The impact of streamflow forecast skill on economic outcomes in the Upper Colorado River Basin

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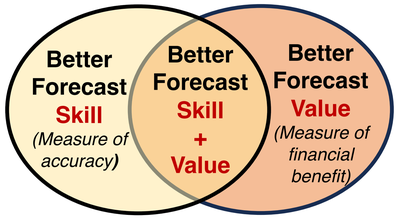
1 BACKGROUND

- Ensemble Streamflow Predictions (ESPs) are a popular choice for producing probabilistic streamflow forecasts operationally.
- These forecasts do provide economic value for hydrological decision-making.

Hypothesis about forecasts



2 STUDY DOMAIN

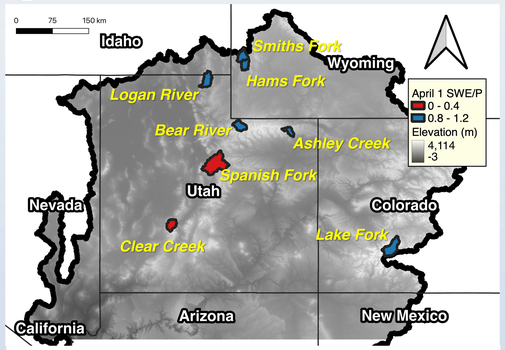
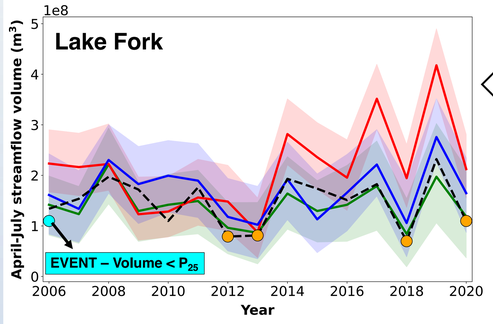


Fig 1: 8 USGS basins colored by the ratio of the April 1 SWE to water–year-to-date cumulative precipitation.

4 FORECAST SKILL AND VALUE DIAGRAM – LAKE FORK



Normalized RMSE (%)	Model	Area under PEV_{max}
102	WRFH	0.19
34	LSTM	0.38
14	CBRFC	0.77

- We compare Normalized RMSE (%) from three models across the years below the 25th percentile. Lower NRMSE values indicate better model performance.
- Our findings suggest that taking action to mitigate losses when streamflow volume falls below the 25th percentile yields significant value, particularly when using CBRFC and LSTM forecasts, which have reasonable skill.

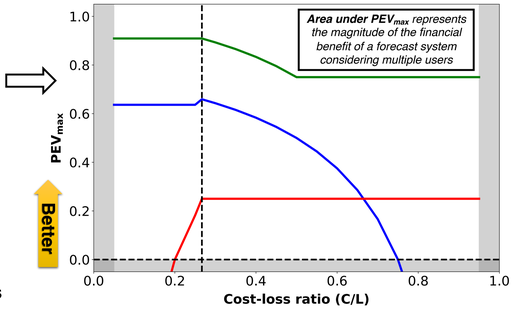


Fig 5: ESPs showing April-July streamflow volume from different models in WY2006-2020 at Lake Fork (USGS 09124500).

Fig 6: Maximum PEV quantified using three different models. A binary decision for taking action when AMJJ volume falls below the 25th percentile of observations is considered.

3 METHODOLOGY

3a. ENSEMBLE STREAMFLOW PREDICTIONS

- In ESP, historical weather observations are used as inputs to process-based or deep-learning models.
- The result is a probabilistic forecast ranging from 30 up to 180 days from the forecast date that uses spread in the historical data as an analogue for the uncertainty in climate after the forecast date (Day, 1985).

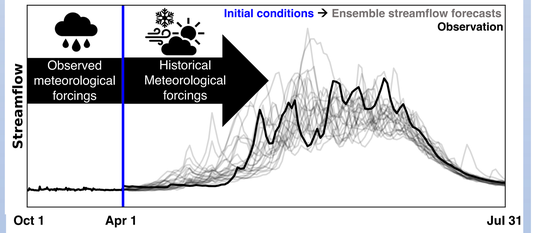


Fig 2: Illustration of an ESP forecast issued on April 1. The black line indicates a 'true' forecast (i.e., observation). Using the initial conditions (shown in blue) and meteorological forcings from the past ~20 to 30 years, ensemble streamflow forecasts are generated (shown in grey). Data based on USGS 13313000 – WY2011.

3b. MODELS APPLIED IN ESP

- Probabilistic Seasonal Streamflow forecasts are produced using different modeling setups except "Operational", which is obtained from the Colorado Basin River Forecast Center.

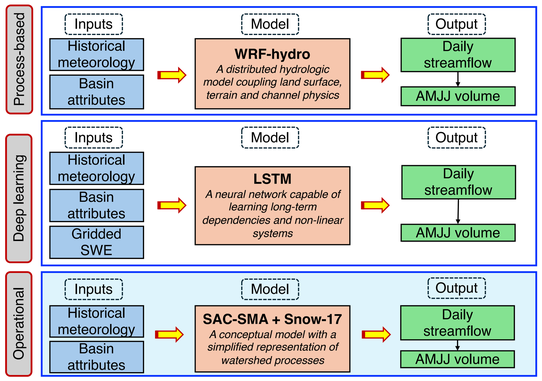


Fig 3: Schematic of model workflows applied in ESP framework.

5 RELATIONSHIP BETWEEN SKILL AND VALUE

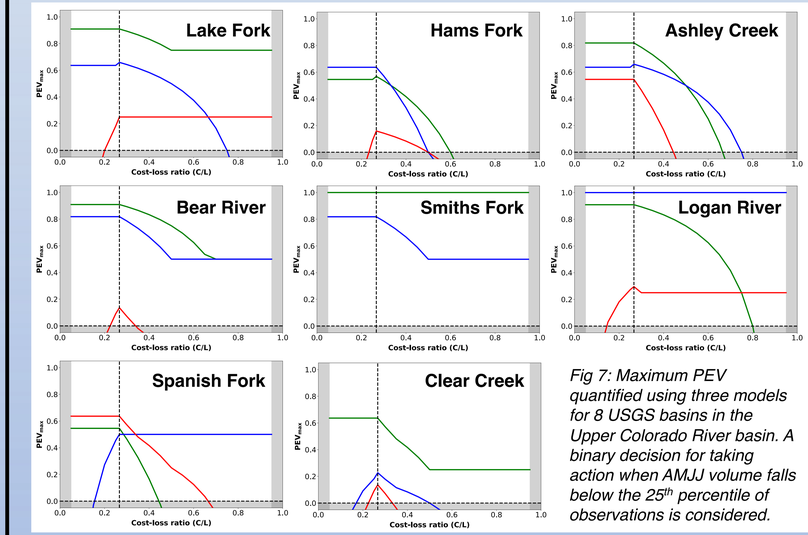
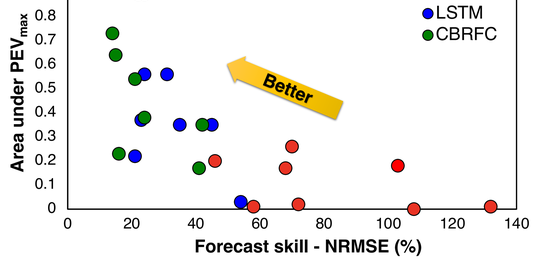


Fig 7: Maximum PEV quantified using three models for 8 USGS basins in the Upper Colorado River basin. A binary decision for taking action when AMJJ volume falls below the 25th percentile of observations is considered.



- LSTM and CBRFC offer the greatest benefit across most of the basins, considering their high forecast skill. The WRFH showed limited benefit primarily due to a lack of calibration.
- The comparison of forecast skill (NRMSE) and forecast value (Area under PEV_{max}) reveals a non-linear relationship, indicating some financial benefit can be obtained using a forecast having skill up to 80% compared to climatology. In general, LSTM and WRFH show consistently low skill and value due to the absence of post-processing, a practice commonly employed by CBRFC.

3c. POTENTIAL ECONOMIC VALUE (PEV) – MEASURE OF FINANCIAL BENEFIT FROM EARLY ACTION MITIGATION OF AN EXTREME EVENT

Probabilistic Seasonal Streamflow Forecasts

Categorical forecasts using critical probability threshold

Predicted volume					
Years	Ensemble volumes				
2006	2	3	4	3	2
2007	2	2	2	3	3

Forecast Probability (Event: vol < 2.5)						
Years	Ensemble volumes					
2006	1	0	0	0	1	0.4
2007	1	1	1	0	0	0.6

Threshold = 0.5

Categorical	
2006	0 (No)
2007	1 (Yes)

Threshold = 0.7

Categorical	
2006	0 (No)
2007	0 (No)

Decide to act or not

2x2 Contingency Table for all critical probability thresholds

Action Taken	Event Occurs	
	Yes	No
Yes	Hit rate (H) **C**	False alarm rate (F) **C**
No	Miss rate (M) **L**	Correct rejection rate (Q) **0**

C = Cost of mitigating action
L = Loss due to event

Multiple thresholds

Calculate Expenses

Expected expense of a user of forecast system

$$E_{forecast} = F(1-s)C - Hs(L-C) + sL \quad (1)$$

Expected expense with using climatological information

$$E_{climate} = \min(C, sL) \quad (2)$$

Expected expense given a perfect forecast

$$E_{perfect} = sC \quad (3)$$

Potential Economic Value (PEV)

$$PEV = \frac{E_{climate} - E_{forecast}}{E_{climate} - E_{perfect}}$$

Substituting Eq 1-3

$$PEV = \frac{\min(\alpha, s) - F(1-s)\alpha + Hs(1-\alpha) - s}{\min(\alpha, s) - s\alpha}$$

α = C/L (Cost-loss ratio) & s = climatological frequency

Perfect forecast system → PEV = 1
Equal to climatology → PEV = 0
Worse than climatology → PEV < 0

Economic Value Diagram

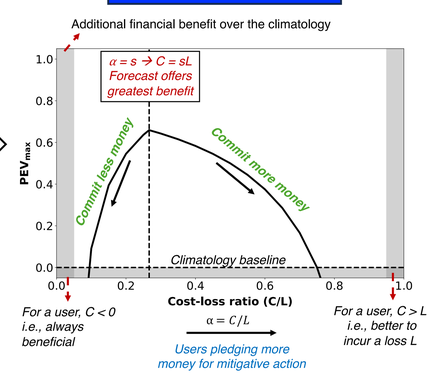


Fig 4: Flowchart showing the workflow to quantify the Potential Economic Value using the probabilistic forecasts. The PEV uses a threshold approach and relies on contingency table parameters (H and F), climatological frequency (s), and cost-loss ratio (α). PEV_{max} is an upper limit of financial benefit, implying a user has perfect foresight or a perfectly reliable forecast (Richardson, 2000).

Figure adapted from Laugesen et al., 2023

6 SUMMARY

- The relationship between forecast skill and value aids in hydrological decision-making by providing a range of possible financial benefits that can be obtained using different models in distinct hydro-climatic settings.
- We plan to broaden the analysis by expanding the ESP forecasts to encompass a larger number of basins using a consistent test bed. This will involve uniformity in meteorological forcings and conducting appropriate model calibration. Furthermore, we intend to extend this analysis to encompass a variety of hydro-climatic regimes, thereby offering deeper insights into the relationship between forecast skill and value.

- **Contact:** parthkumar.modi@colorado.edu
- **Resources:** CURC computing resources @CU Boulder
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