A coupled approach to incorporating deep learning into process-based hydrologic modeling

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Abstract

Machine learning techniques have proven useful at predicting many variables of hydrologic interest, and often out-perform traditional models for univariate predictions. However, demonstration of multivariate output deep learning models has not had the same success as the univariate case in the hydrologic sciences. Multivariate prediction is a clear area where machine learning still lags behind traditional processed based modeling efforts. Reasons for this include the lack of coincident data from multiple variables, which make it difficult to train multivariate deep-learning models, as well as the need to capture inter-variable covariances and satisfy physical constraints. For these reasons process-based hydrologic models are still used to simulate and make predictions for entire hydrologic systems. Therefore, we anticipate that future state of the art hydrologic models will couple machine learning with process based representations in a way that satisfies physical constraints and allows for a blending of theoretical and data driven approaches as they are most appropriate. In this presentation we will demonstrate that it is possible to train deep learning models to represent individual processes, forming an effective process-parameterization, that can be directly coupled with a physically based hydrologic model. We will develop a deep-learning representation of latent heat and couple it to a mass and energy balance conserving hydrologic model. We will demonstrate its performance characteristics compared to traditional methods of predicting latent heat. We will also compare how incorporation of this deep learning representation affects other major states and fluxes internal to the hydrologic model.

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Slides available here!

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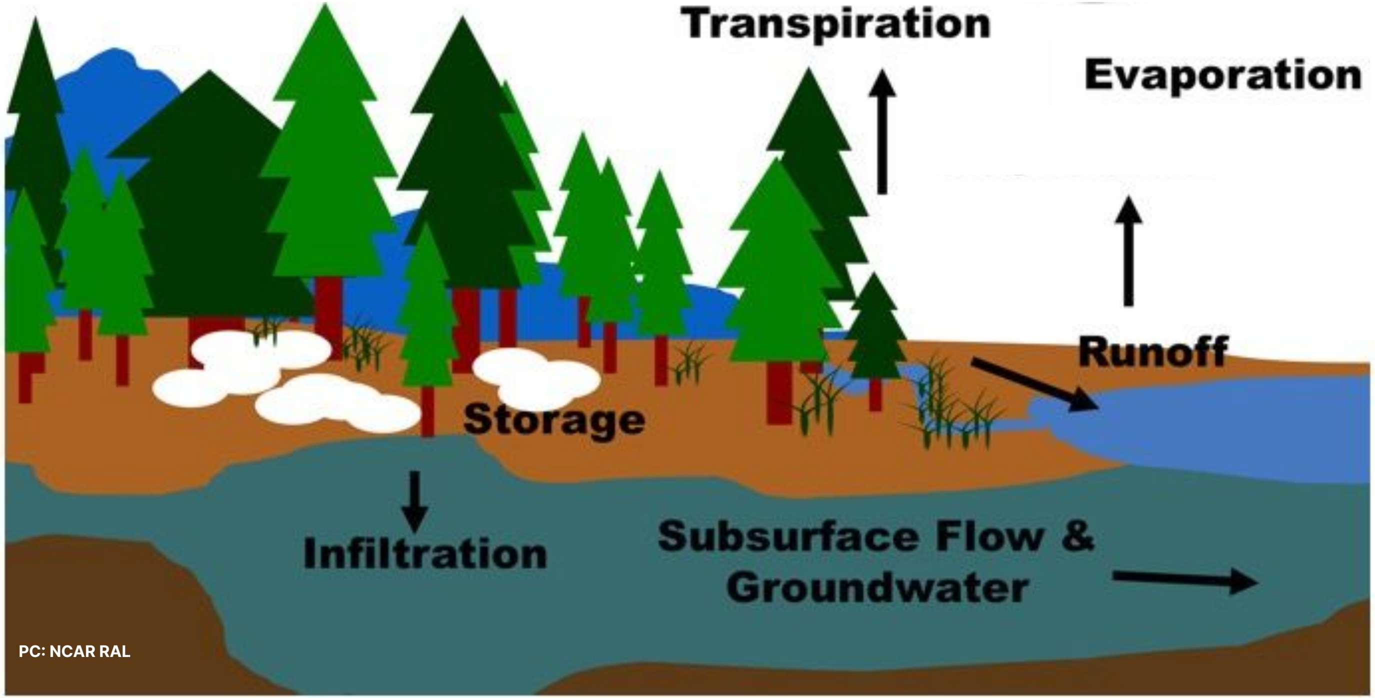
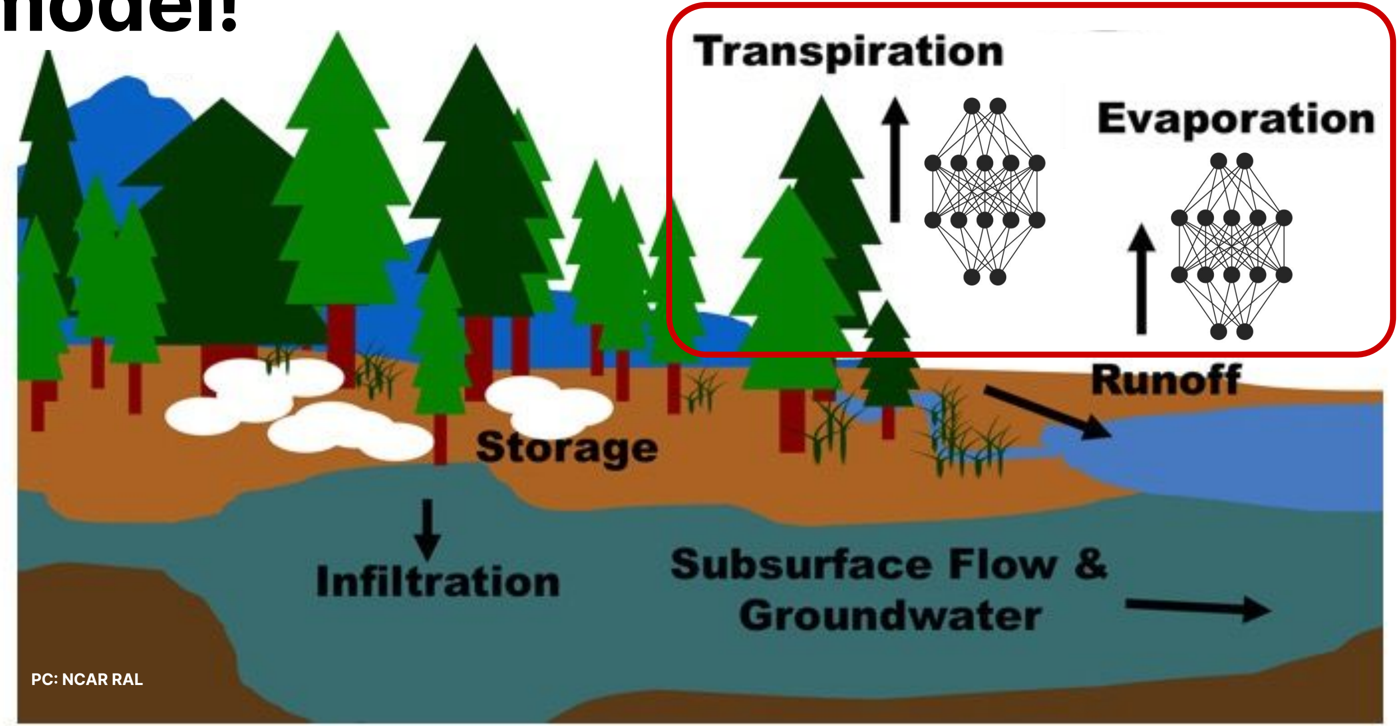

Transpiration
Evaporation
Runoff
Storage
Infiltration
Subsurface Flow &
Groundwater
PC: NCAR RAL

The main idea:

Put the neural network *inside* of the hydrologic model!



Why turbulent heat fluxes?

Evaporation and transpiration are a major component of the terrestrial cycle

Statistical models have been shown to be able to outperform current process-based models of turbulent heat fluxes

Why couple deep learning to a process based model?

Process based (PB) models are transferable, general-purpose, and provide an easy way to enforce constraints

We hypothesize that we can improve our PB models by incorporating DL

Our experiment

We use data from FluxNet towers from around the world to force model simulations for the prediction of turbulent heat fluxes.

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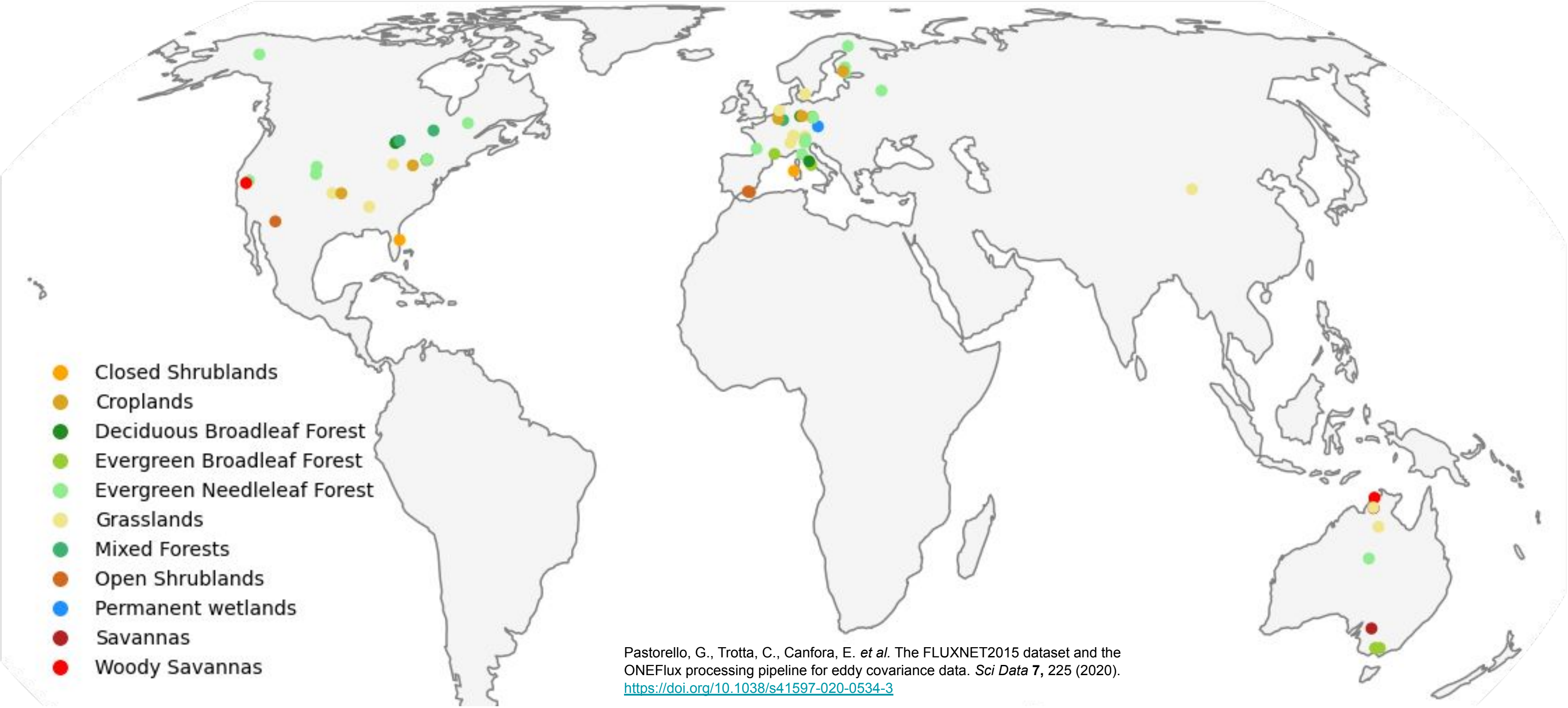
We will use a benchmark process-based model to compare two different coupled DL-PB model configurations

We will show that our coupled DL-PB configurations are able to outperform the benchmark in a number of ways

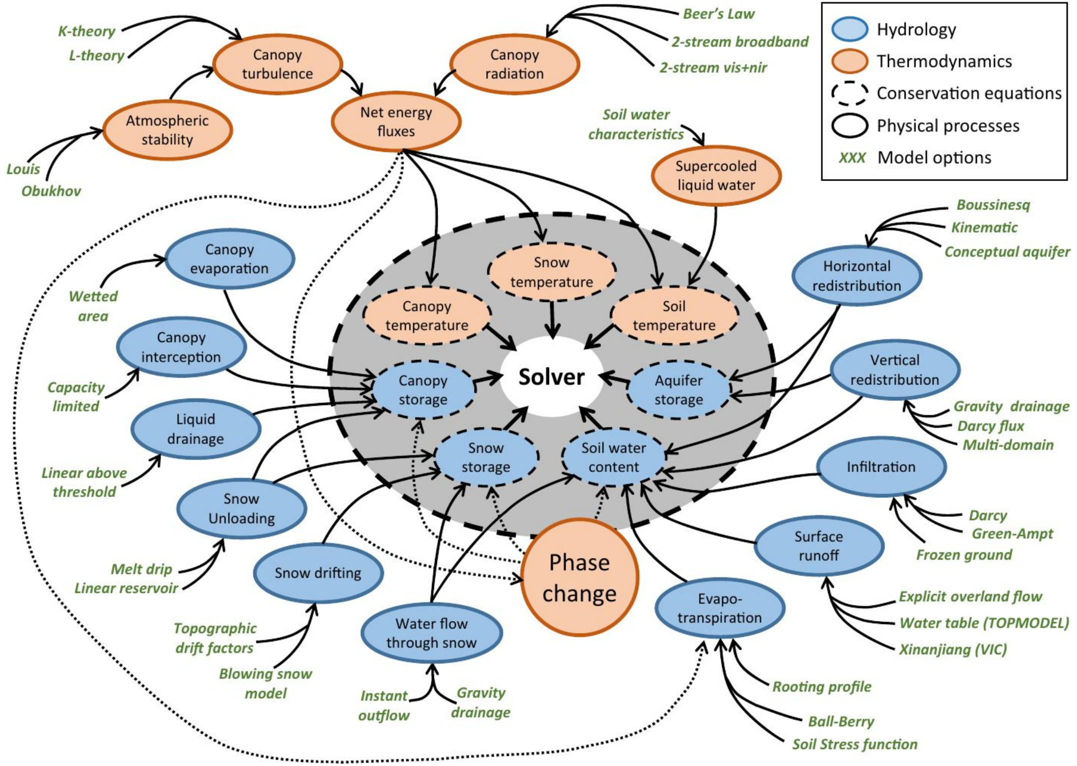
We gathered data from 60 FluxNet sites, totalling over 500 site-years of half-hourly data



Pastorello, G., Trotta, C., Canfora, E. *et al.* The FLUXNET2015 dataset and the ONEFlux processing pipeline for eddy covariance data. *Sci Data* **7,** 225 (2020). https://doi.org/10.1038/s41597-020-0534-3

We used the SUMMA hydrologic modeling framework for all of our configurations

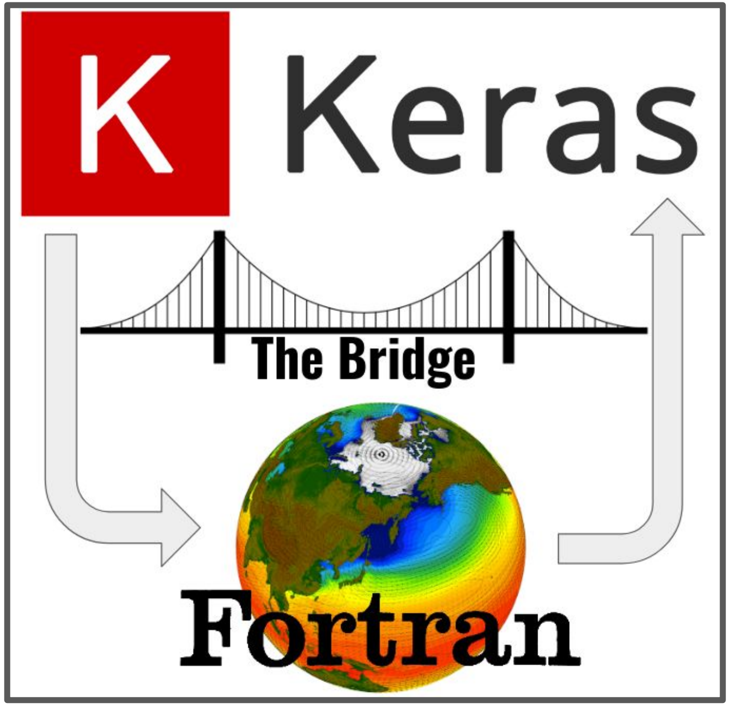
- **Standalone (SA)** uses SUMMA with only minor modifications



Clark, M. P., Nijssen, B., Lundquist, J. D., Kavetski, D., Rupp, D. E., Woods, R. A., et al. (2015). A unified approach for process-based hydrologic modeling: 1. Modeling concept. Water Resources Research, 51, 1–17. https://doi.org/10.1002/2015WR017200.A

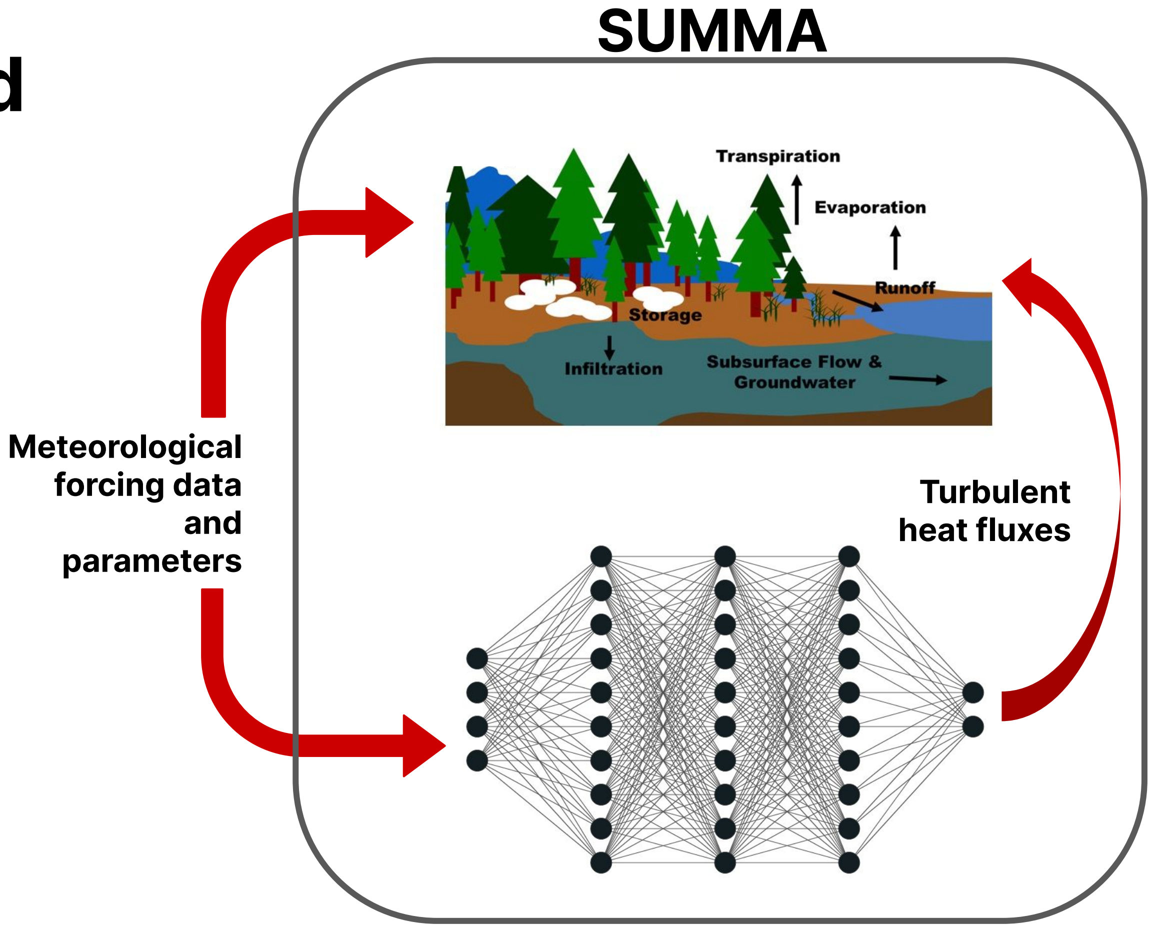
We used the SUMMA hydrologic modeling framework for all of our configurations

- **Standalone (SA)** uses SUMMA with only minor modifications
- **Neural network 1-way (NN1W)** and **Neural network 2-way (NN2W)** use the Fortran-Keras Bridge (FKB) to integrate the neural networks directly into the SUMMA simulations

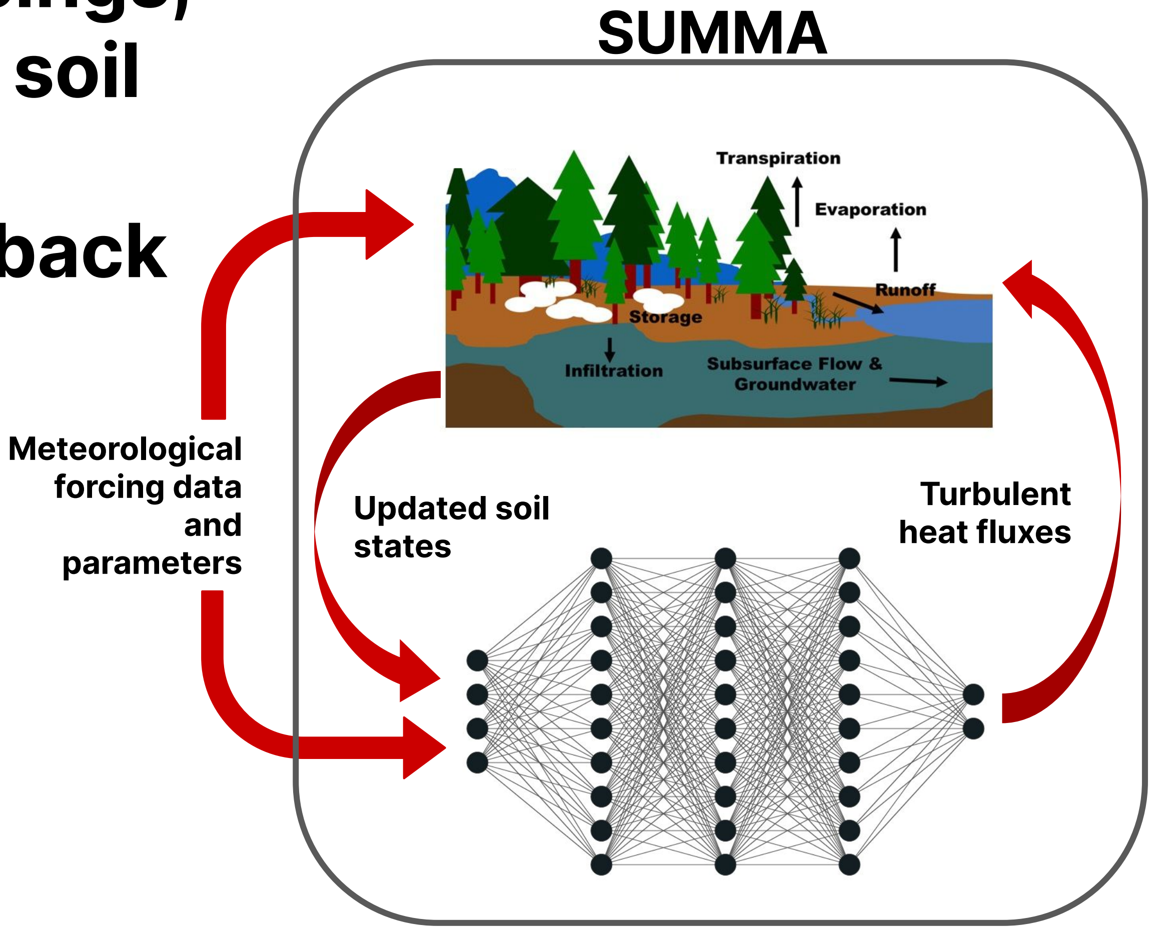


Ott, J., M. Pritchard, N. Best, E. Linstead, M. Curcic, and P. Baldi (2020). A Fortran-Keras deep learning bridge for scientific computing.arXiv preprint arXiv:2004.10652

NN1W takes forcing data and parameters as inputs



NN2W takes forcings, parameters, and soil states as inputs, resulting in feedback at runtime



To summarize: We created three model setups to predict the latent and sensible heat fluxes

Standalone (SA)

We calibrated, then evaluated SA simulations "in sample"

Calibrated individually at each FluxNet site

Benchmark simulations using a process-based hydrologic model

Neural Network 1 Way (NN1W)

Trained a neural network out of sample (5-fold cross validation)

Inputs are only meteorological forcing data and parameter values

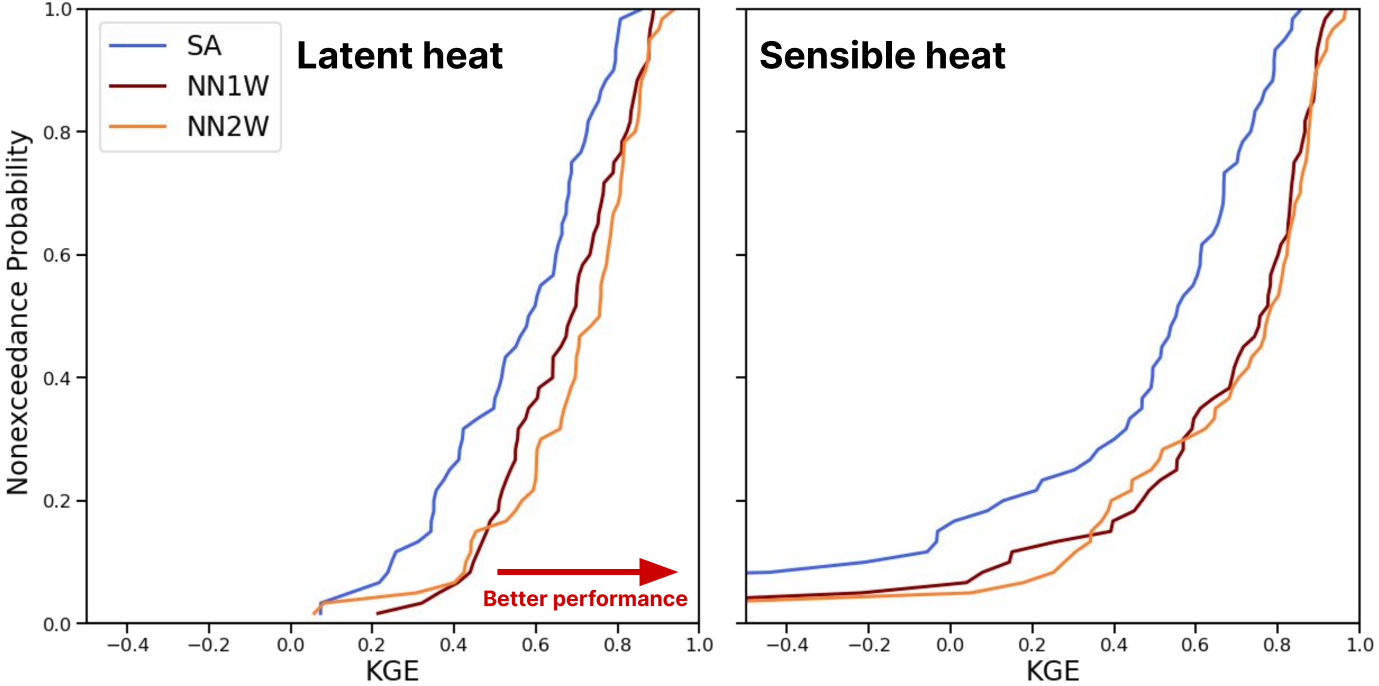
1-way coupling since no information from the hydrologic model is included

Neural Network 2 Way (NN2W)

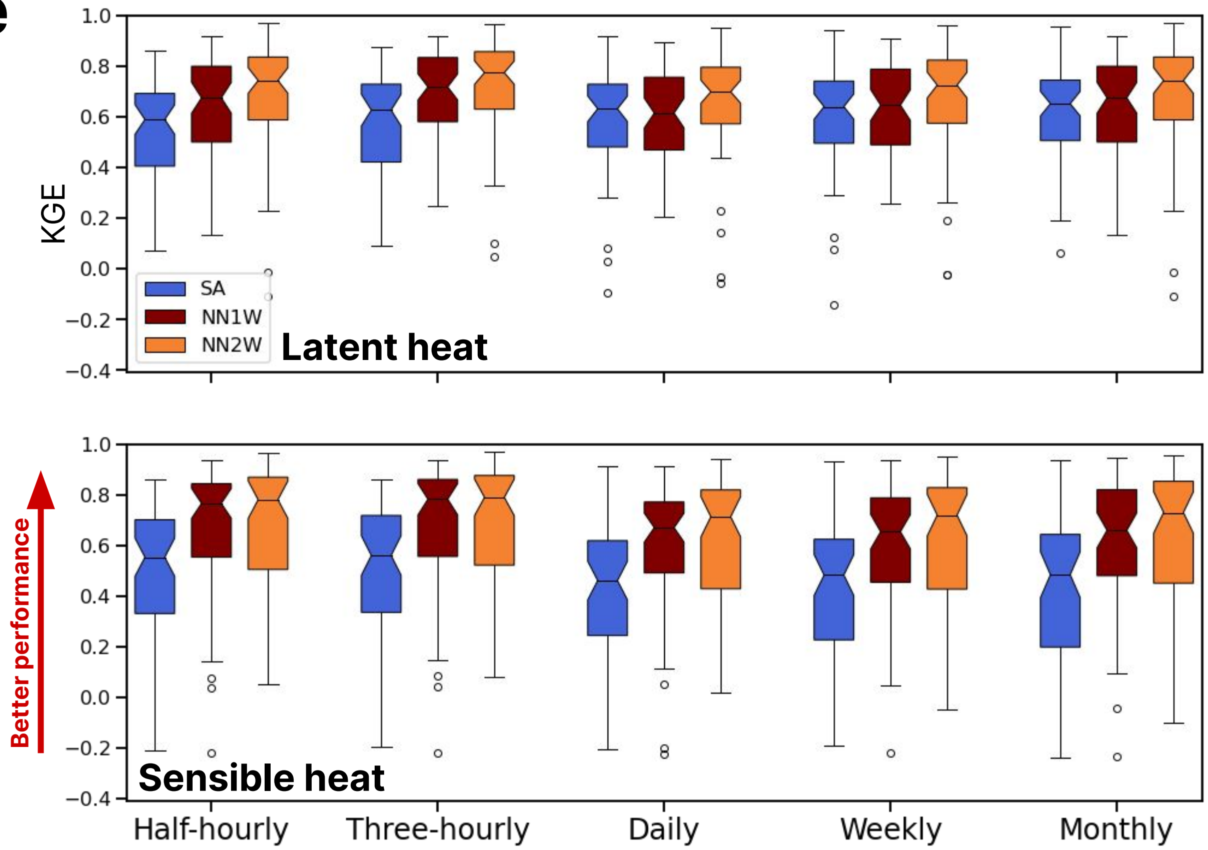
Same as NN1W, but includes soil states (temperature, moisture content, etc) as an input

2-way coupling since the hydrologic model provides feedback at runtime

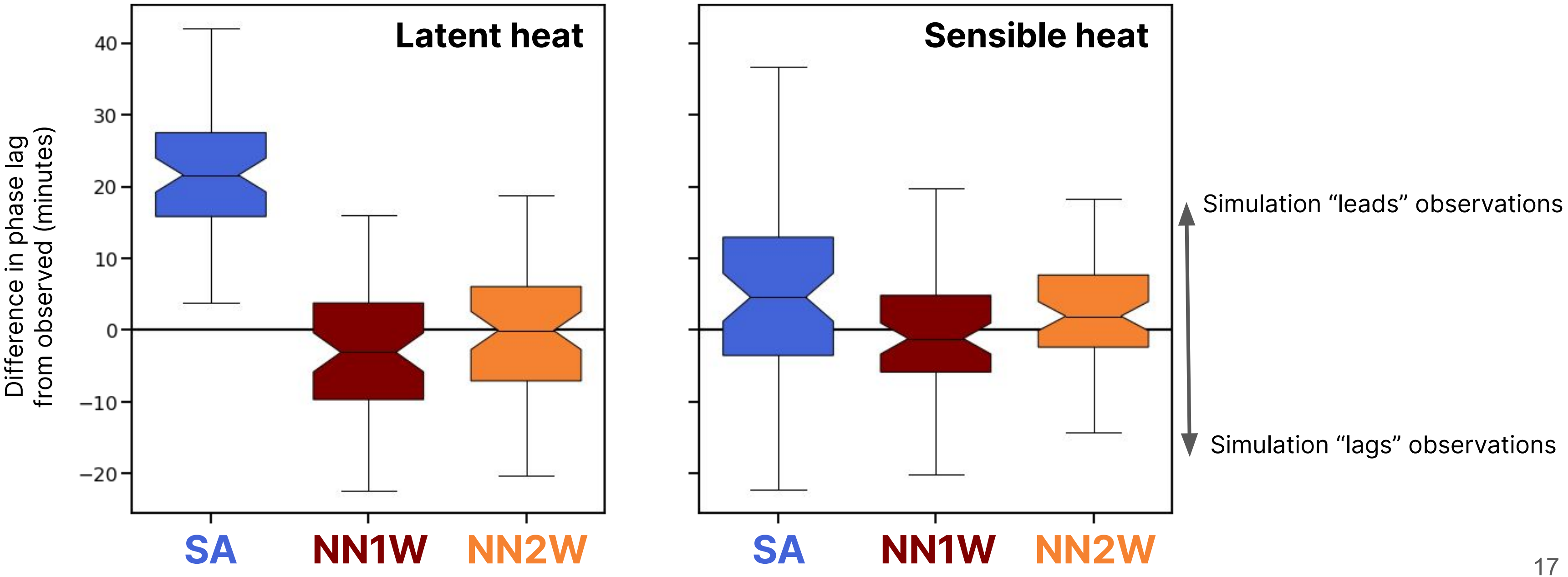
Both neural network parameterizations outperformed the standalone model, for both latent and sensible heat



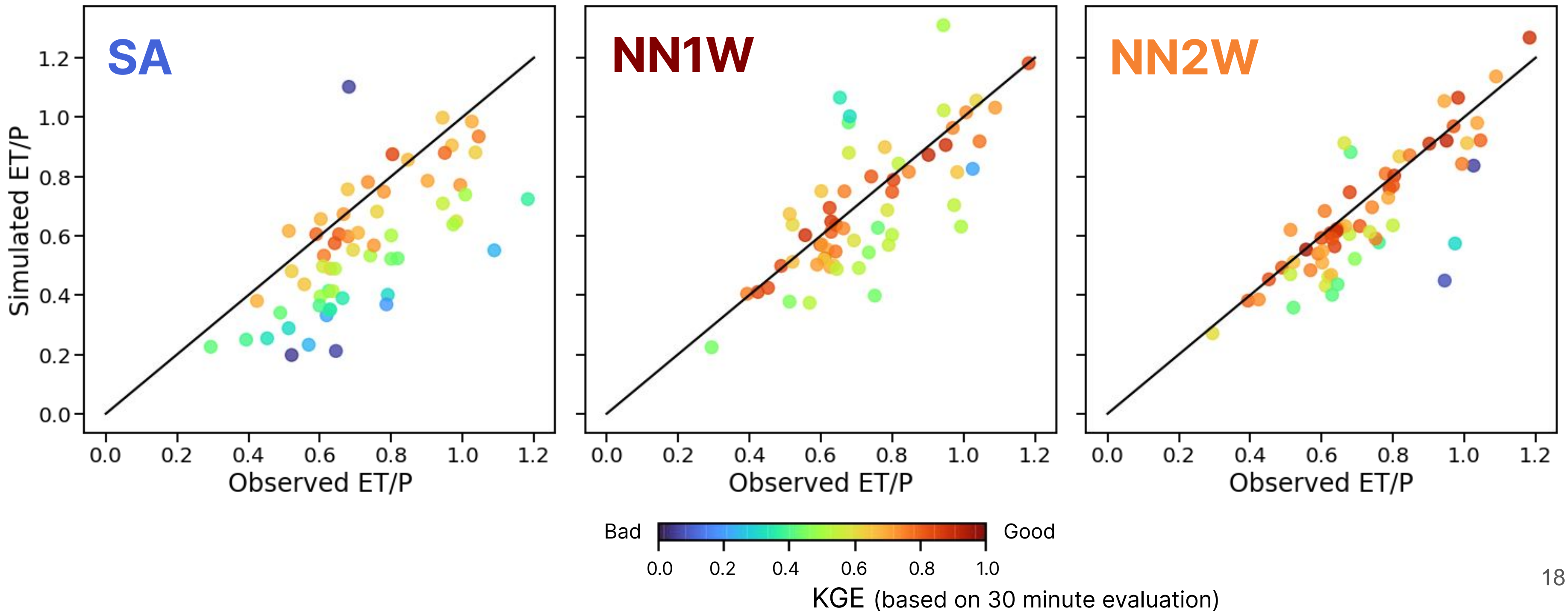
Better performance held for NN2W for latent heat and both NN1W and NN2W across multiple temporal scales



Both NN1W and NN2W have better representations of the diurnal cycle than SA



Inclusion of soil states in NN2W improves long-term water balance over NN1W



Thanks for listening!
A few takeaways:

Coupling of machine learned parameterizations for turbulent heat fluxes provides better performance on a variety of measures

Coupling ML and process based models allows for including feedbacks which can help to implicitly enforce constraints

More advanced tools and workflows will likely lead to even larger gains in performance

If you have any questions or would like to discuss further, send me an email:
andrbenn@uw.edu

Slides available here!