Snowledge is Power

Multi-task hydrologic deep-learning provides explainability and assimilation of sparse land surface observations
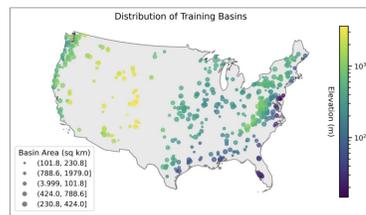
Upstream Tech

Simon Topp, Cesar Augusto Suarez, Margo Crawford, Alex Gontar, Mostafa Elkurdy, Lauren Gulland, Phillip Butcher, David Lambl, **Alden Keefe Sampson**
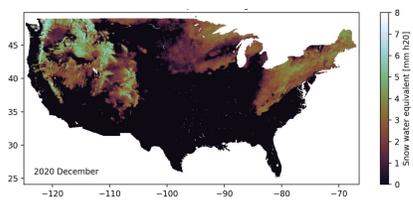
1. Data

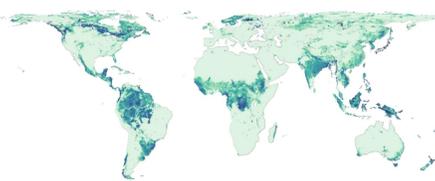Copernicus ERA5-Land, NOAA GEFS, ECMWF IFS ENS meteorological forcings
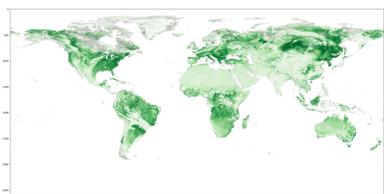
USGS gauged discharge

U Arizona / NASA SWANN Snow

NASA SMAP Soil Moisture

NOAA VIIRS + AVHRR Vegetation (NDVI)

All data aggregated to sub-basin average time series
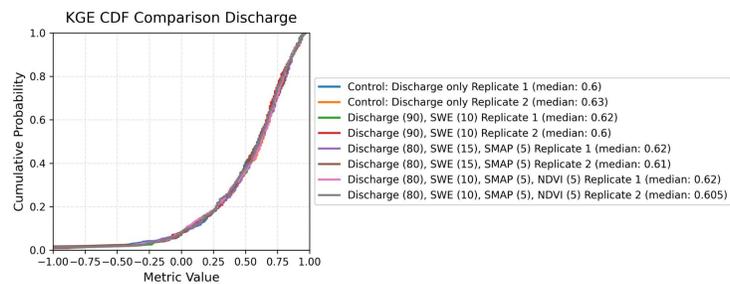
2. Training & Evaluation

Long Short-term Memory (LSTM) based deep neural network

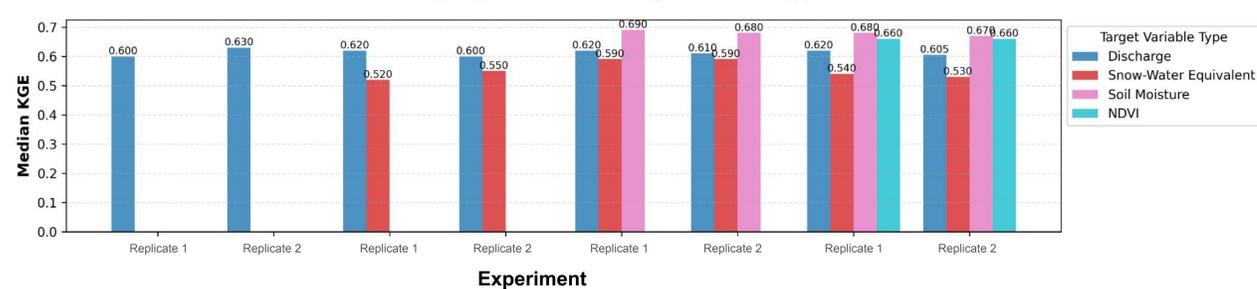**Inputs:** precipitation, daily min/max temperature

Outputs: discharge, snow water equivalent, soil moisture, normalized difference vegetation index

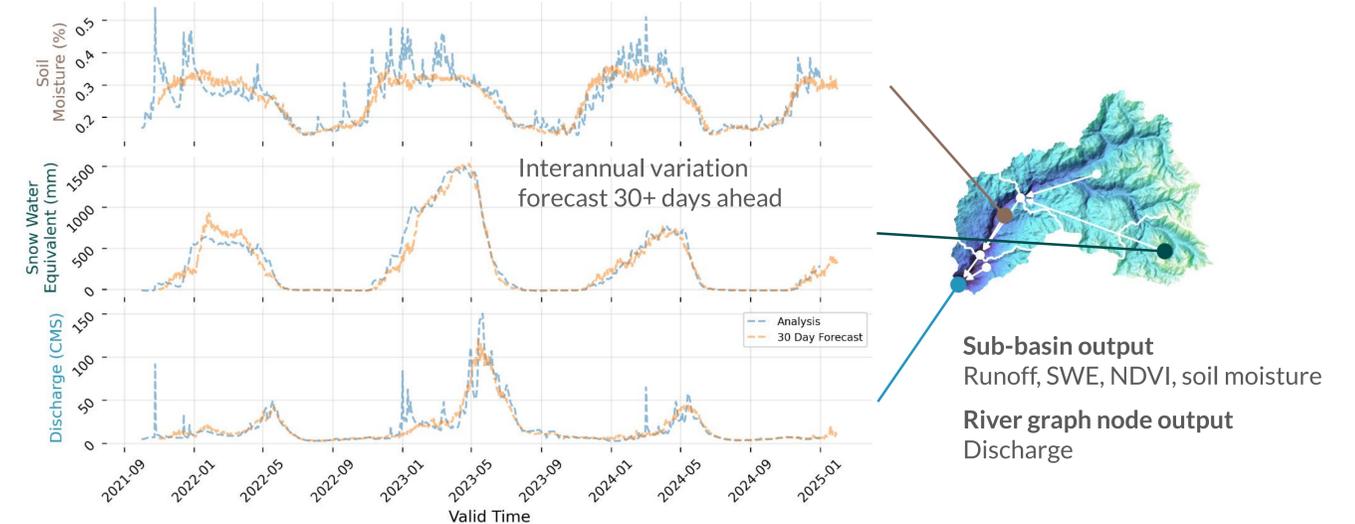80% - 90% loss weight given to discharge (our primary output of interest)

Adding new, related output variables does not meaningfully impact discharge performance (KGE, RMSE, bias, etc) →

KGE CDF Comparison Discharge

- Control: Discharge only Replicate 1 (median: 0.6)
- Control: Discharge only Replicate 2 (median: 0.63)
- Discharge (90), SWE (10) Replicate 1 (median: 0.62)
- Discharge (90), SWE (10) Replicate 2 (median: 0.6)
- Discharge (80), SWE (15), SMAP (5) Replicate 1 (median: 0.62)
- Discharge (80), SWE (15), SMAP (5) Replicate 2 (median: 0.61)
- Discharge (80), SWE (10), SMAP (5), NDVI (5) Replicate 1 (median: 0.62)
- Discharge (80), SWE (10), SMAP (5), NDVI (5) Replicate 2 (median: 0.605)

Median KGE by Experiment and Target Variable Type

3. Distributed forecasts

Interannual variation forecast 30+ days ahead

Analysis / 30 Day Forecast

Sub-basin output
Runoff, SWE, NDVI, soil moisture

River graph node output
Discharge

4. Assimilation

Basin-Averaged Snow Water Equivalent (SWE)

- High SWE scenario (120% observed SWE assimilated)
- Baseline SWE scenario (observed SWE assimilated)
- Low SWE scenario (80% observed SWE assimilated)
- ✕ Assimilated SWE observation

← Analysis | Forecast →

Discharge

Probabilistic prediction confidence intervals omitted for visualization clarity.

Variational data assimilation adjusts model states to align with observations

Sparse observations e.g. point-in-time airborne lidar or snow courses supported

Gap filling and forecasting between and beyond land surface observations

Shared process representations result in hydrologically meaningful adjustments across output variables during assimilation

HydroForecast