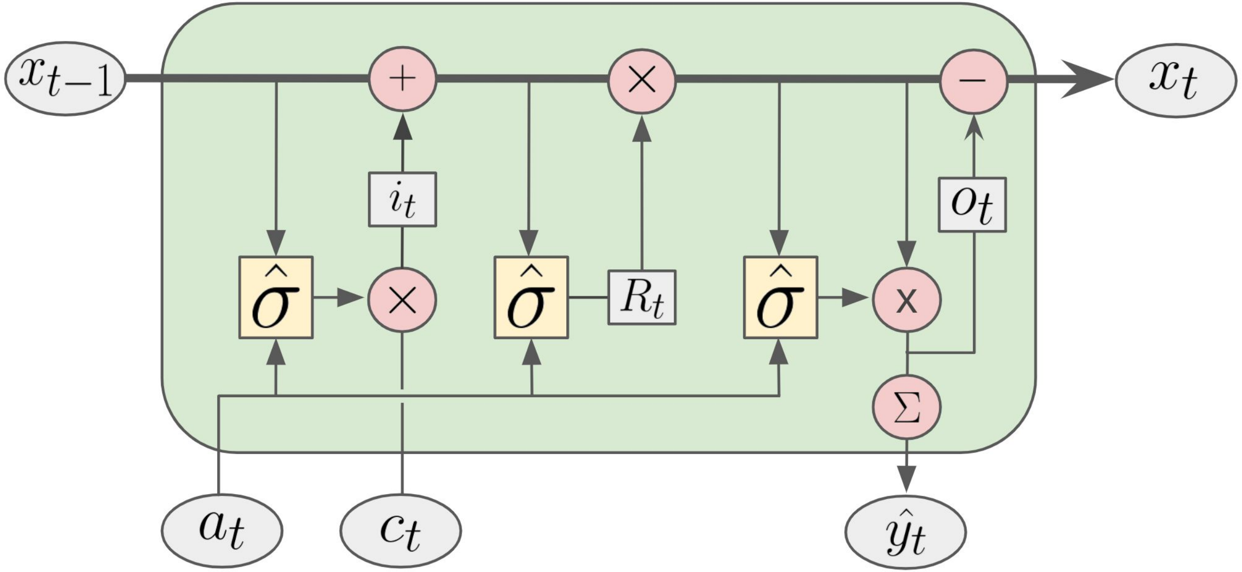
Physics into Deep Learning Models

A standard LSTM



Physics into Deep Learning Models

An "LSTM" with conservation laws



$$\vec{x_t} = \vec{x_{t-1}} + \vec{i_t} - \vec{o_t}$$

Physics into Deep Learning Models

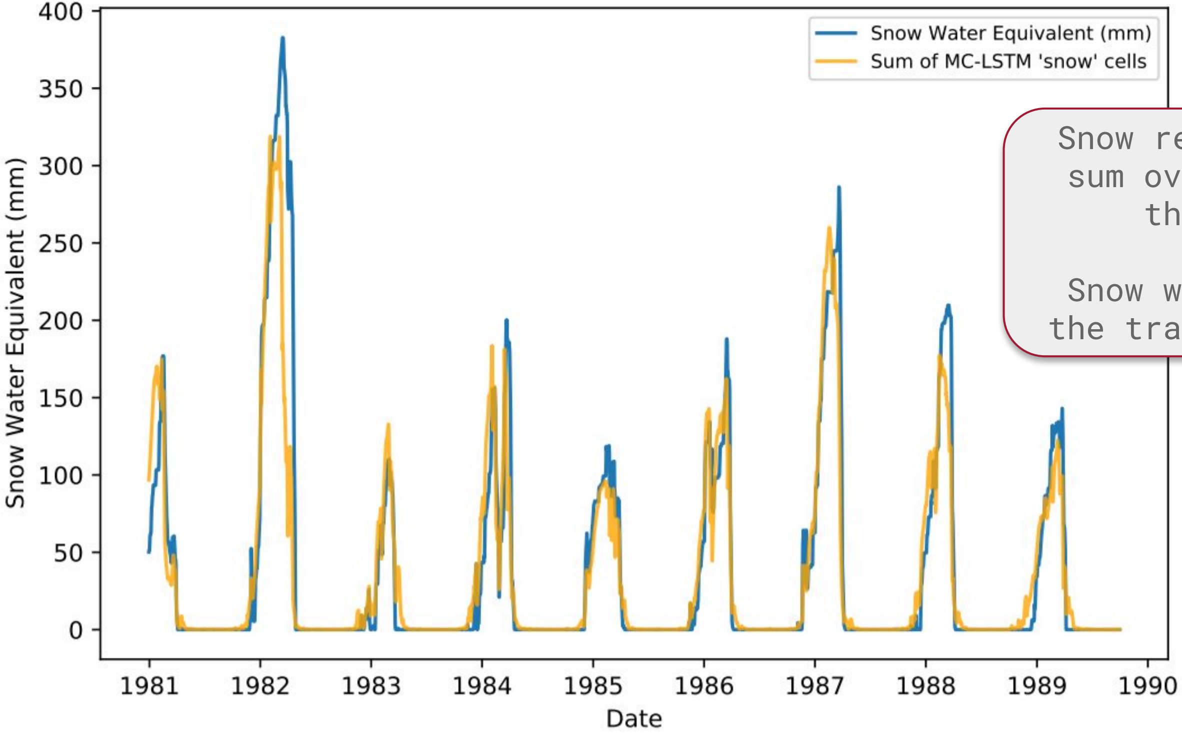
Table 1: Benchmarking Results. All values represent the median over the 447 basins.

Model	MC?[a]	KGE[b]	Bias[c]	σ_{rat}[d]	r^2	FHV[e]	FLV[f]
Deep Learning Models							
MC-LSTM Ens.	yes	0.764*	-0.020*	0.842	0.873*	-14.689*	-24.651*
LSTM Ens.	no	0.762	-0.034	0.838	0.886	-15.740	36.267
Conceptual Hydrology Models							
SAC-SMA	yes	0.632	-0.066	0.779	0.792	-20.356	37.415
VIC (basin)	yes	0.588	-0.018	0.725	0.760	-28.139	-74.769
VIC (regional)	yes	0.257	-0.074	0.457	0.651	-56.483	18.867
mHM (basin)	yes	0.691	-0.040	0.807	0.832	-18.640	11.433
mHM (regional)	yes	0.468	-0.039	0.589	0.793	-40.178	36.795
HBV (lower)	yes	0.391	-0.023	0.584	0.713	-41.859	23.883
HBV (upper)	yes	0.681	-0.012	0.788	0.833	-18.491	18.341
FUSE (900)	yes	0.668	-0.031	0.796	0.815	-18.935	-10.538
FUSE (902)	yes	0.690	-0.047	0.802	0.821	-19.360	-68.224
FUSE (904)	yes	0.644	-0.067	0.783	0.808	-21.407	-67.602

[a] *Mass conservation (MC).*
[b] *Kling-Gupta Efficiency: $(-\infty, 1]$, values closer to one are desirable.*
[c] *Bias: $(-\infty, \infty)$, values closer to zero are desirable.*
[d] *Variance Ratio: $(-\infty, \infty)$, values closer to one are desirable.*
[e] *Top 2% high flow bias: $(-\infty, \infty)$, values closer to zero are desirable.*
[f] *Bottom 30% low flow bias: $(-\infty, \infty)$, values closer to zero are desirable.*
[*] *MC-LSTM is significantly different than the LSTM by Wilcoxon rank test at $\alpha = 0.05$.*

Slight performance increase over LSTM, but currently the best peak-flow model we've tested.

Physics into Deep Learning Models



Snow represented as a sum over 4 states in the MC-LSTM.

Snow was not part of the training data set.

Contributors

Google Research

University of Alabama

Johannes Kepler University

Upstream Tech, PBC

University of Arizona

NASA

Frederik Kratzert

Daniel Klotz

Sepp Hochreiter

Craig Pelissier

Grey Nearing

Alden Sampson

Jonathan Frame

Hoshin Gupta