

Joint USBR, USACE and NCAR project:

“Over the loop” streamflow forecasting

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Contributors/Collaborators:

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Jeff Arnold (*USACE*), Ken Nowak, Levi Brekke (*Reclamation*)

Sponsors:

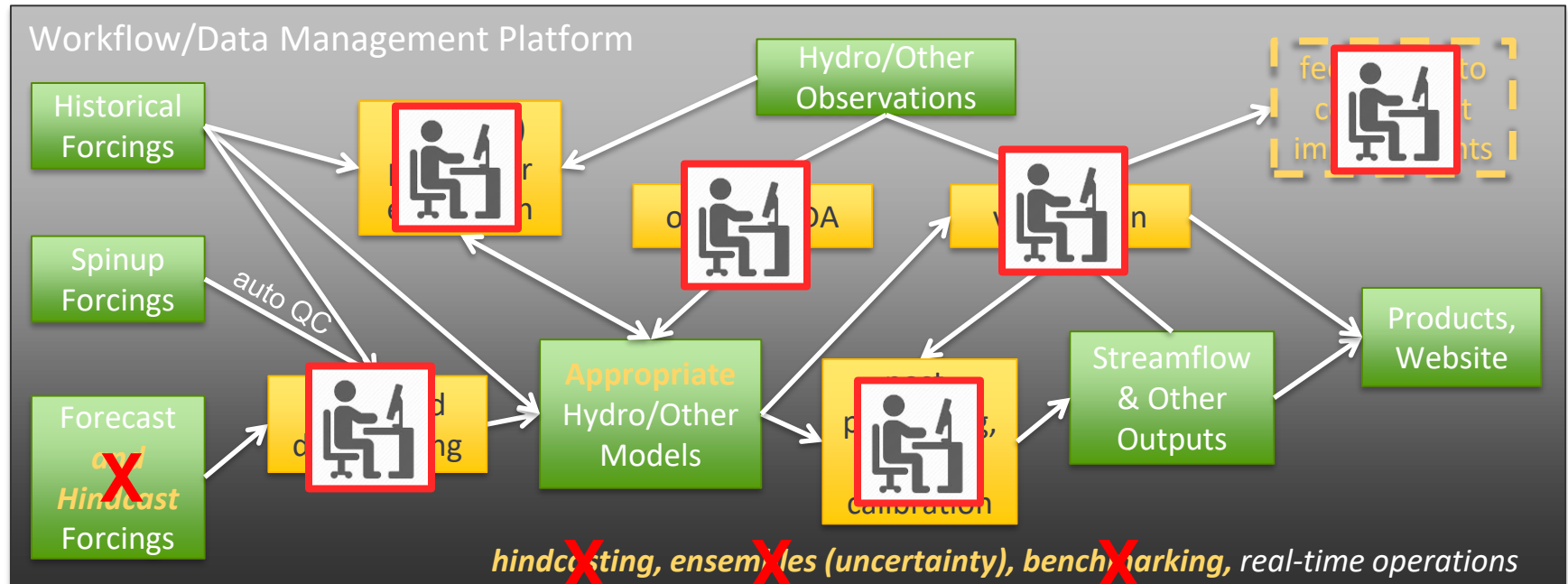
Reclamation, USACE, NOAA

*FIRO Science Meeting, NOAA-ESRL, Boulder
May 31, 2017*



Tackling key hydrologic prediction challenges

Hydrologic Forecasting: *methods are a critical complement to data & models*



- Since the 1970s, operational forecasting has implemented key methods in real-time via mostly human forecaster effort.
- The biggest methodological challenges to alternatives:
 - **data assimilation** (making the model accurate in real-time)
 - **model calibration** – especially for ungaged areas
 - optimal model parameters are dependent on model forcings

Challenges

biased / erroneous forcings

poor hydrologic model (parameters, structure)

inconsistent real-time vs retro forcings

missing or bad hydromet data

biased / erroneous met. forecasts

residual hydrologic error

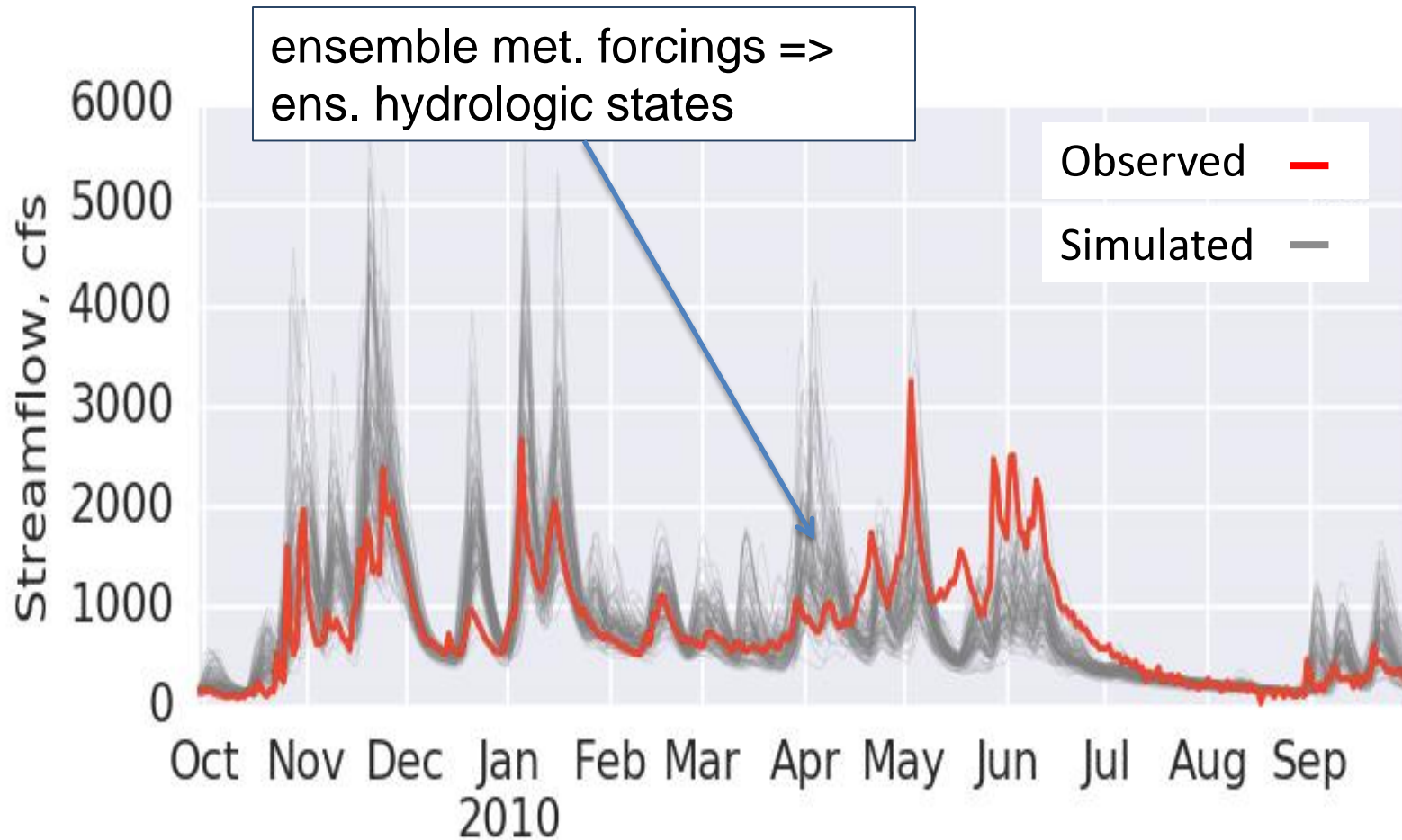
These are the main science challenges in hydrologic forecasting

- automatic generation of **real-time forcings** using methods & data that are consistent with retrospective forcings
- automated / objective **model calibration** (parameter estimation)
- automated **downscaling** and statistical calibration to improve meteorological forecasts
- automated **hydrologic data assimilation**
- automated **streamflow post-processing**

The Over-the-Loop Project Objectives

- Build an over-the-loop system (all processes automated) to produce short-range to seasonal ensemble flow predictions using currently available methods
 - drawing methods from HEPEx ideas and philosophy
- Provide a ***public demonstration*** of the performance of over-the-loop forecasts for locations that are relevant to the forecasting and water management communities
- ***Promote discussion*** about *alternative forecaster roles* in a modern hydrologic prediction operations

- **Model parameter estimation (calibration)**
 - local (for now) optimizations using MOCOM
 - NWS models during development phase; VIC, mHM, SUMMA next
 - Multi-scale Parameter Regionalization (MPR-Flex; N. Mizukami)
- **Consistent Retro + Real-time daily ensemble forcing analysis**
 - GMET; Newman et al. (2015) – ensemble forcings
 - Jan 1970 to yesterday, daily 1/16th degree, western US regions
 - *A first of its kind*
- **GEFS ensemble (11 member) downscaling and calibration**
 - GARD (Generalized Analog Regression Downscaling) tool
 - NCAR Ethan Gutman and Joe Hamman contributing
- **Hydrologic data assimilation**
 - Sequential and Non-Sequential Particle Filter methods
 - Liz Clark, Bart Nijssen (UW) contributing



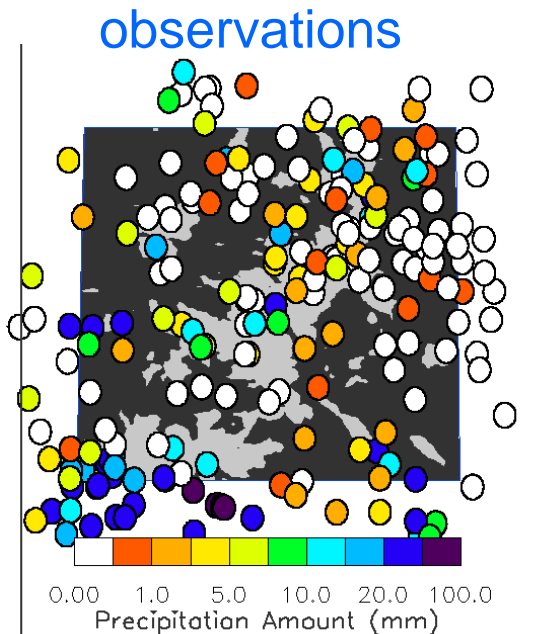
- Generate consistent hydrologic states representing uncertainties as basis for forecast initialization

Ensemble Forcing Generation

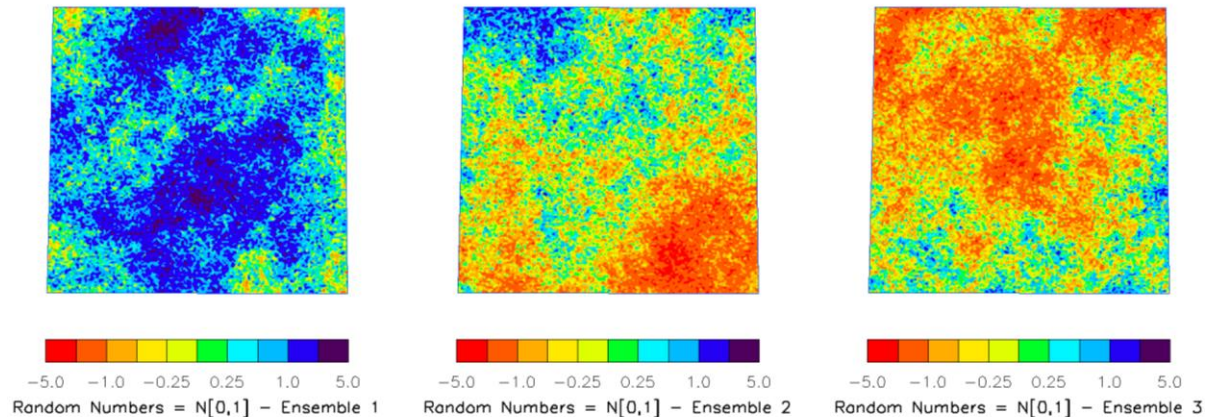
Synthesize ensembles from PoP, amount & **uncertainty** using spatially correlated random fields (SCRFs)

Other Methodological choices:

- Topographic lapse rates derived at each grid cell for each day vs. climatology
- Used serially complete (filled) station data rather than only available obs vs. using only available observations

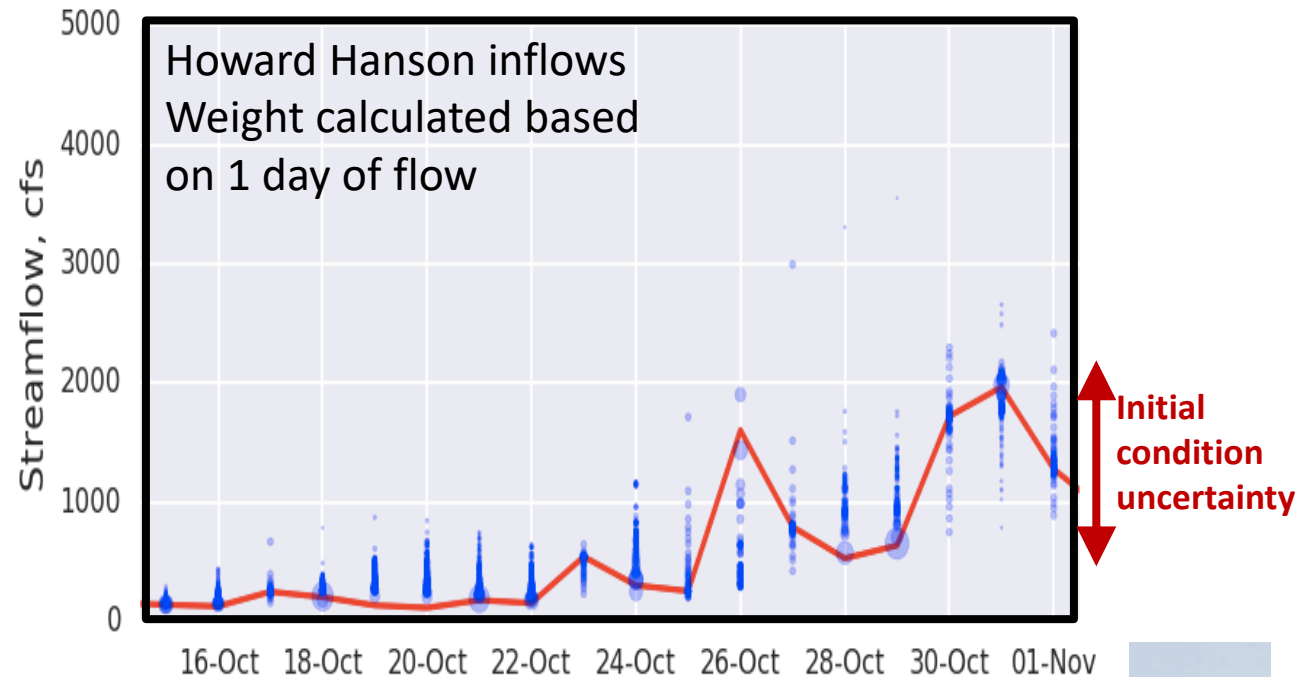
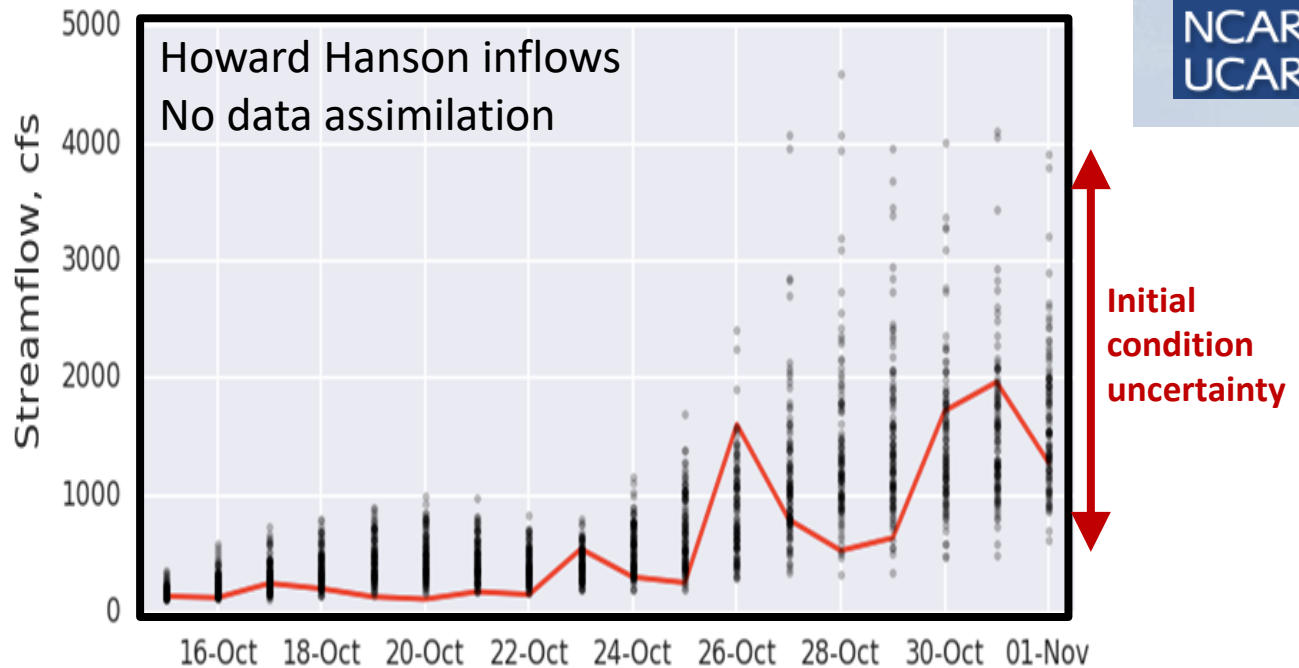


Final Product: 1/16th degree, daily 1970-present, 100 members, precipitation & temperature



Data Assimilation

- Mimic operational forecaster by selecting initial states (& inputs/parameters) that agree best with observations
- Technically, this is formulated as a particle filter hydrological data assimilation

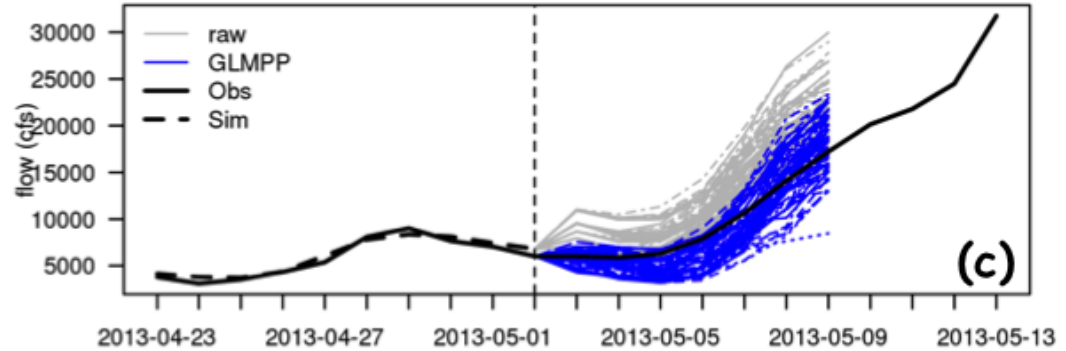


- **Model parameter estimation**
 - local (for now) optimizations using MOCOM
 - NWS models (Snow17, Sacramento) during development phase
 - working to link with MPR for next phase of project (N. Mizukami)
- **Consistent Retro + Real-time daily ensemble forcing analysis**
 - GMET; Newman et al. (2015) – earlier talk this session
 - 1970 Jan 1 to yesterday, 1/16th degree, western US regions
- **GEFS ensemble (11 member) downscaling and calibration**
 - GARD (Generalized Analog Regression Downscaling) tool
 - Ethan Gutman with Joe Hamman contributing
- **Hydrologic data assimilation**
 - Sequential and Non-Sequential Particle Filter methods
 - Liz Clark and Bart Nijssen (UW), Andy Wood
- **Streamflow post-processing**
 - Comparing 6-8 methods – Pablo Mendoza (NCAR)

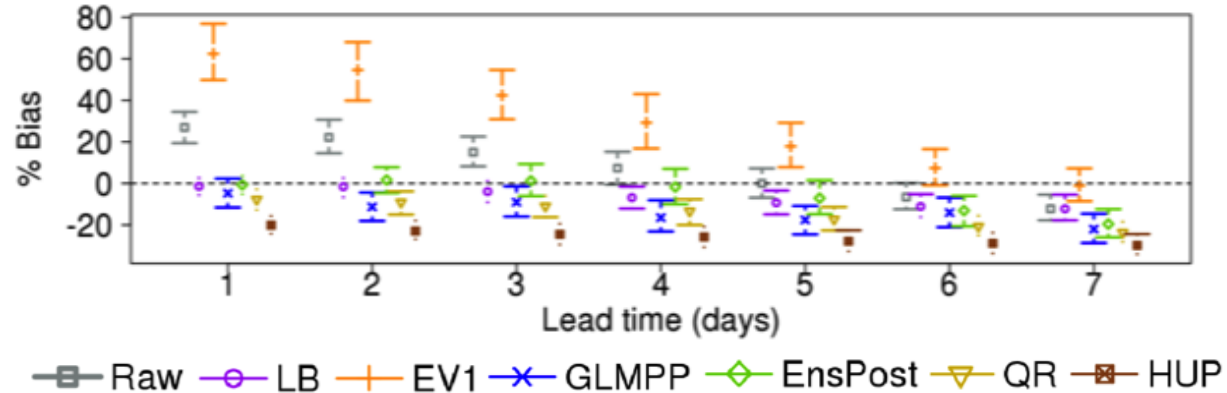
Post-processing is also critical

- reduces residual uncertainty after other parts of the process

Method	Name
LB	Linear blending
EV1	Error in variable Model Output Statistics with one variable
GLMPP	Generalized Linear Model Post-Processor
EnsPost	Ensemble Post-Processor
QR	Quantile Regression
HUP	Hydrologic Uncertainty Processor



hindcast based skill evaluation



contribution by Pablo Mendoza

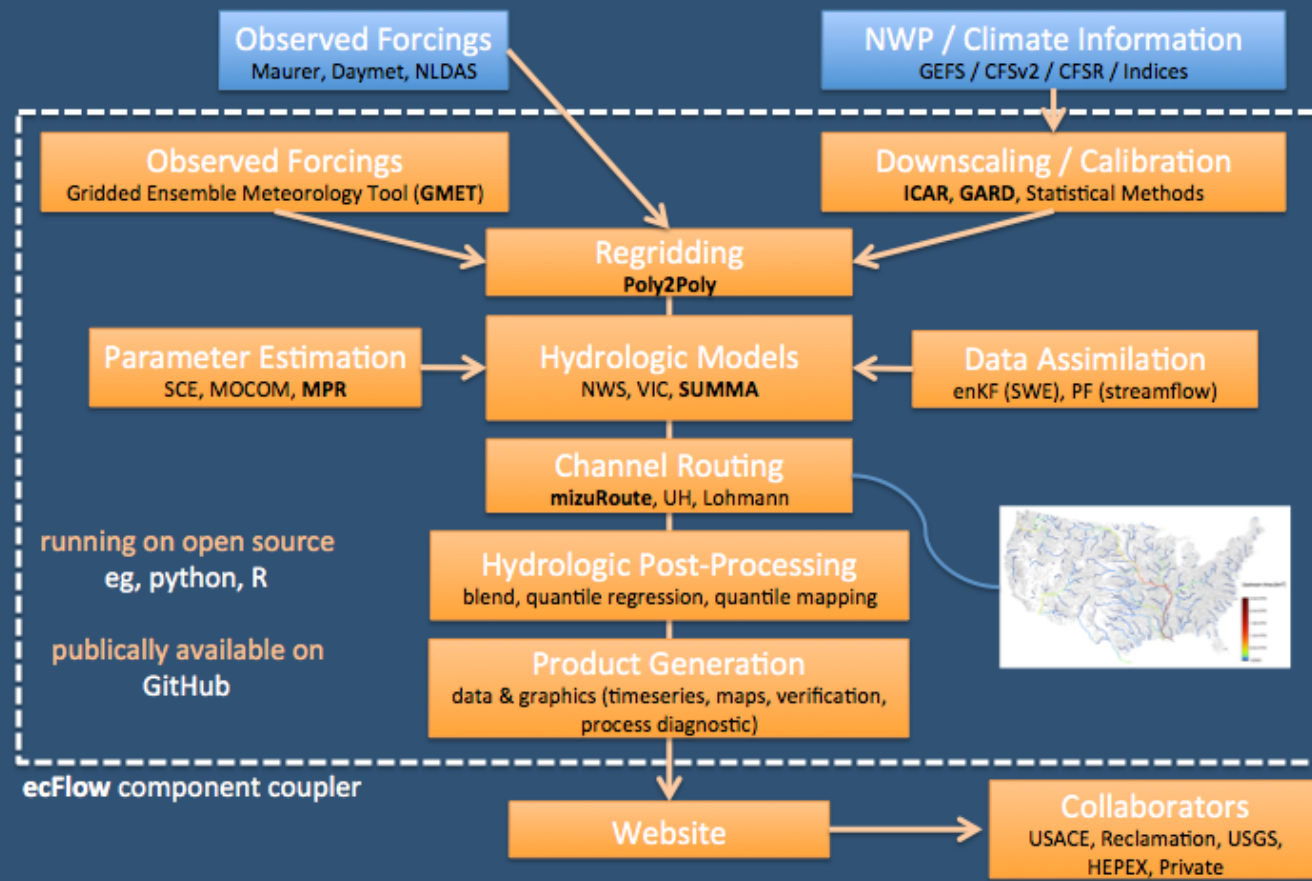
Require consistent hindcasts to implement

Real-Time System Implementation

The SHARP system is now running at NCAR to generate real time short and seasonal range forecasts for a number of pilot case study basins

System for Hydromet Analysis Research and Prediction (SHARP)

an agile effort supporting ensembles, hindcasting, benchmarking, and development



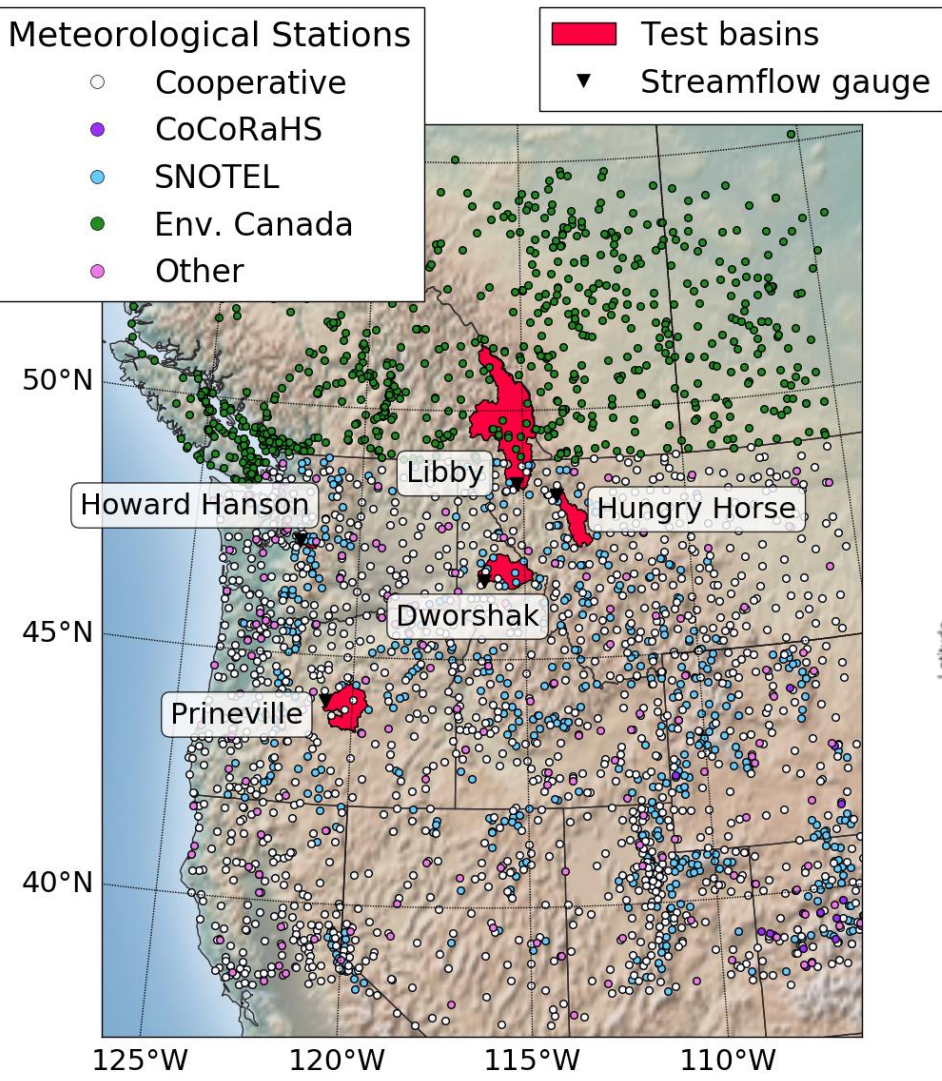
sample real-time workflow web monitor

SHARP System Status Report

Updated: Tue Dec 13 15:13:57 UTC 2016

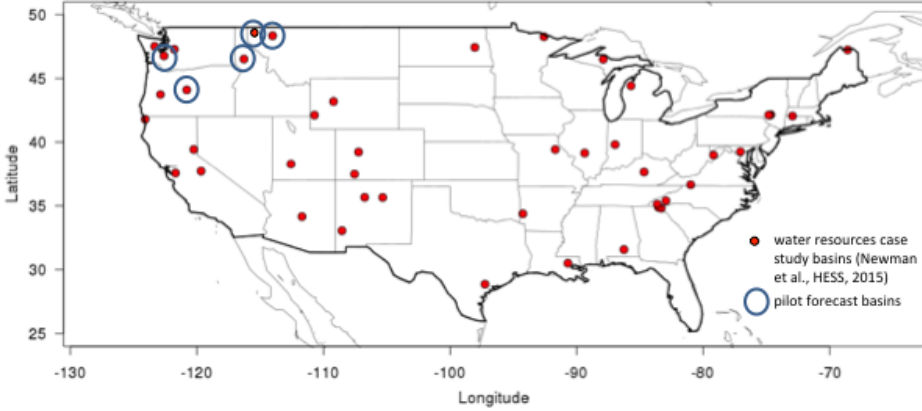
Job	Submitted	Completed	Failed
get_ghcnd	14:00:00	14:16:35	
get_nwcc	14:00:01	14:05:17	
get_gefs	pending	pending	
get_cfsr	14:00:01	14:02:13	
get_flow	14:00:01	14:01:03	
reformat_ghcnd	14:16:36	14:33:58	
reformat_nwcc	14:33:59	14:34:12	
QC_stn_data	14:34:12	14:38:30	
fill_stn_data_pass1	14:38:31	15:13:56	
fill_stn_data_pass2	15:13:56	pending	
fill_stn_data_pass3	pending	pending	
fill_stn_data_pass4	pending	pending	
gen_ens	pending	pending	
grid2poly	pending	pending	
make_nws_forc	pending	pending	
run_nws_spinup	pending	pending	
downscale_gefs_fcst	pending	pending	
downscale_gefs_fcst_regr	pending	pending	
reformat_gard_output	pending	pending	
reformat_gard_output_regr	pending	pending	
met_forecast_grid2poly	pending	pending	
make_nws_met_forecast	pending	pending	
run_nws_gefs_fcst	pending	pending	
plot_stn_data_map	pending	pending	
plot_mr_fcst	pending	pending	

Focus on case study basin study sites



Initial pilot domain was the **Pacific Northwest** with test basins selected out of interest for water management purposes.

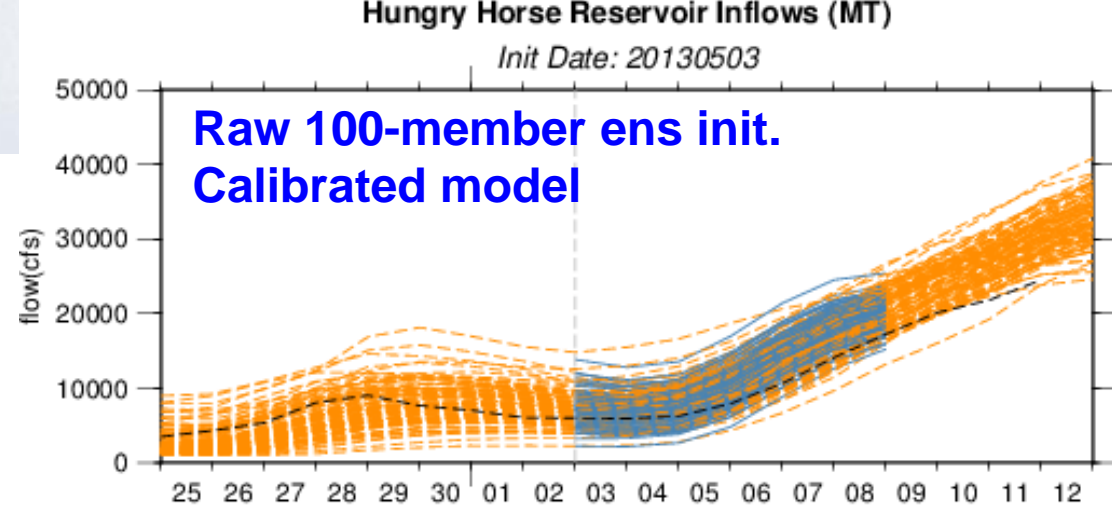
A broader US selection of basins was also used for evaluating modeling and seasonal prediction methods.



The models used initially have been the NWS lumped (Snow17/Sac/UH) and VIC run at a daily timestep. A daily timestep is too coarse for flows in some of the California basins.

Putting it together

- objective model calibration
- ensemble forcings
- particle filter DA
- post-processing
- hindcasting



Figure

(**top**) Ensemble-initialized GEFS-based flow forecast ensembles

(**middle**) 5 highest weighted ICs and forecasts

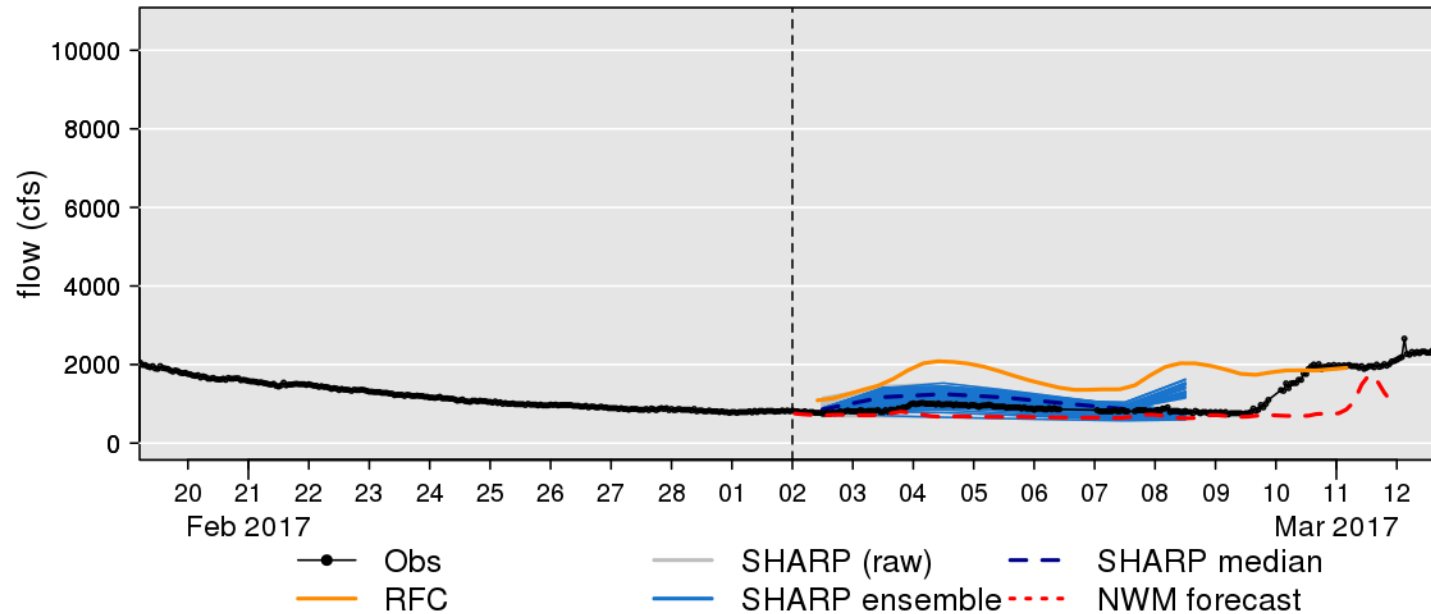
(**bottom**) same 5 ICs blended via LB

Real-time prediction example

- Howard Hanson Reservoir Inflow (WA)
- 7 day lead flow predictions made real-time

Streamflow forecasts for Howard Hanson Reservoir Inflow WA (HHDW1)

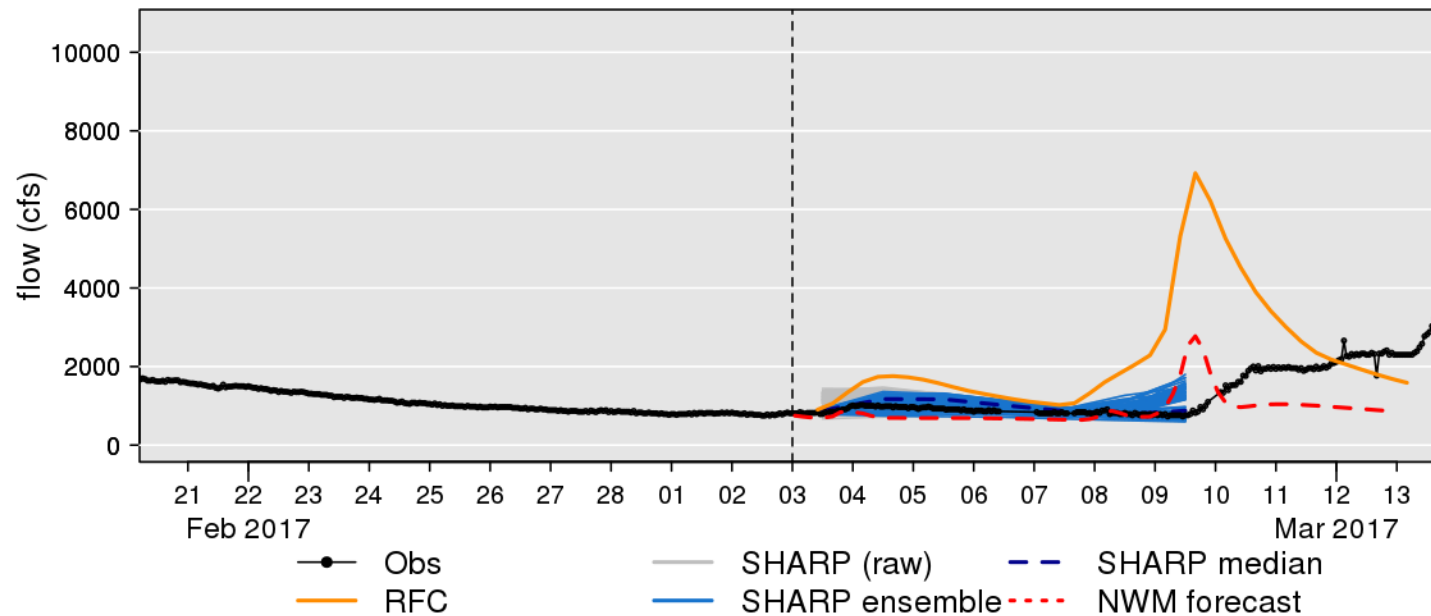
Initialized on Mar 02 2017



Real-time prediction example

Streamflow forecasts for Howard Hanson Reservoir Inflow WA (HHDW1)

Initialized on Mar 03 2017

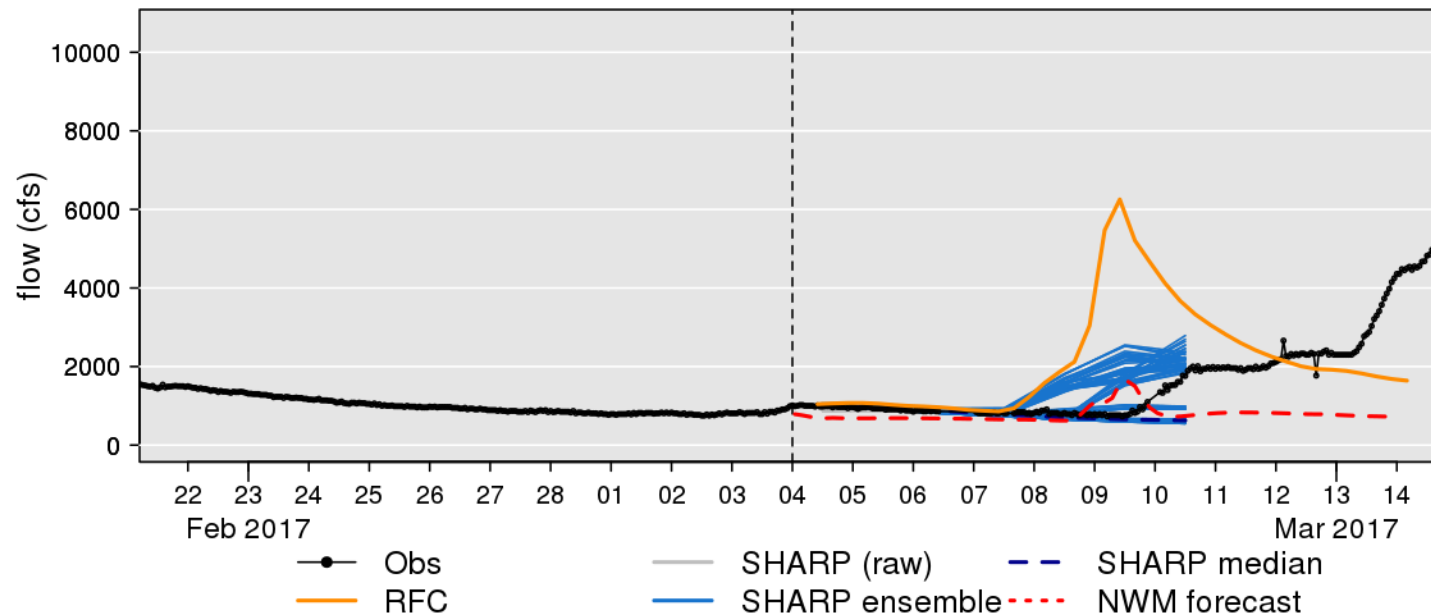


Howard Hanson Reservoir Inflow (WA)

Real-time prediction example

Streamflow forecasts for Howard Hanson Reservoir Inflow WA (HHDW1)

Initialized on Mar 04 2017

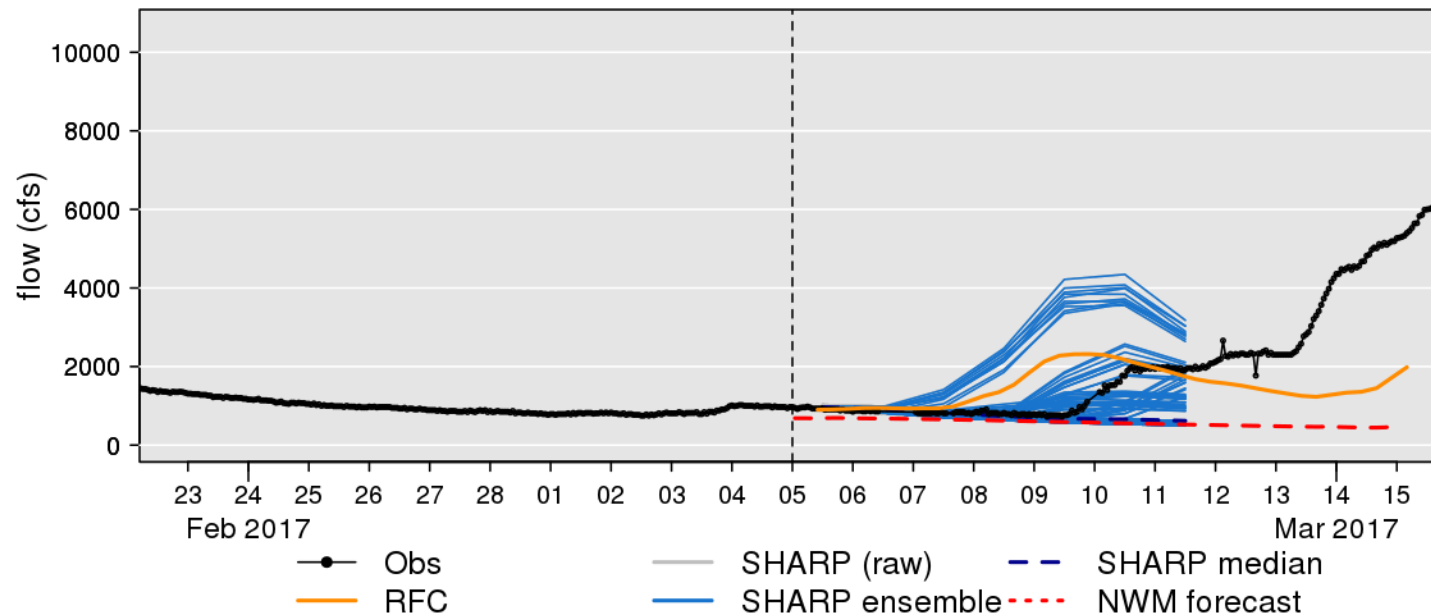


Howard Hanson Reservoir Inflow (WA)

Real-time prediction example

Streamflow forecasts for Howard Hanson Reservoir Inflow WA (HHDW1)

Initialized on Mar 05 2017

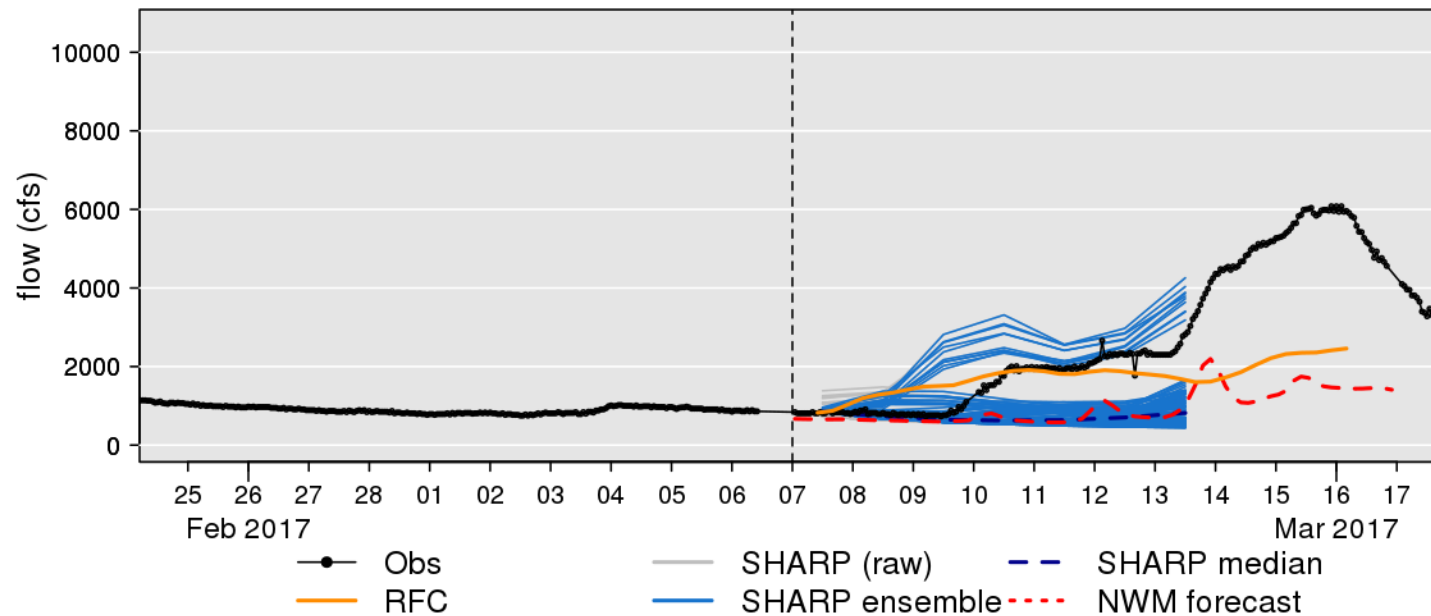


Howard Hanson Reservoir Inflow (WA)

Real-time prediction example

Streamflow forecasts for Howard Hanson Reservoir Inflow WA (HHDW1)

Initialized on Mar 07 2017

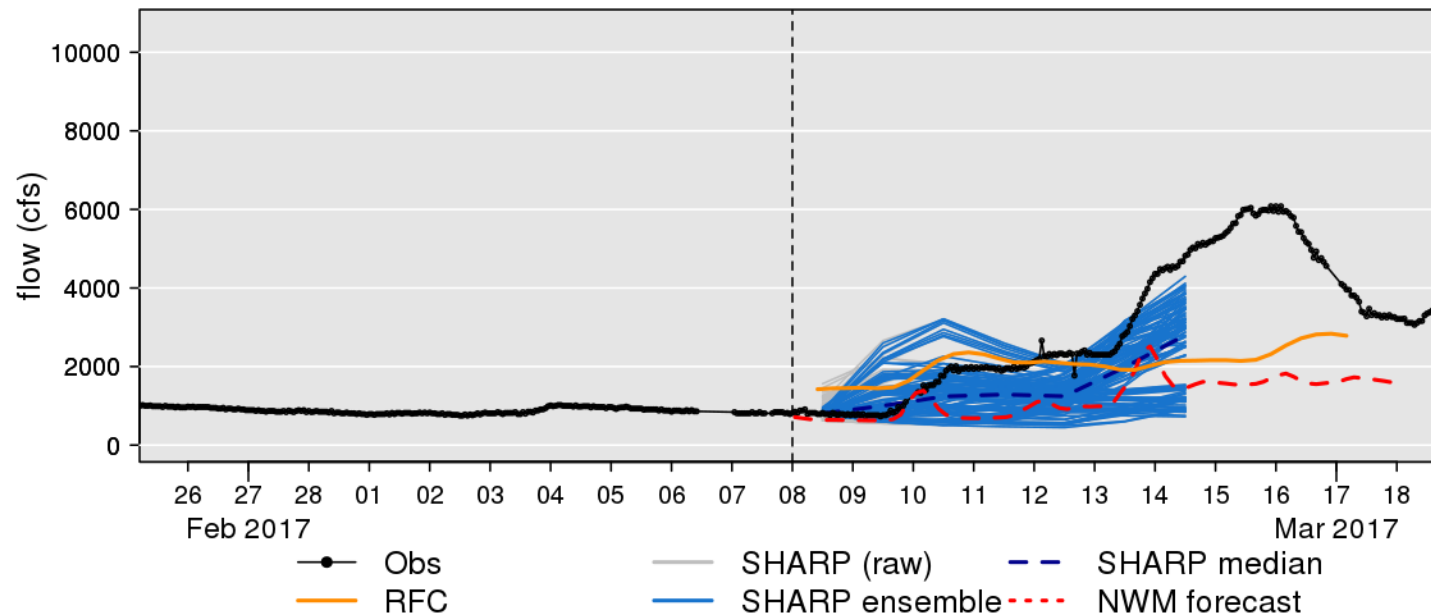


Howard Hanson Reservoir Inflow (WA)

Real-time prediction example

Streamflow forecasts for Howard Hanson Reservoir Inflow WA (HHDW1)

Initialized on Mar 08 2017

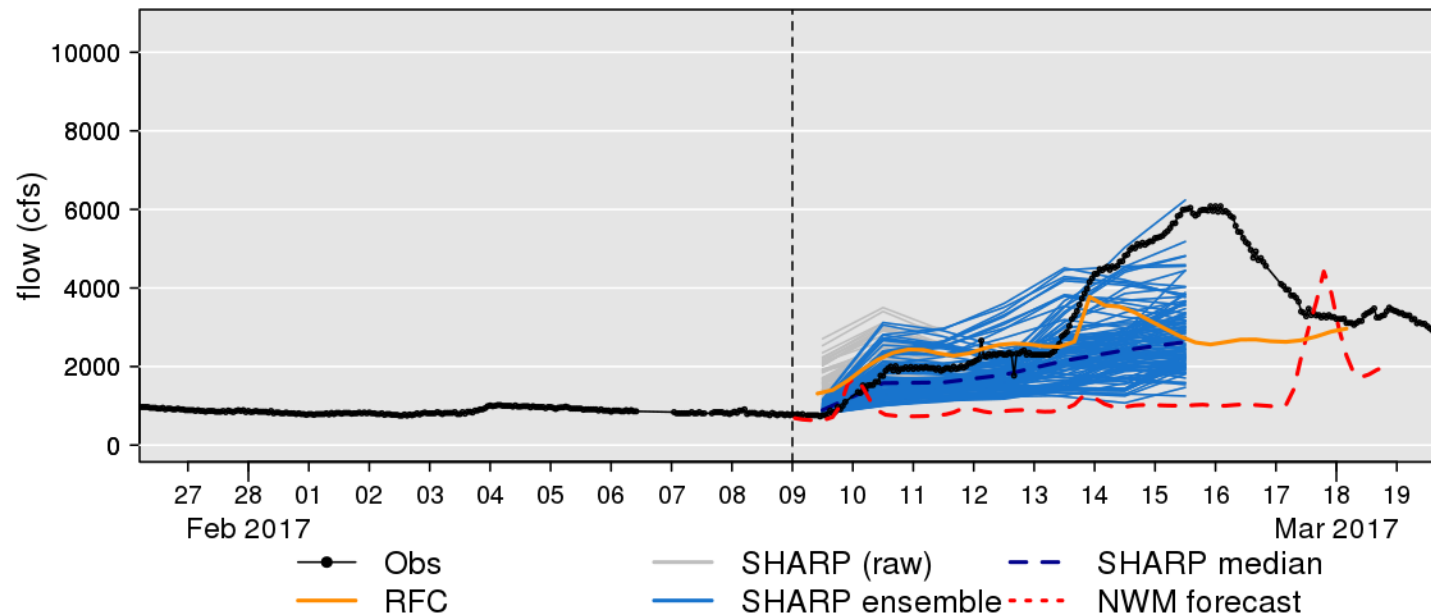


Howard Hanson Reservoir Inflow (WA)

Real-time prediction example

Streamflow forecasts for Howard Hanson Reservoir Inflow WA (HHDW1)

Initialized on Mar 09 2017

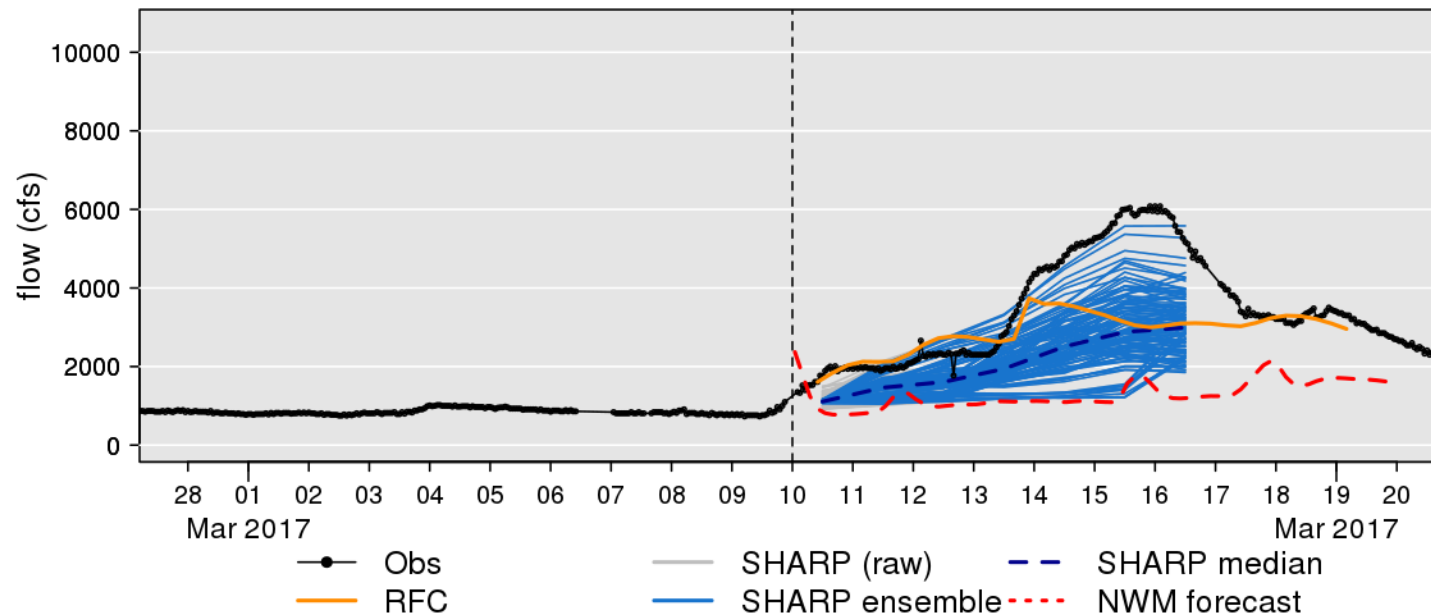


Howard Hanson Reservoir Inflow (WA)

Real-time prediction example

Streamflow forecasts for Howard Hanson Reservoir Inflow WA (HHDW1)

Initialized on Mar 10 2017

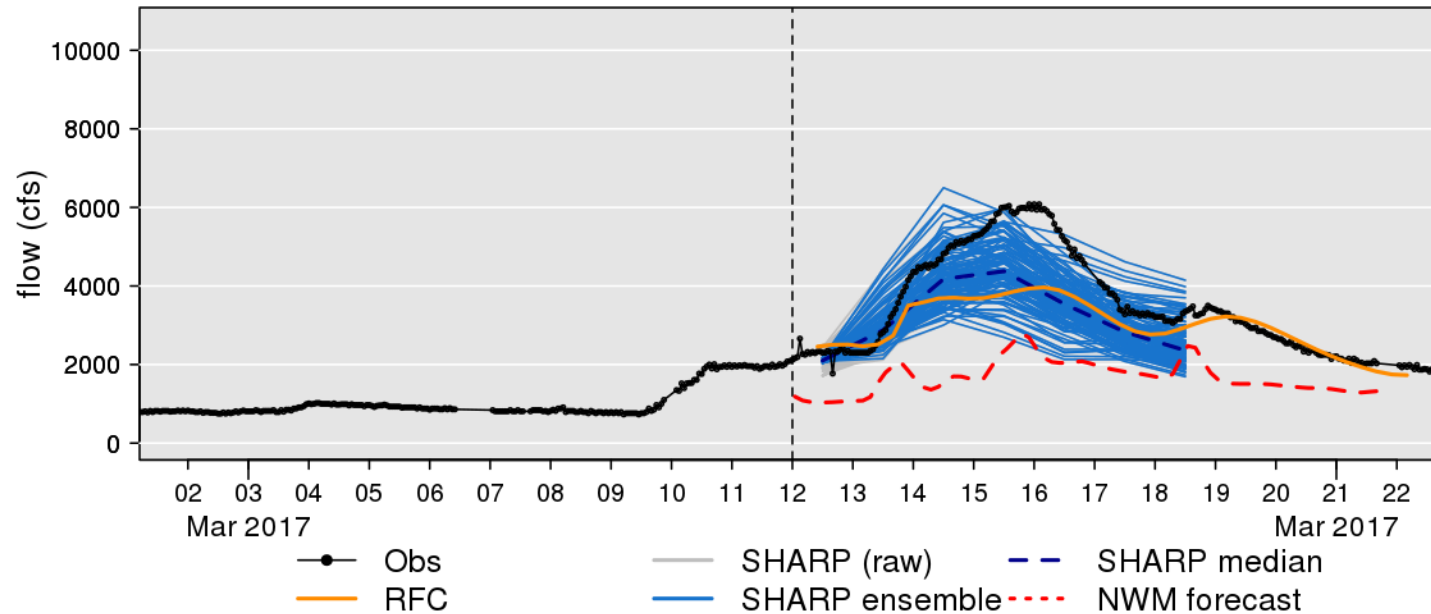


Howard Hanson Reservoir Inflow (WA)

Real-time prediction example

Streamflow forecasts for Howard Hanson Reservoir Inflow WA (HHDW1)

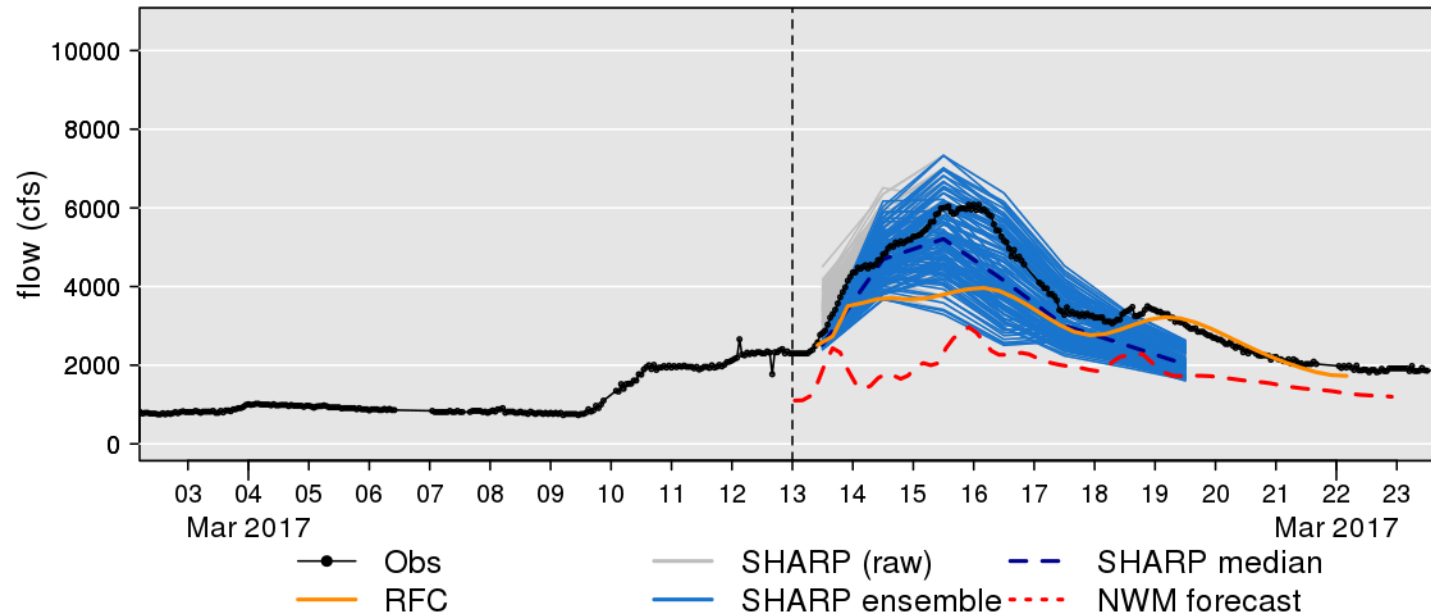
Initialized on Mar 12 2017



Howard Hanson Reservoir Inflow (WA)

Real-time prediction example

Streamflow forecasts for Howard Hanson Reservoir Inflow WA (HHDW1)
Initialized on Mar 13 2017

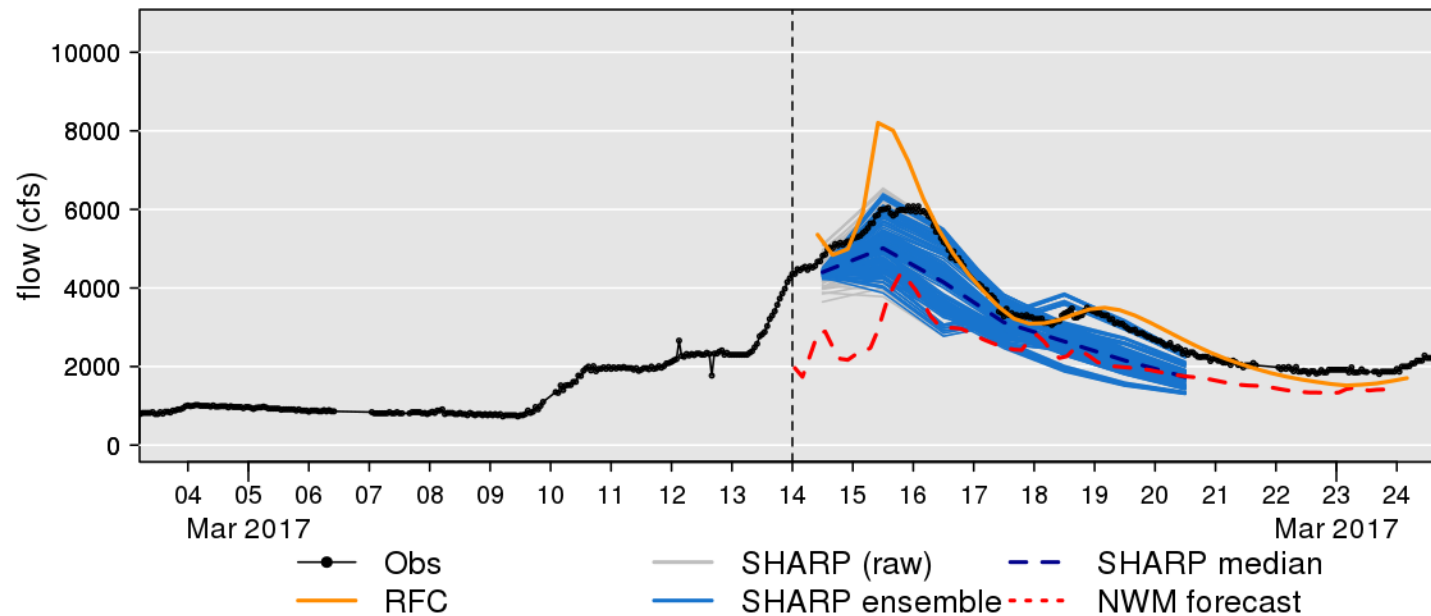


Howard Hanson Reservoir Inflow (WA)

Real-time prediction example

Streamflow forecasts for Howard Hanson Reservoir Inflow WA (HHDW1)

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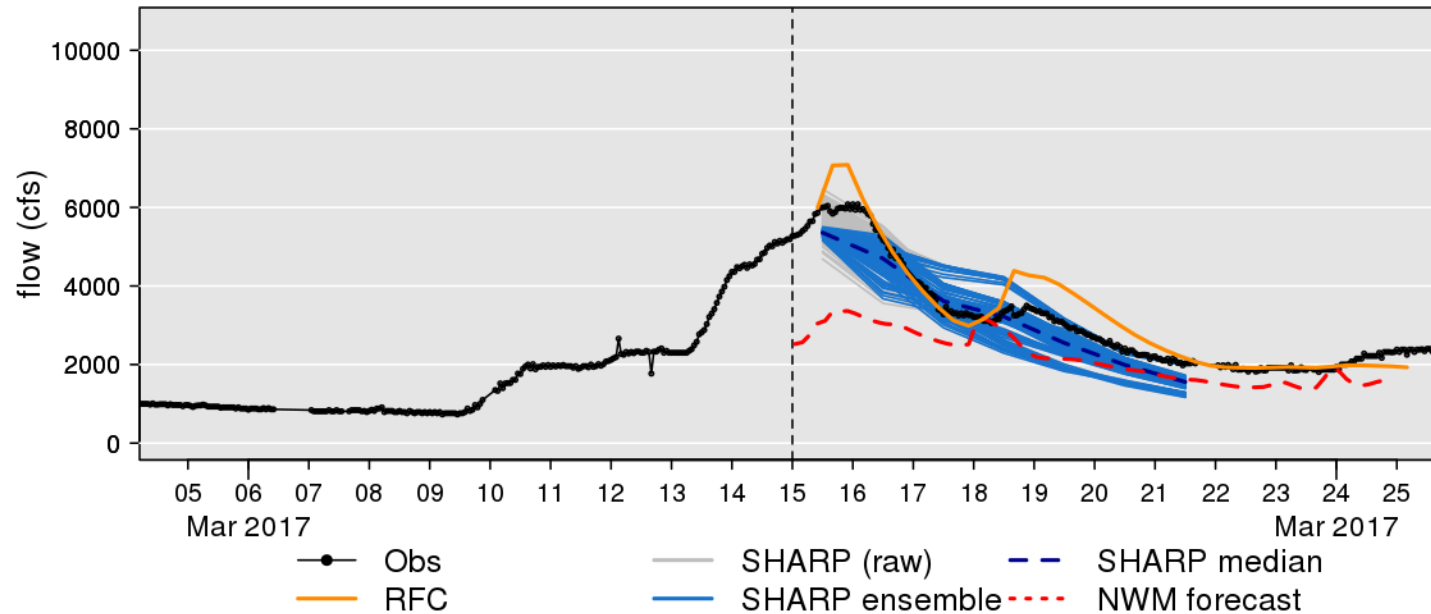


Howard Hanson Reservoir Inflow (WA)

Real-time prediction example

Streamflow forecasts for Howard Hanson Reservoir Inflow WA (HHDW1)

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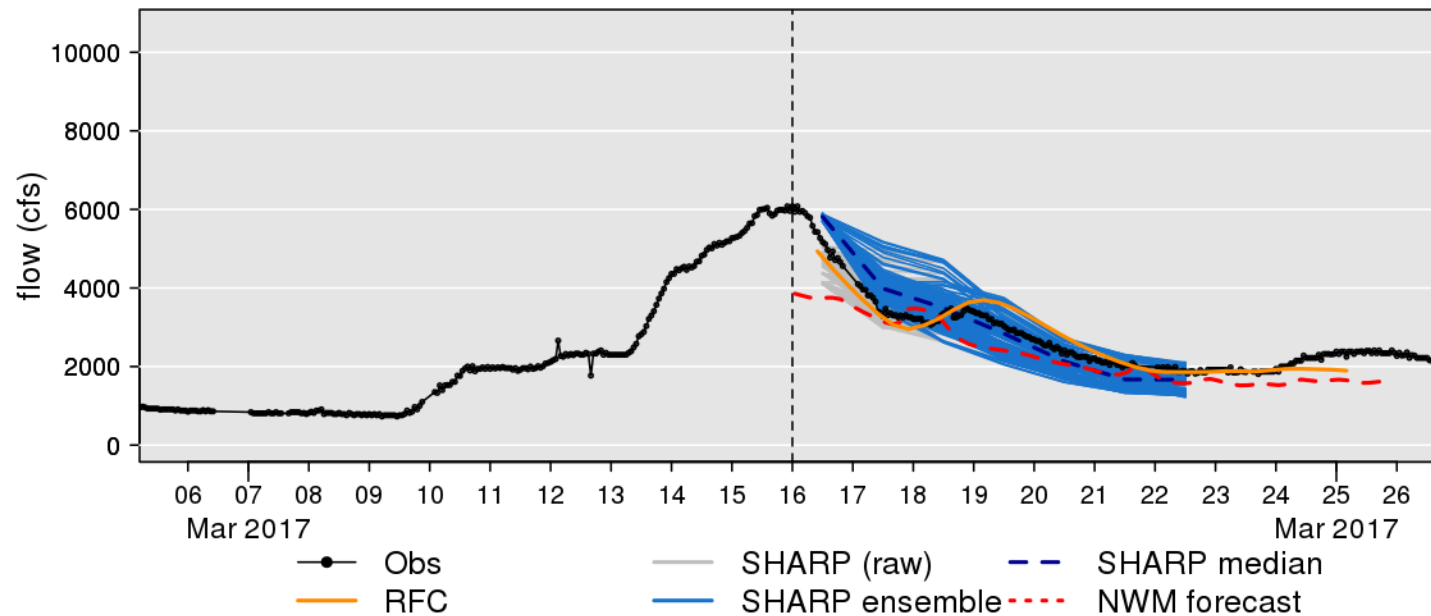


Howard Hanson Reservoir Inflow (WA)

Real-time prediction example

Streamflow forecasts for Howard Hanson Reservoir Inflow WA (HHDW1)

Initialized on Mar 16 2017

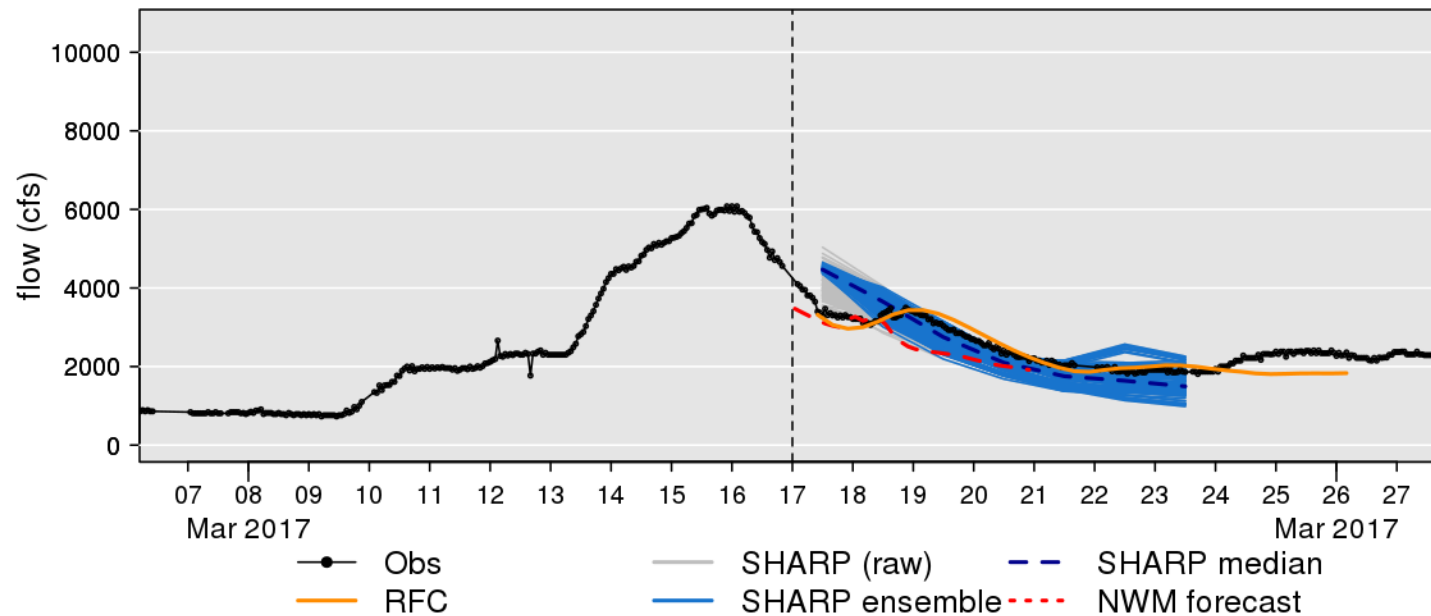


Howard Hanson Reservoir Inflow (WA)

Real-time prediction example

Streamflow forecasts for Howard Hanson Reservoir Inflow WA (HHDW1)

Initialized on Mar 17 2017

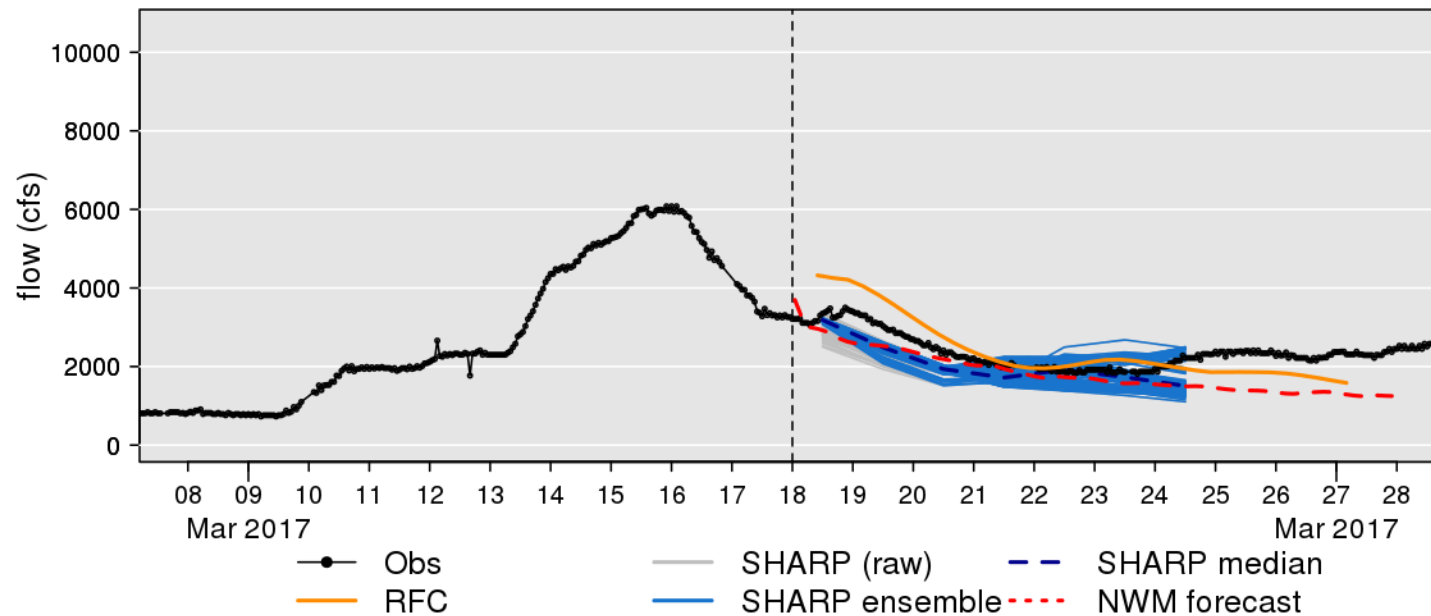


Howard Hanson Reservoir Inflow (WA)

Real-time prediction example

Streamflow forecasts for Howard Hanson Reservoir Inflow WA (HHDW1)

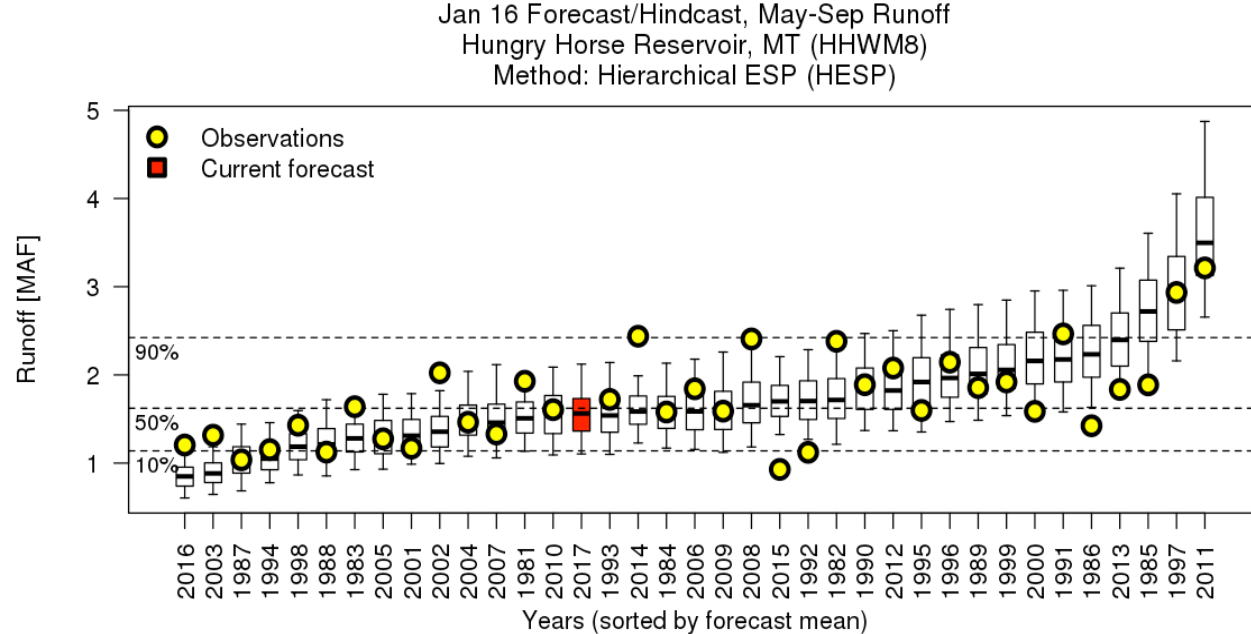
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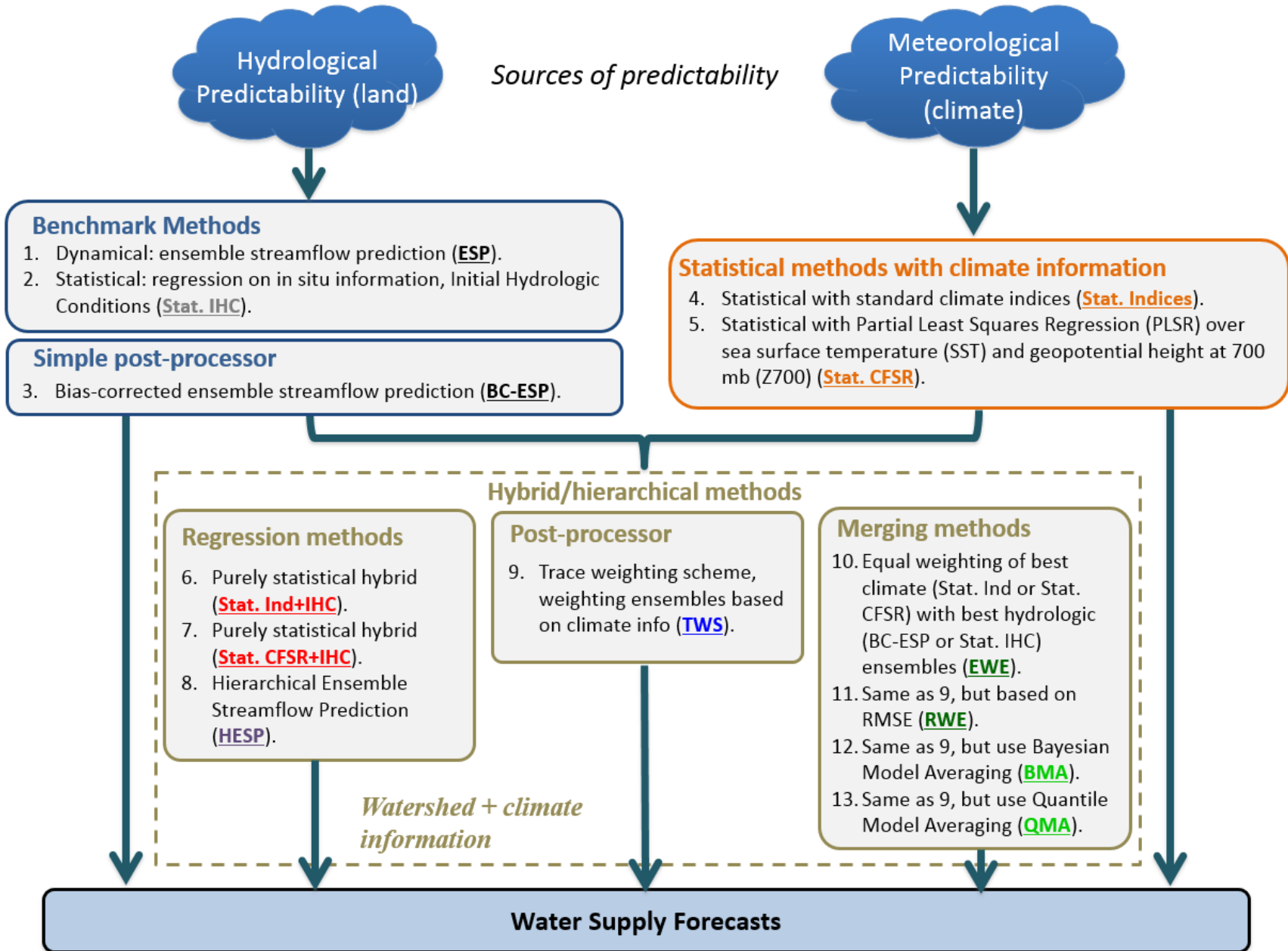
Howard Hanson Reservoir Inflow (WA)

Advantages

- benchmarking and verifying alternative methods
- training and applying statistical techniques
 - objective data assimilation
 - post-processing
- giving stakeholders hindcasts to support the training and evaluation of decision support systems or rules
- **hybrid frameworks** for seasonal prediction
 - combining data-driven and modeling approaches to enhance skill
- transparency & reproducibility to support diagnostic evaluation



Intercomparing seas. forecast methods

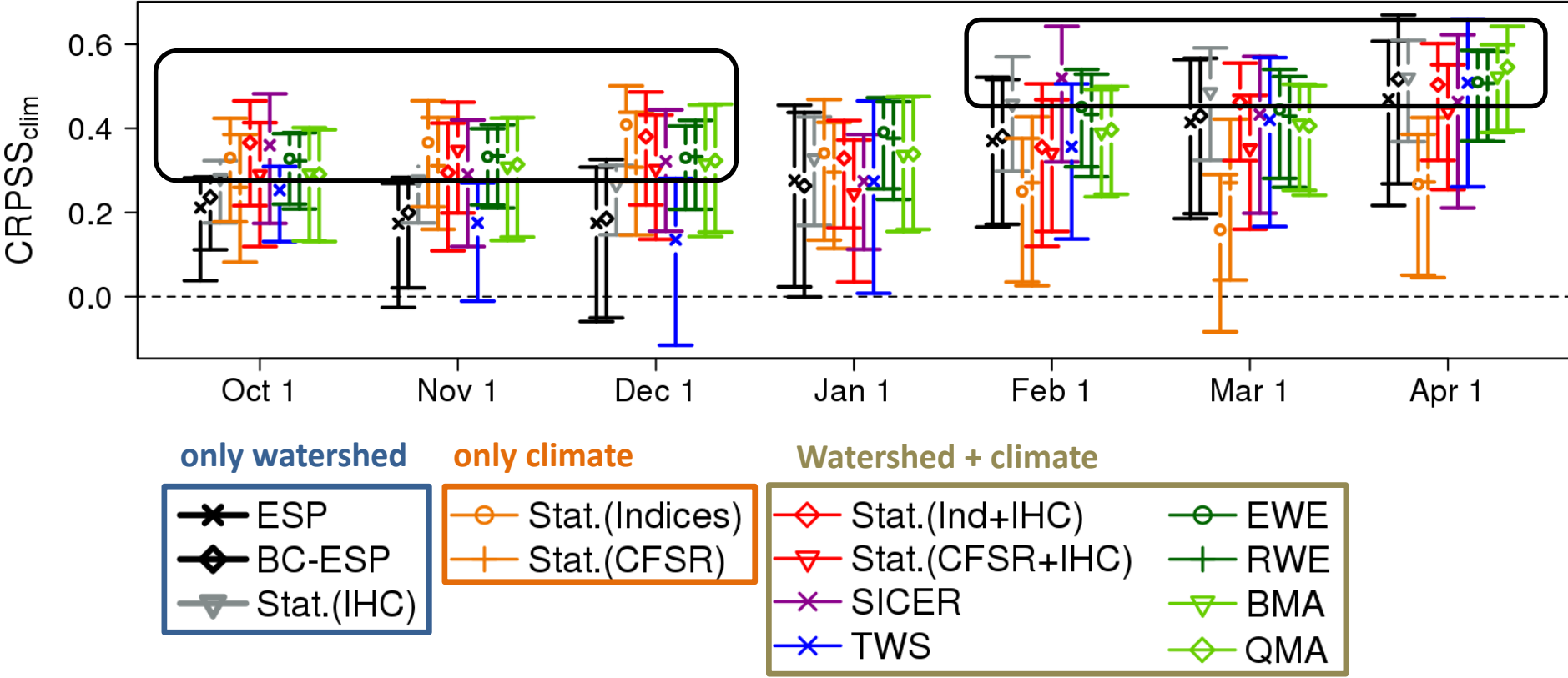


Intercomparison of range of methods

What added value does climate information bring?

Example:
Hungry Horse

Forecast skill across methods for Apr-Jul runoff



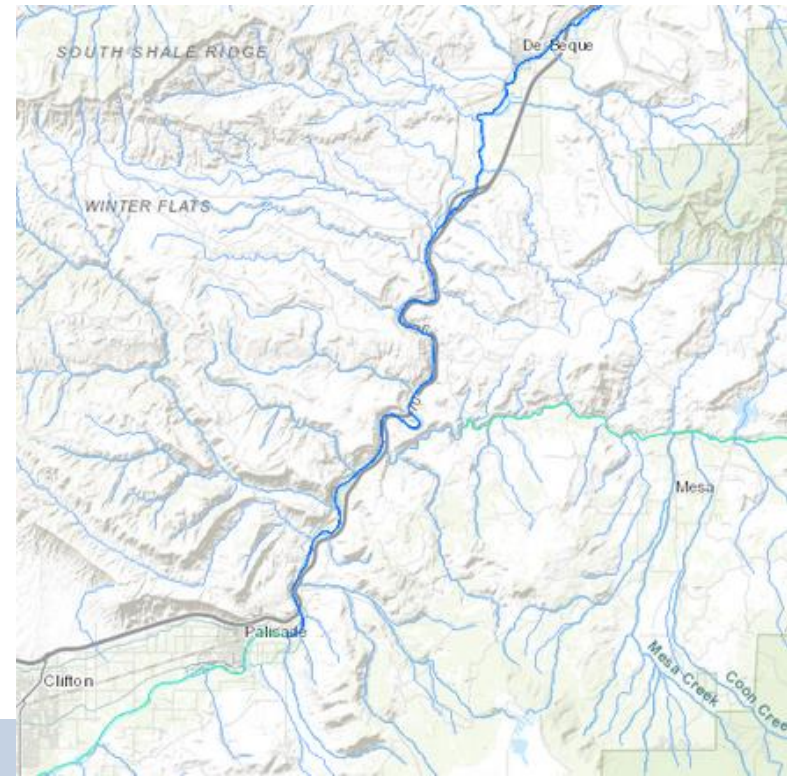
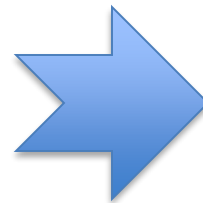
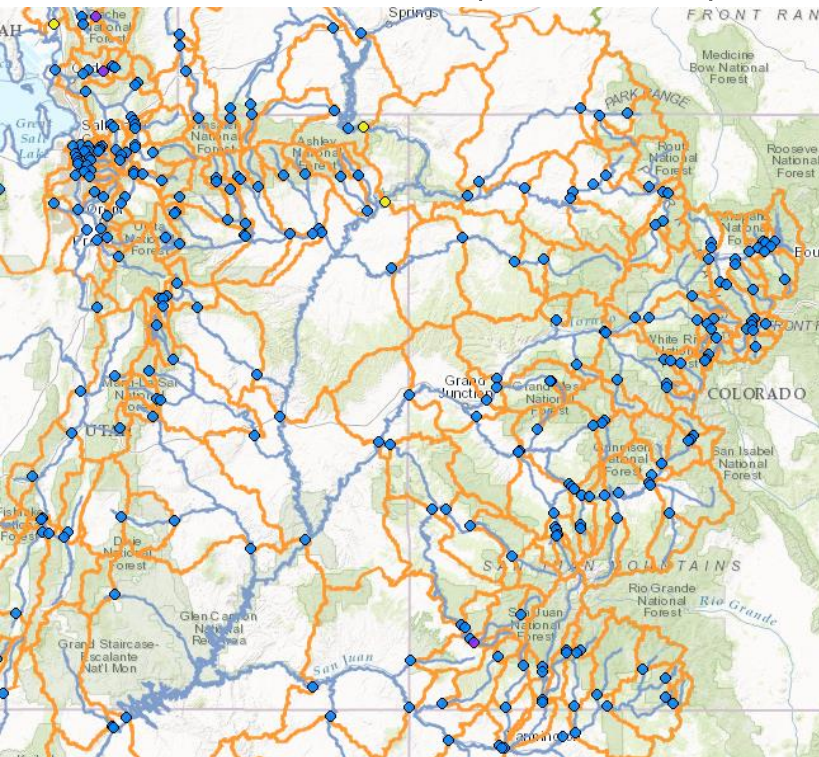
- ❑ Early in water year: we can improve WSFs using climate info.
- ❑ Later initialization: WSFs harder to improve upon when using a calibrated model
- ❑ Hybrid approaches (include watershed and climate info) most robust overall

An irony

- Since this project started, the pendulum has swung toward a different form of ‘over-the-loop’ forecasting

traditional / conceptual
calibrated models
ensemble products
forecast community experience
intermediate scale (~1-10 km)

hyper-resolution large domain
uncalibrated models
mostly deterministic products
science gaps ‘solved’ by resolution
~250m

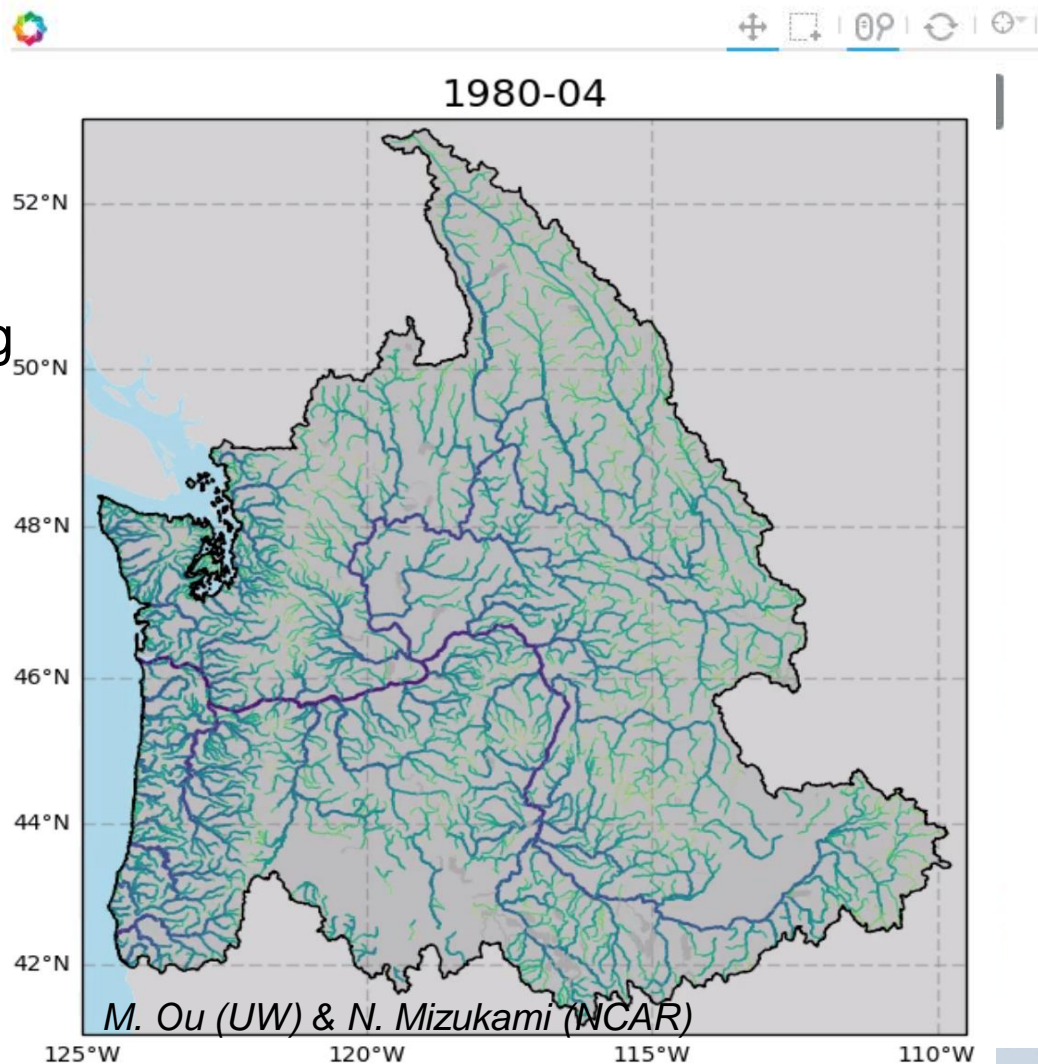


This presents a new challenge

- **Restoring** the relevance of hydrologic prediction science & uncertainty methods to the hyper-resolution initiatives

Scaling Challenges

- regional model calibration (parameter estimation)
- spatial obstacles in downscaling and post-processing
- propagation of obs info in data assimilation
- understanding appropriate complexity of modeling
 - scale
 - physics
 - tradeoffs



Take-aways for FIRO Science

There are two dominant philosophies in improving prediction

- try to eliminate error in all components of the forecast process so as to get ‘the right answer’
 - better precip forcings and forecast
 - higher resolution and higher complexity models
 - more observations (meteorological, hydrological)
 - model processes viewed literally
 - more deterministic prediction
- error can never be eliminated, so make sure you can represent uncertainty
 - ensemble meteorology and hydrology
 - hindcastable techniques to support verification
 - proactive approach to handling biases
 - model processes viewed as parameterizations
 - more probabilistic prediction

It's best if the science incorporates elements of both.

Contacts

- **NCAR**

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- **University of Washington**

Bart Nijssen (Co-PI)

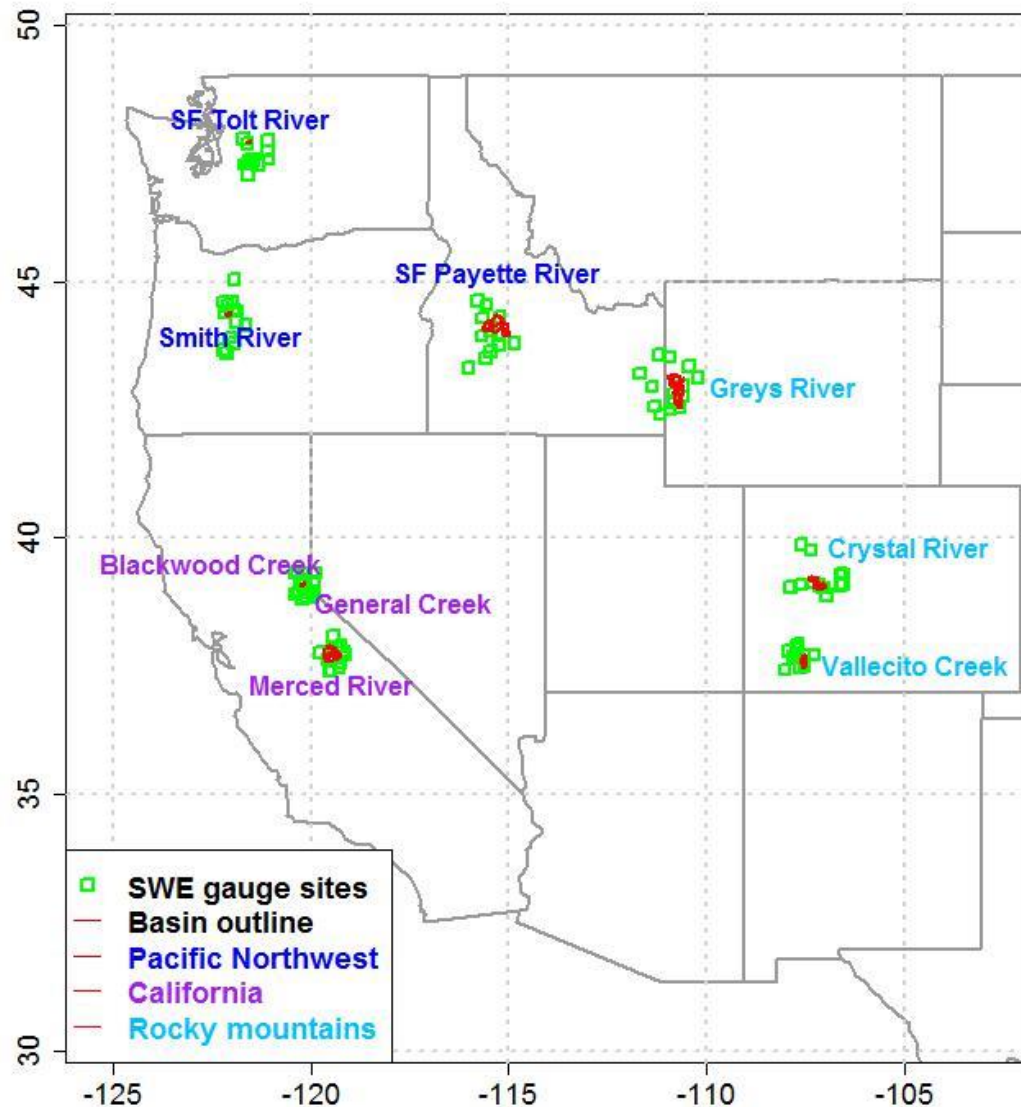
Elizabeth Clark



SWE Hydrologic Data Assimilation

- SWE measurements can be used objectively to update hydrologic model states and improve forecasts
- Using NWS models with Ensemble Kalman Filter (EnKF)
- Hindcast-based study
- Huang et al, 2016 (HESS)

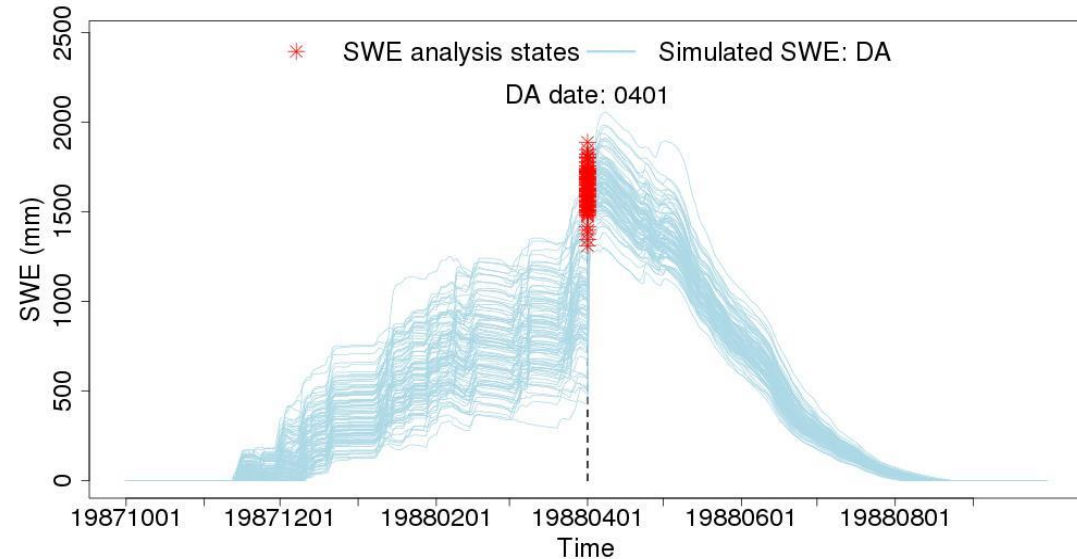
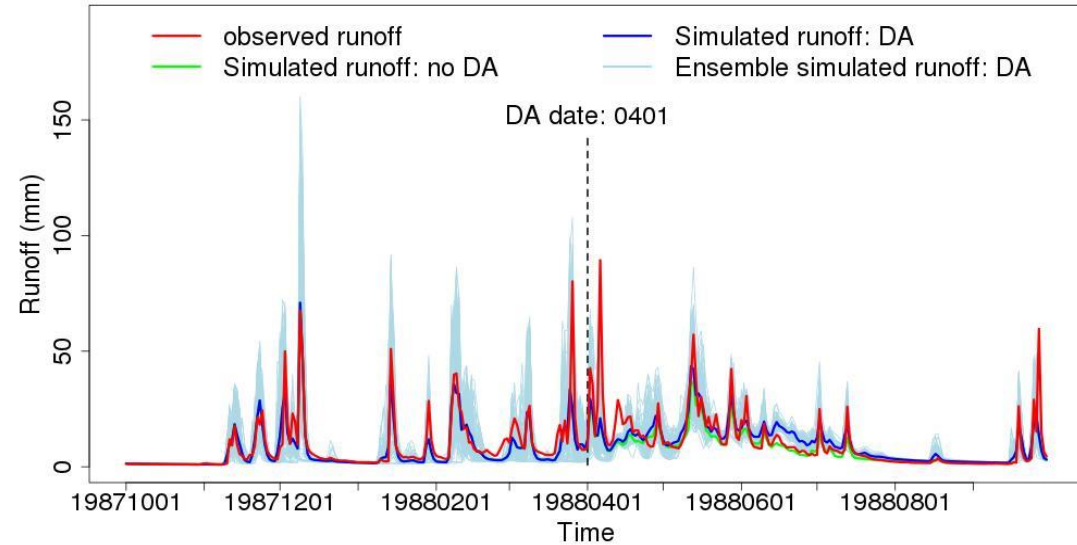
Position of 9 case basins and SWE gauge sites



Example

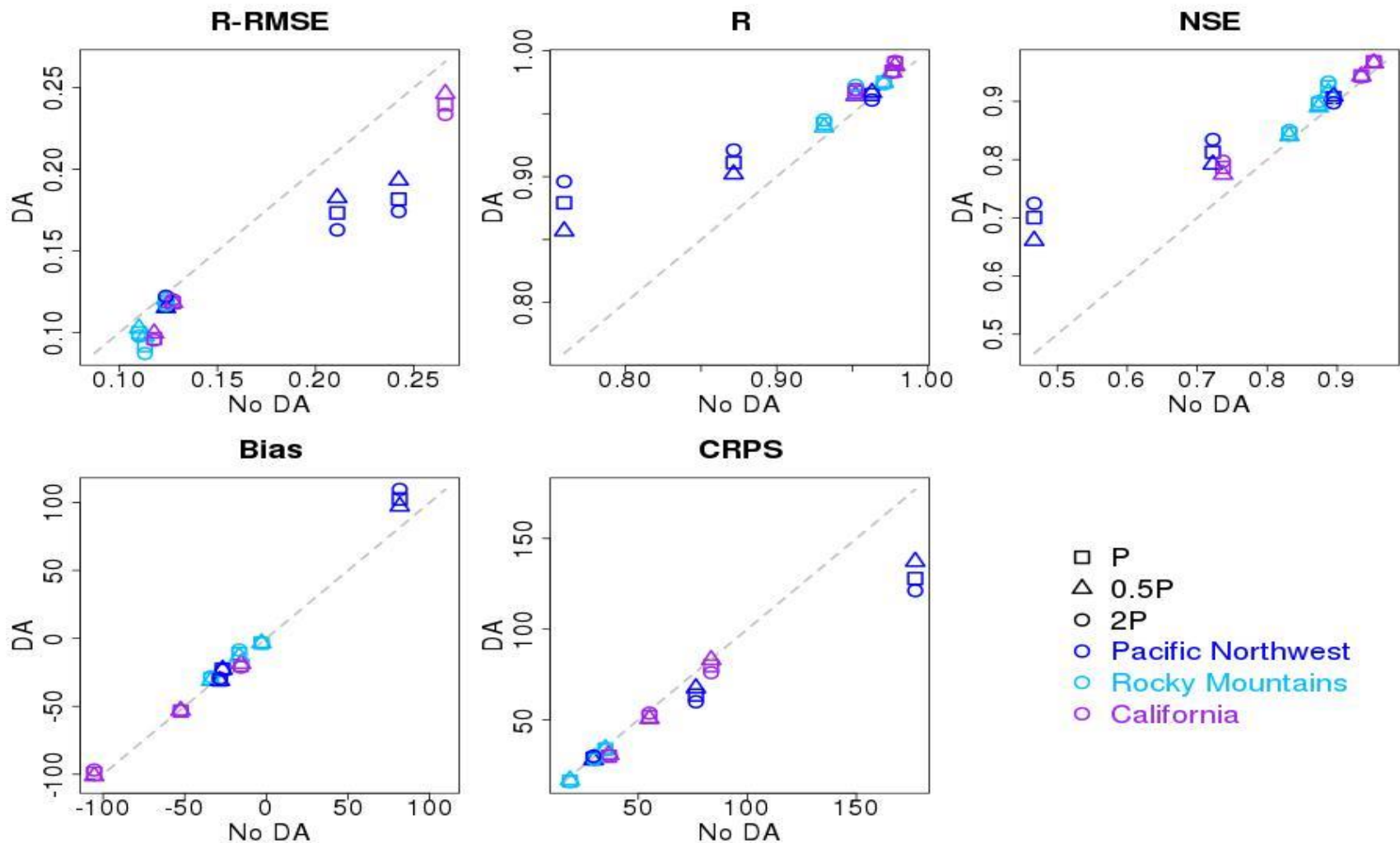
- Use an ensemble method to estimate initial conditions
- Update those conditions with SWE observations
- Make ESP predictions from mean model states
- Assess forecast skill after assimilation

Region: 17 Basin ID: 12147600 Name: SF Tolt River



Hydrologic Data Assimilation

- Evaluation metrics generally show improvements for April-July ESP mean streamflow forecast for the nine case basins.



2012 User Needs

Category: Forecasting

Short-Term Water Management Decisions

User Needs for Improved Climate, Weather, and Hydrologic Information



Enhanced suite of hydrologic predictions spanning lead times of days to seasons and consistent with the continuum of weather to climate forecast products

More reliable quantitative precipitation forecasts (QPF) with lead times of hours to days

Improved precipitation forecasts for landfalling storms in coastal areas

Enhanced streamflow predictions with lead times of hours to days, particularly during storm events

Enhanced streamflow predictions with lead times of days to weeks, particularly during the snowmelt season

Improved anticipation of runoff volumes with lead times of months to seasons

Enhanced prediction products characterizing potential water levels during storm events

Multivariate suite of climate to hydrologic predictions that comprehensively characterizes the state and evolution of basin hydrologic conditions with lead times of days to seasons

A comprehensive survey of water management and operational users found a widespread need and desire for improved precip and streamflow forecasts at all scales.



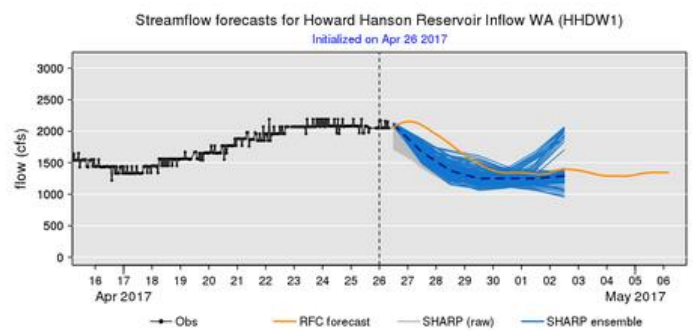
The *OverTheLoop* Streamflow Forecast Demonstration Project

Short to Medium Range Streamflow Forecasts

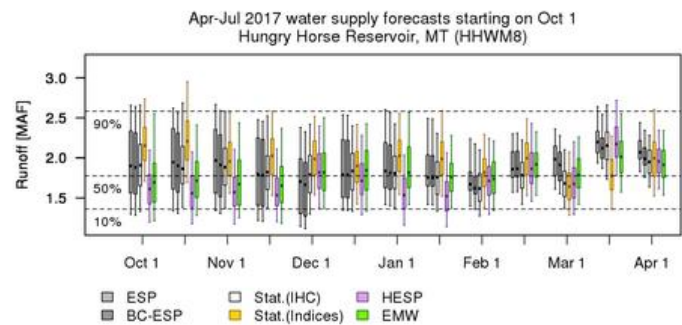
Streamflow forecasts from hours out to 15 days (ie, 'short to medium range') are used for flood control and other daily reservoir operations that achieve water management objectives such as hydropower generation, stream temperature control, navigation support, and irrigation scheduling, among others. [Latest Medium-Range Forecasts](#)

Seasonal Streamflow Forecasts

In many parts of the world, and particularly where reservoirs supply water needs during a dry season, or where rivers are fed by snowmelt (giving long-lead predictability), seasonal streamflow forecasts are a critical prediction. A common example is the probabilistic seasonal runoff volume forecast, which supports high-value seasonal to annual water system allocation decisions for agriculture and water supply among other uses. [Latest Seasonal Forecasts](#)



Short/medium range reservoir inflow forecast, including both deterministic and ensemble predictions



Seasonal reservoir inflow volume forecast evolution plot

What added value does climate information bring?

Example:
Hungry Horse

Forecast skill across methods for Apr-Jul runoff

