Benchmarking different approaches for harnessing predictability in climate and hydrologic initial conditions for seasonal runoff prediction

Andy Wood[1], Pablo Mendoza[1], Eric Rothwell[2], Martyn Clark[1], Levi Brekke[3] and Jeffrey Arnold[4]

MOTIVATION, OBJECTIVES and APPROACH

- Seasonal streamflow forecasts of spring runoff (eg, April-July water supply forecasts) are critical for anticipating and managing water systems in snowmelt-dependent regions.
- Operational seasonal streamflow forecasts in the US use two primary approaches, both of which leverage initial watershed conditions but not climate forecast information:
  1. regress future streamflow on point observations of rainfall, snow water equivalent, river flow
  2. run ensemble hydrologic model simulations that combine initial watershed moisture states with historically observed weather sequences for the forecast period (called ESP, *ensemble streamflow prediction*)
- New opportunities – eg, climate prediction datasets (eg, CFSv2, CFSR), physically-explicit hydrologic models, and statistical techniques – have emerged that could improve current practice.
- **There is a need for a *systematic intercomparison* of alternative streamflow forecasting approaches to assess the marginal benefit of different types of information in water supply prediction**
- We are conducting seasonal streamflow hindcasts in selected case study watersheds to assess and intercompare strategies

SEASONAL and SPRING RUNOFF PREDICTABILITY

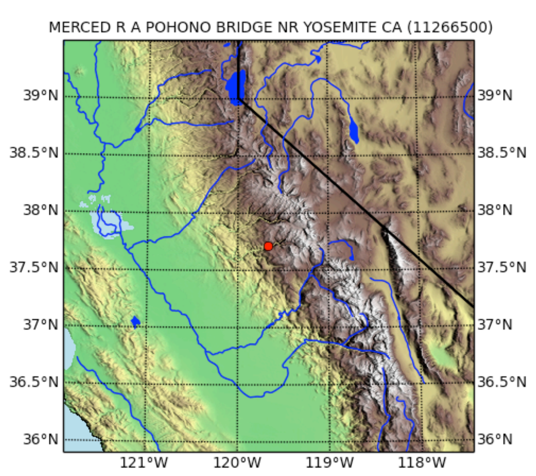
Runoff forecasts are driven by initial hydrologic conditions (IHCs) and future seasonal climate (SCF) (Wood and Lettenmaier, 2008). The impact of skill in each predictability source varies greatly throughout the year.

***Plot**: runoff predictions initialized in each month (Wood et al, 2015) with varying levels of uncertainty in each predictability source*

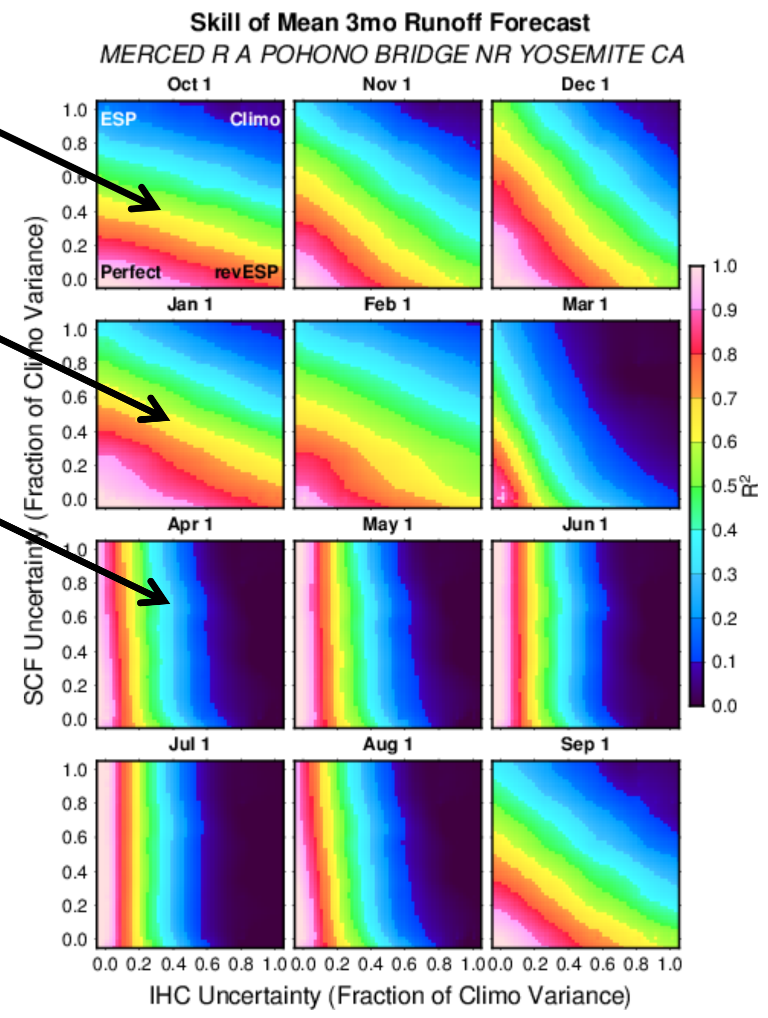
Climate forecast (SCF) skill dominates seasonal runoff forecast skill (R^2)

SCF skill and initial watershed moisture (IHC) accuracy both influence runoff forecast skill

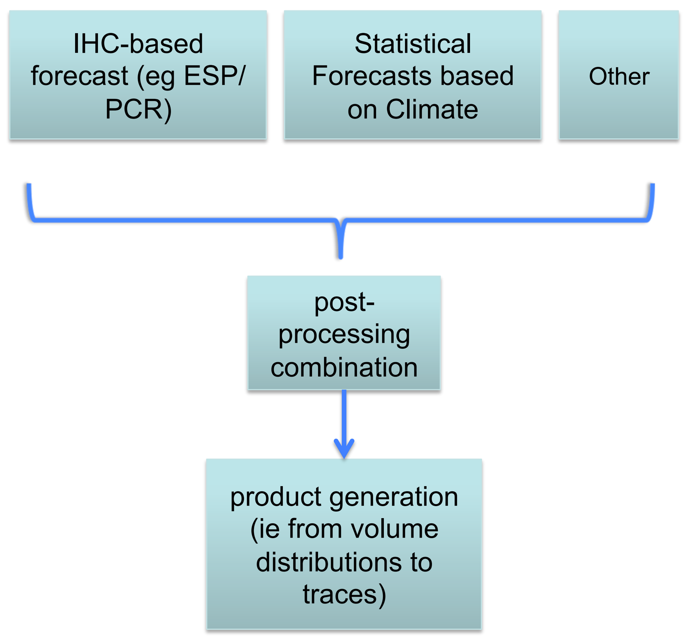
Only IHC accuracy influences runoff forecast skill



case study example



We can use a hierarchical approach to combine both sources of predictability



EXPERIMENTAL FRAMEWORK

In a range of case study watersheds, explore alternatives spanning a range of data requirements & complexity. From simplest to most complex (light to heavy data lift):

~statistical

a. regression (eg MLR, PCR) of flow on in situ obs (rainfall, SWE, flow)
b. the same but with teleconnection indices (eg, Nino3.4) included as predictors
c. the same but with custom climate state predictors (eg, EOFs of SST)
d. the same but with climate forecasts as predictors (eg, CFSv2, NMME)
e. land model based ensemble simulation (eg ESP or HEPS) without climate forecast info
   - possibly with short to medium range prediction embedded
f. climate index (or custom index) trace-weighted ESP
g. climate forecast trace-weighted ESP (using CFSv2)
h. hierarchical multi-forecast combination (eg of ESP and statistical prediction results; cf AU BOM approach)
i. climate forecast downscaled outputs with weather generation for land model ESP/HEPS
   - from one land/climate model or multi-model; from simple land model to hyper-resolution
j. e-g with statistical post-processing to correct model bias
k. e-g with DA to correct land model errors (particularly with snow variables)
l. e-g with BOTH post-processing and DA

~dynamical or hybrid

[blue rows are in progress in NCAR experiment; red are baselines; others are planned]

DATA AND MODELS

ESP runs

❑The Sacramento, Snow17 and Unit Hydrograph models for streamflow simulation were implemented for 31 years of ensemble hindcasts using forcings from Daymet

Custom Streamflow Prediction Indices (eg figures to right)

❑NCEP/NCAR reanalyses were used to derive correlated time-averaged climate system variables (eg PWAT, GPH, SST, SLP, SAT, U&V Wind Speeds)
❑Index derivation was k-fold cross-validated, as were all regressions

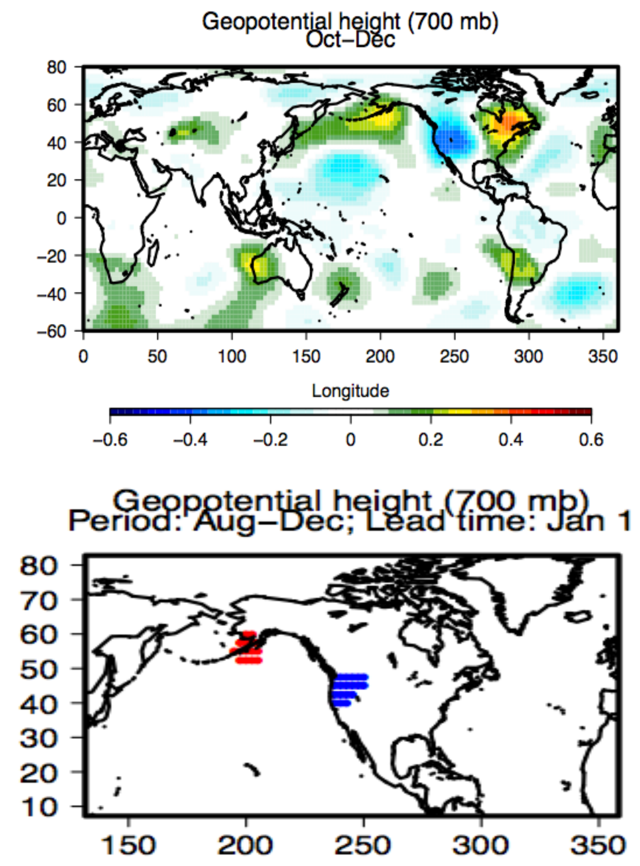
Climate Model Forecasts

❑NCEP Climate Forecast System v2 (CFSv2) monthly precipitation and tempearture forecasts

X-validated correlation patterns

transformed into

indices of high correlation area

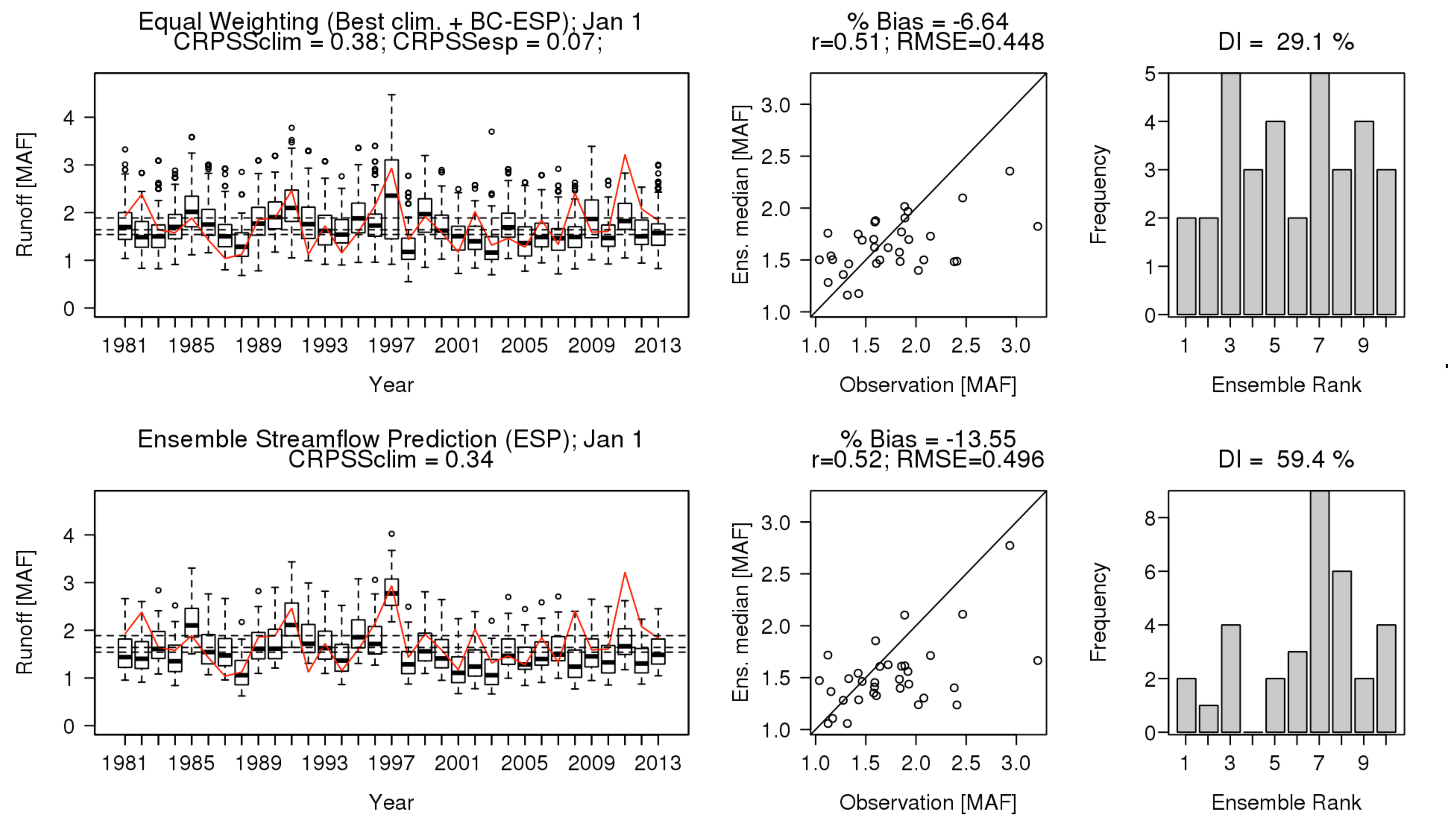


SAMPLE RESULTS AND FINDINGS

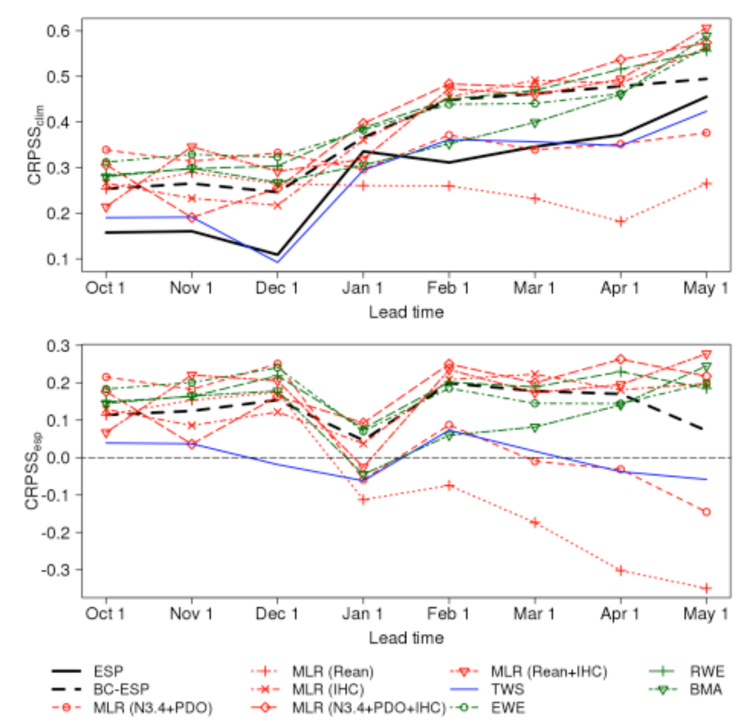
Hindcast timeseries for Jan 1 predictions of Apr-July runoff, showing individual event performance

A multi-model combination of IHC prediction (BC-ESP) and CFSR-based prediction

Raw ESP, a baseline forecast



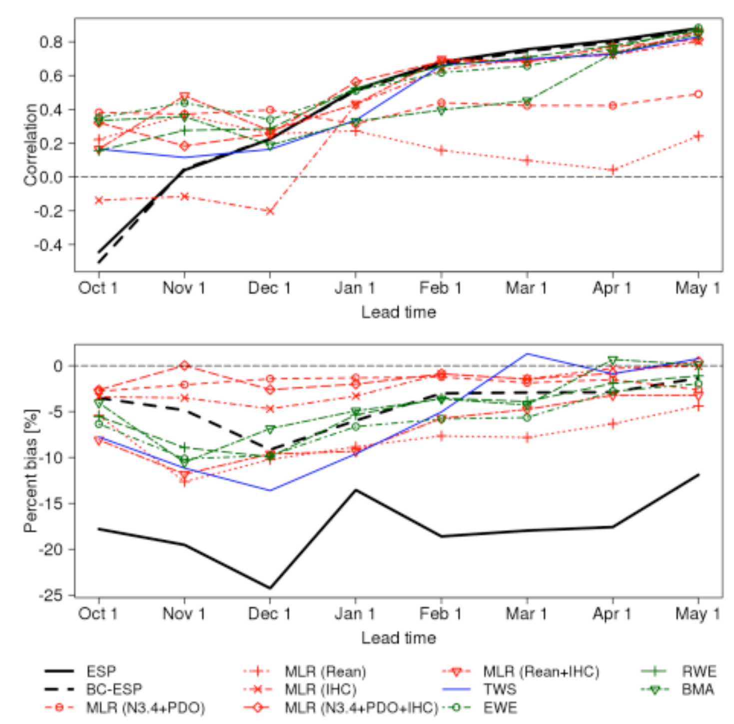
Performance statistics for method alternatives, showing skill for Apr-July runoff prediction at different lead times



Findings:
IHC-based predictors contribute nearly all skill after February, whereas climate-related predictors (from CFS Reanalysis) add marginal skill in fall and winter (giving longer lead information than is currently available).

Colors:
Black = IHC-only forecasts
Red = Statistical forecasts
Blue = ESP Trace Weighting
Green = Multi-model combination

Location: Hungry Horse Reservoir inflows, Montana, UA



REFERENCES / ACKNOWLEDGEMENTS / AFFILIATIONS

The research is supported by US Army Corps of Engineers and the US Bureau of Reclamation

Wood, AW and D.P. Lettenmaier, 2008. An ensemble approach for attribution of hydrologic prediction uncertainty, *Geophys. Res. Lett.*, 35, L14401, doi: 10.1029/2008GL034648.
Wood, AW, T Hopson, A Newman, L. Brekke, J. Arnold, M Clark, 2015, Quantifying streamflow forecast skill elasticity to initial condition and climate prediction skill. *J. Hydromet.*(in review)

Affiliations: (1) NCAR (2) Reclamation PN Area Office (3) Reclamation Technical Services Center (4) US Army Corps of Engineers Inst. for Water Res.