Assimilation of snow data for ensemble streamflow prediction

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Objectives & Motivation

Advance and improve US National Weather Service hydrologic modeling and prediction

- DA assimilation framework
  - Significant uncertainty in initial states in snow-dominated basins.
- Applications of satellite-based remotely sensed data

Data Assimilation not an established method in the NWS River Forecast System

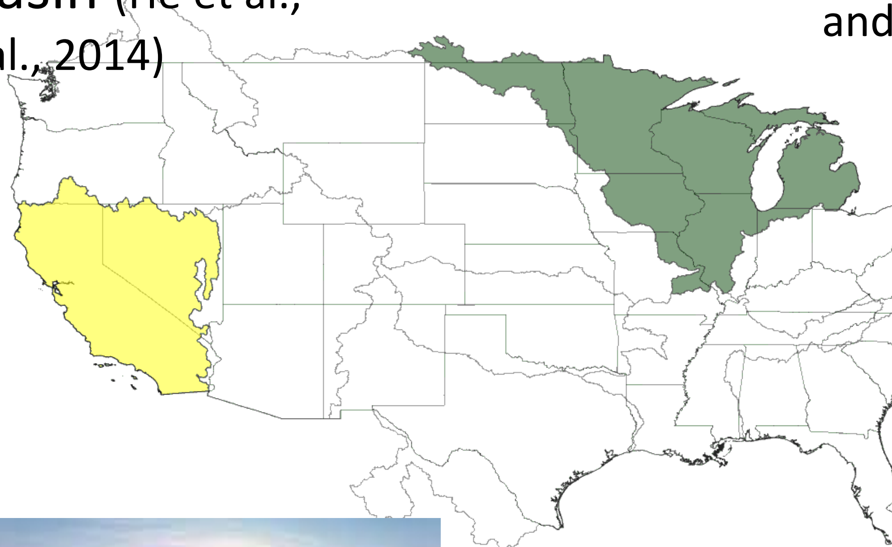
Several ongoing projects to evaluate DA and data products into forecasting

Need systematic evaluation of new methods within operational forecasting framework

Two SWE DA Studies

1. Ground-based SWE in snow dominated mountain basin (He et al., 2012; Franz et al., 2014)

2. Satellite SWE data in north-central US basins (Dziubanski , 2013; Dziubanski and Franz, in prep).

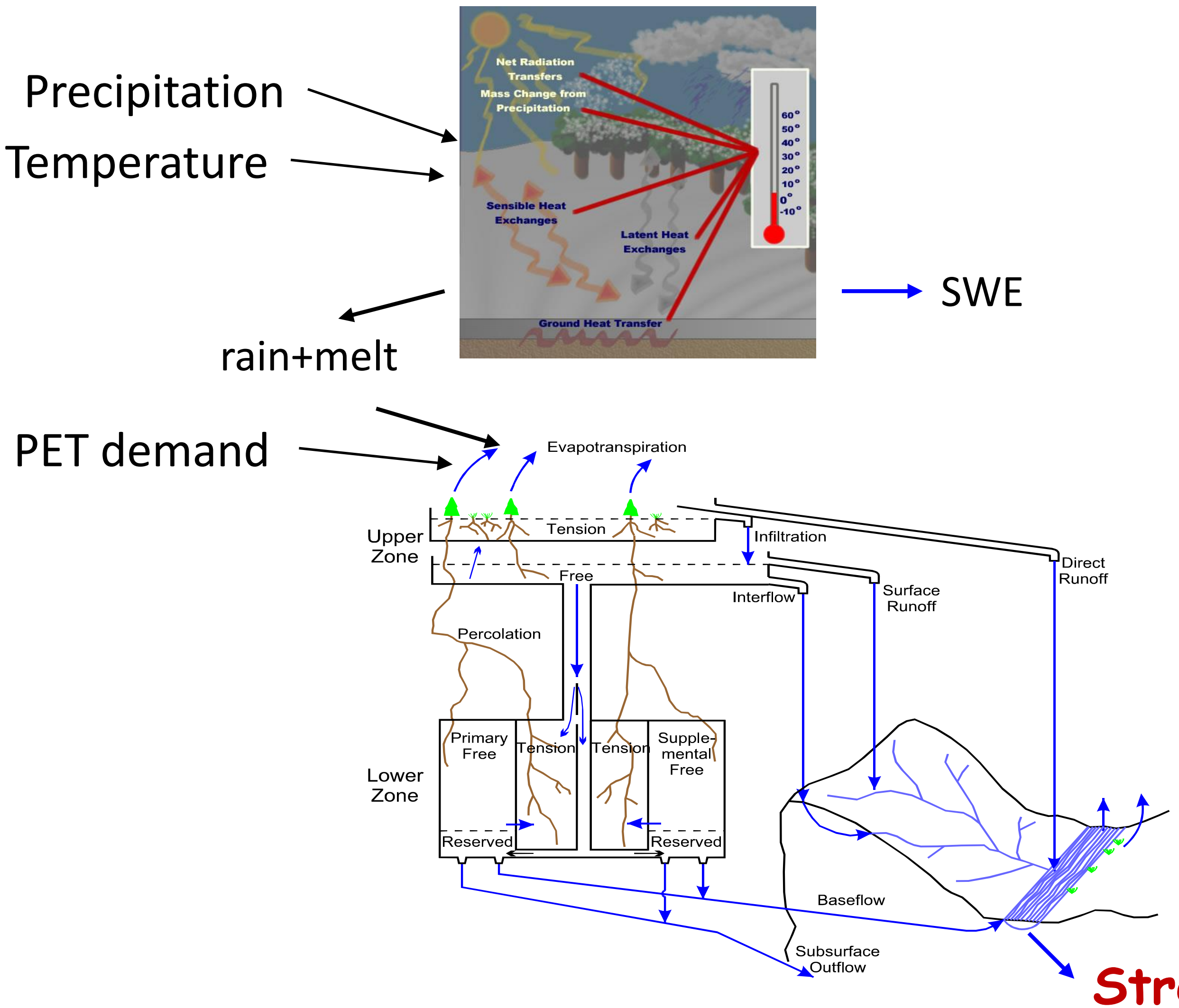


California Snow pillow sites

Advanced Microwave Scanning Radiometer

National Weather Service modeling system

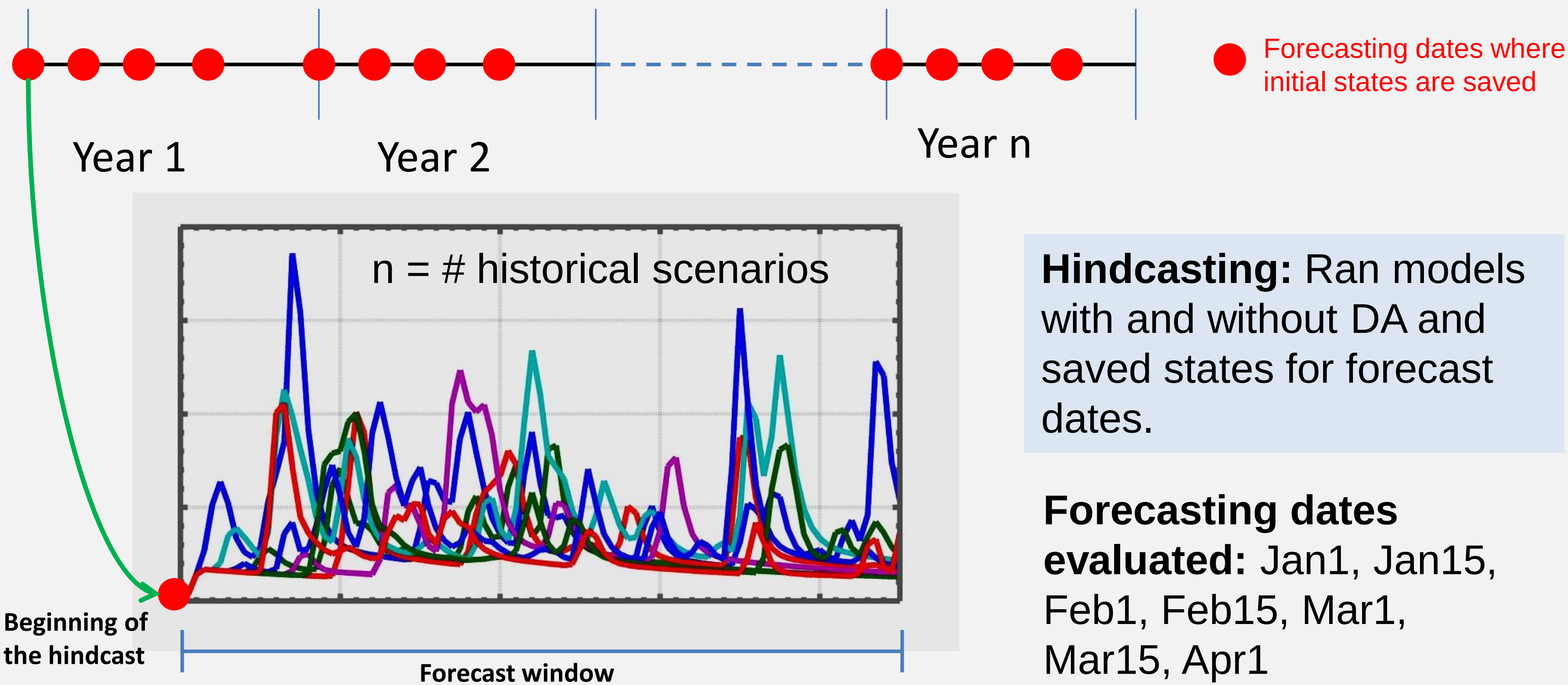
SNOW17 Temperature Index Model (Anderson, 1973)
Sacramento Soil Moisture Accounting Model (Burnash et al., 1973)



- Modeling system used for short- and long-term **streamflow predictions** across US
- **Empirically-based** snow model simulates accumulation and melt
- **Conceptual** rainfall-runoff model simulates watershed residence and runoff

Ensemble Streamflow Prediction

- Initialize models with current states
- Run with past weather data (spanning forecast window) to generate streamflow scenarios.



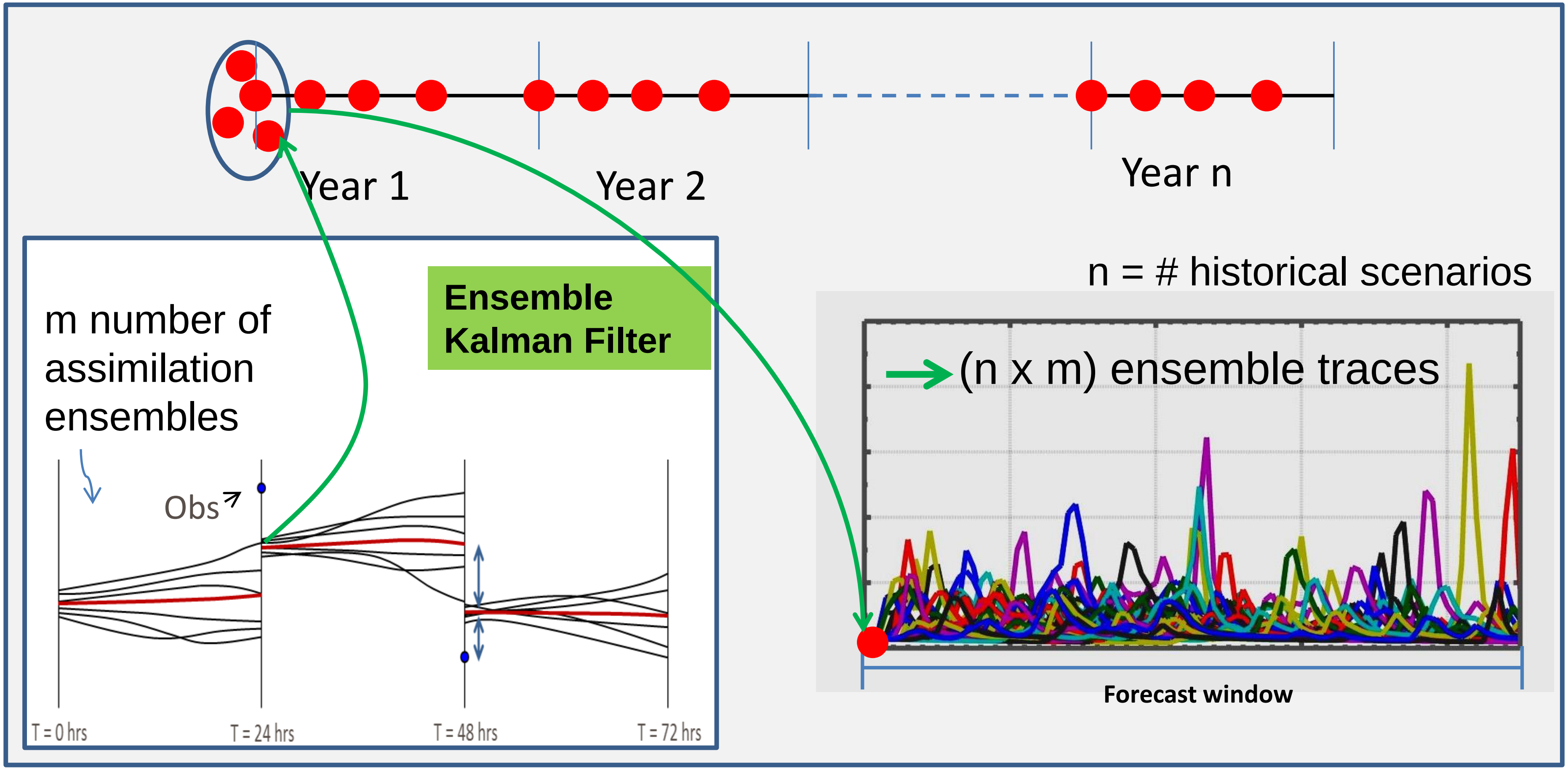
Hindcasting: Ran models with and without DA and saved states for forecast dates.

Forecasting dates evaluated: Jan1, Jan15, Feb1, Feb15, Mar1, Mar15, Apr1

(described in Day et al., 1985 & Franz et al. 2003)

Hindcasting with Assimilation

- Hindcasting with EnKF uses entire ensemble of initial states.
- Ran models for each set of states with past weather data.



Evaluation

Deterministic Metrics:

- ❑BIAS
- ❑Root Mean Square Error
- ❑Normalized mean absolute error

} Summary Statistics

Probabilistic Metrics:

- ❑ Continuous Ranked Probability Score
  - ↳ Accuracy
- ❑ Containing ratio
  - ↳ Accuracy/Bias
- ❑ Discrimination & Reliability Plots
  - ↳ Conditional Statistics

Study 1 – California Sierra Nevada Mountains

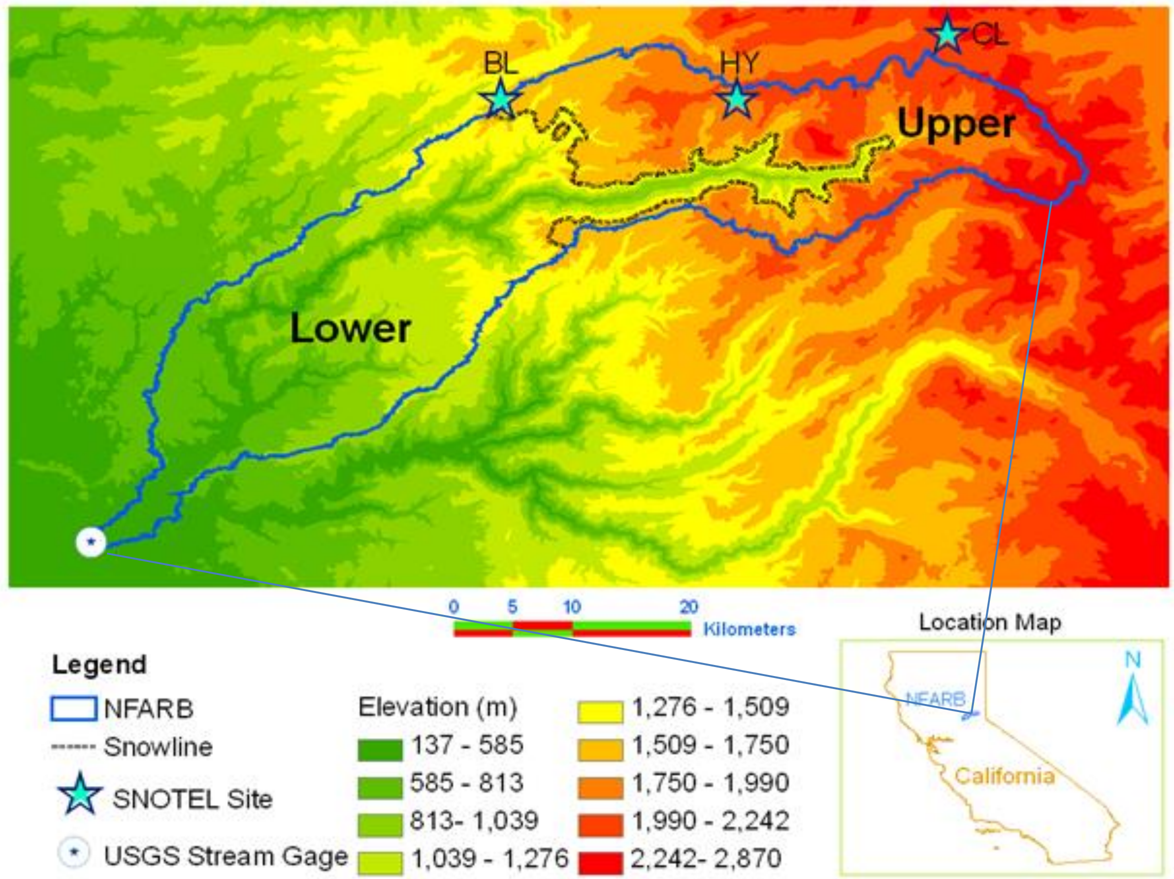
North Fork American River Basin (NFARB)

Test: Assimilation of SWE data from 3 SNOTEL sites

Data Period: WY1979-WY2002

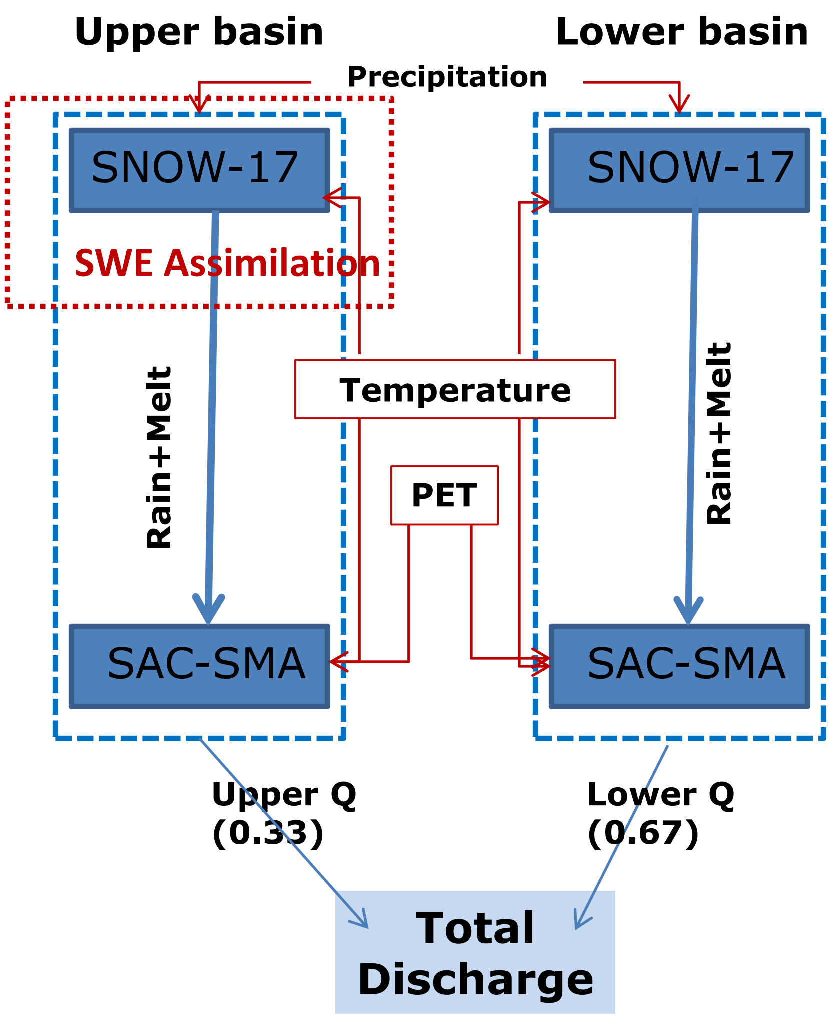
Snow: persistent in upper zone, transient or none in lower zone

Area: 886 km^2
Annual Ppt: 1514mm
Annual Runoff: 837 mm



(He et al., 2012, HESS; Franz et al., 2014, in press, JOH)

Model & Assimilation Setup



- Basin modeled two elevation zones, 6-hourly
- SWE assimilation in upper sub-basin only
  - weighted average of point SWE observations
  - Updating frequency 7 days
  - Forcing uncertainty based on uncertainty of SCF and PXTEMP parameters

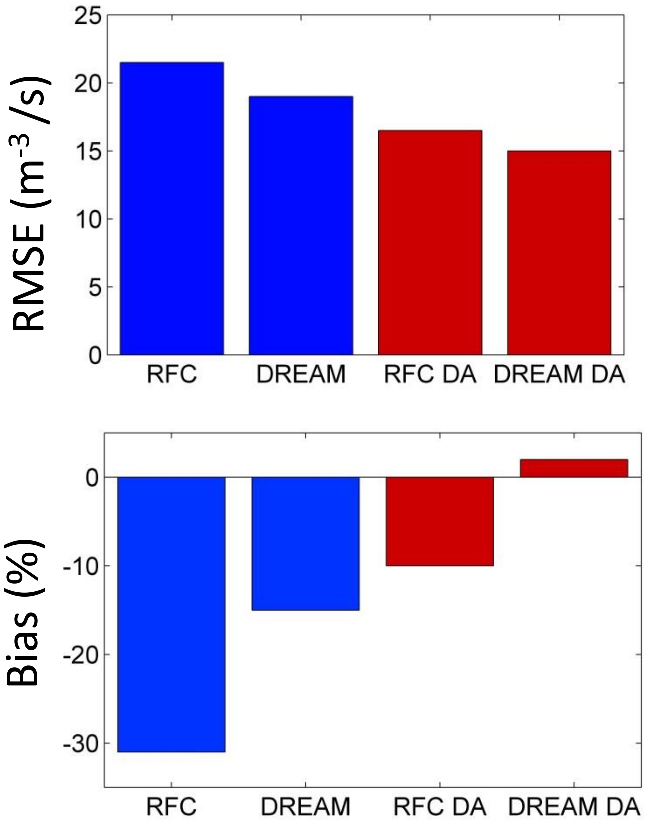
- Forecast analysis period is April 1 – July 31
  - Forecasting begins Jan 1
- 26 hindcast samples for each forecast date
  - Non-DA: 58 member ensemble
  - DA: 5800 member ensemble (58 climate scenarios x 100 states)
- Two sets of parameters examined
  - NWS RFC operational calibration
  - DREAM automatic calibration (considers parameter uncertainty)

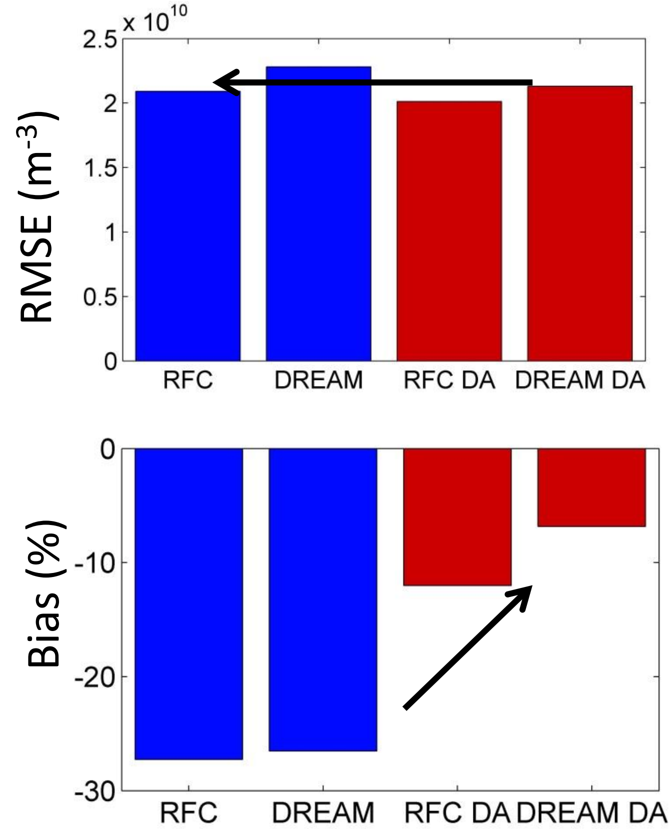
Ensemble mean Simulations (1991-1996)

Ensemble mean Hindcasts (Jan 1 –Ap 1)

No DA

With DA

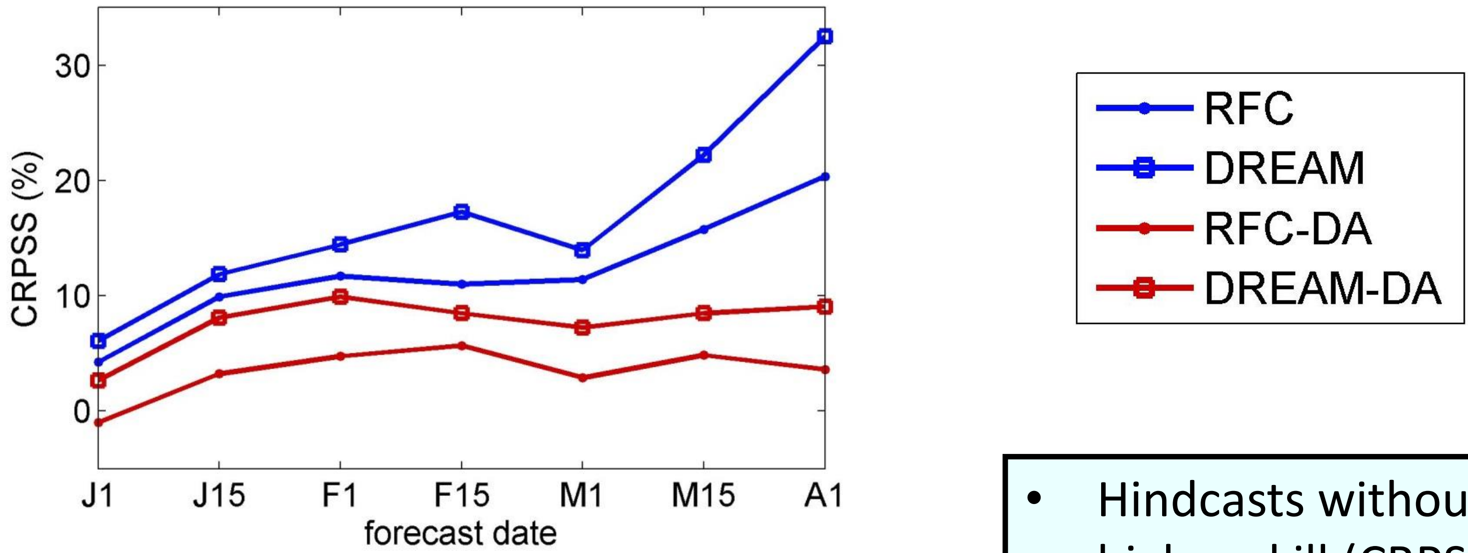


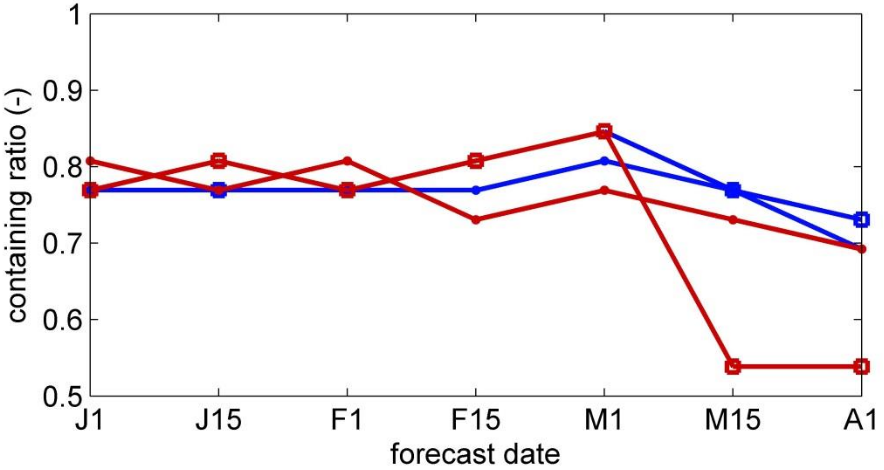


Simulated discharge: DA tests improved in terms of all metrics considered. See improved peaks.

Hindcasts: DA improved bias and RFC-DA had lowest RMSE. But DREAM DA had higher RMSE than RFC w/no DA

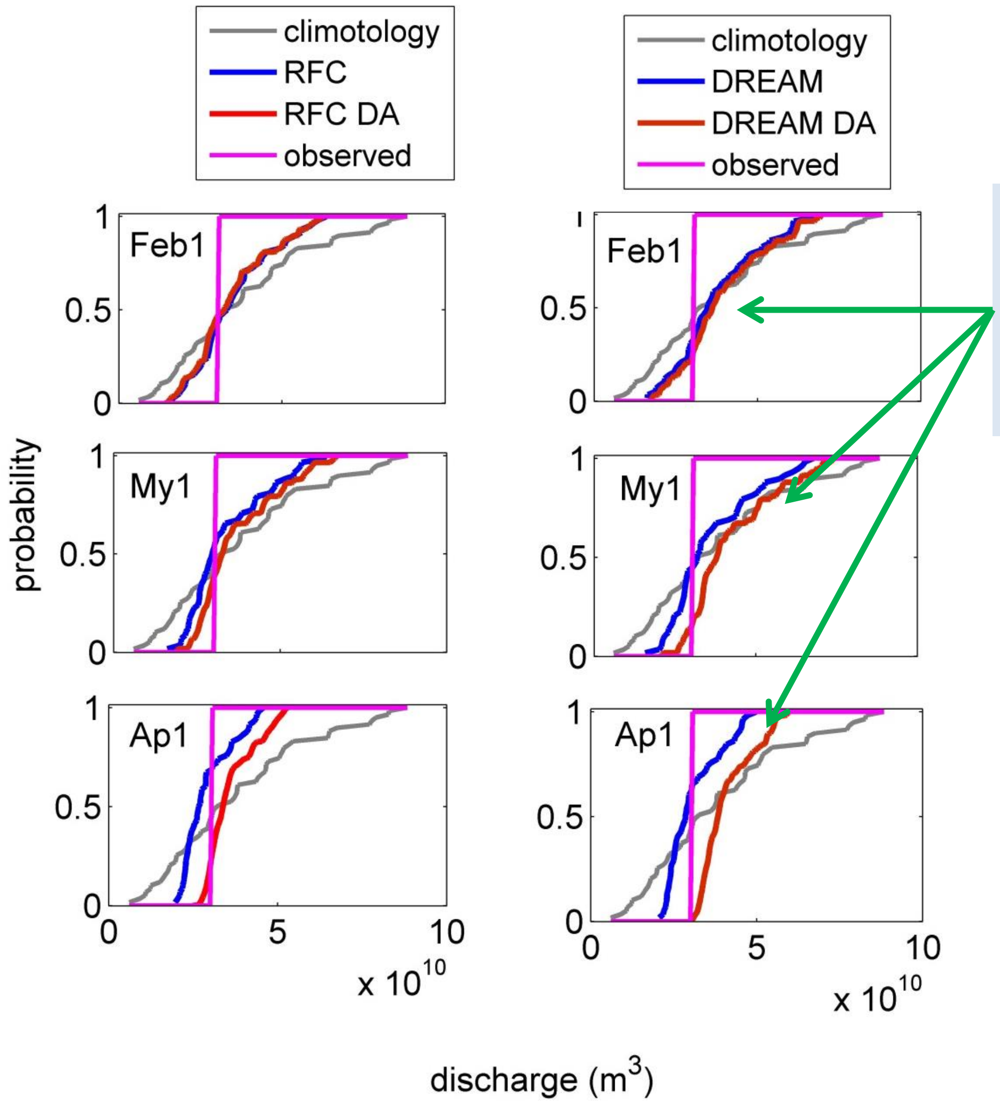
Ensemble Hindcasts





- Hindcasts without DA have higher skill (CRPSS)
- Containing ratios similar for all cases
- DREAM parameters produce higher CRPSS

What is happening?



DA (red) shifts forecast probability away from observed (pink) towards higher flows. “Missed” observation.

- Comparing all CDFS
  - 57% : non-DA closer match to the observations than DA
  - 23% : DA more accurate than non-DA
  - 20% showed no noticeable difference in CDFs.

Additional comments

- Hindcast skill improved as season progress
- Reliability and discrimination were not significantly changed by DA
- Best discrimination occurred for low flow (lowest 40%)
  - RFC calibration performed better for discrimination

Study 2 – North Central US

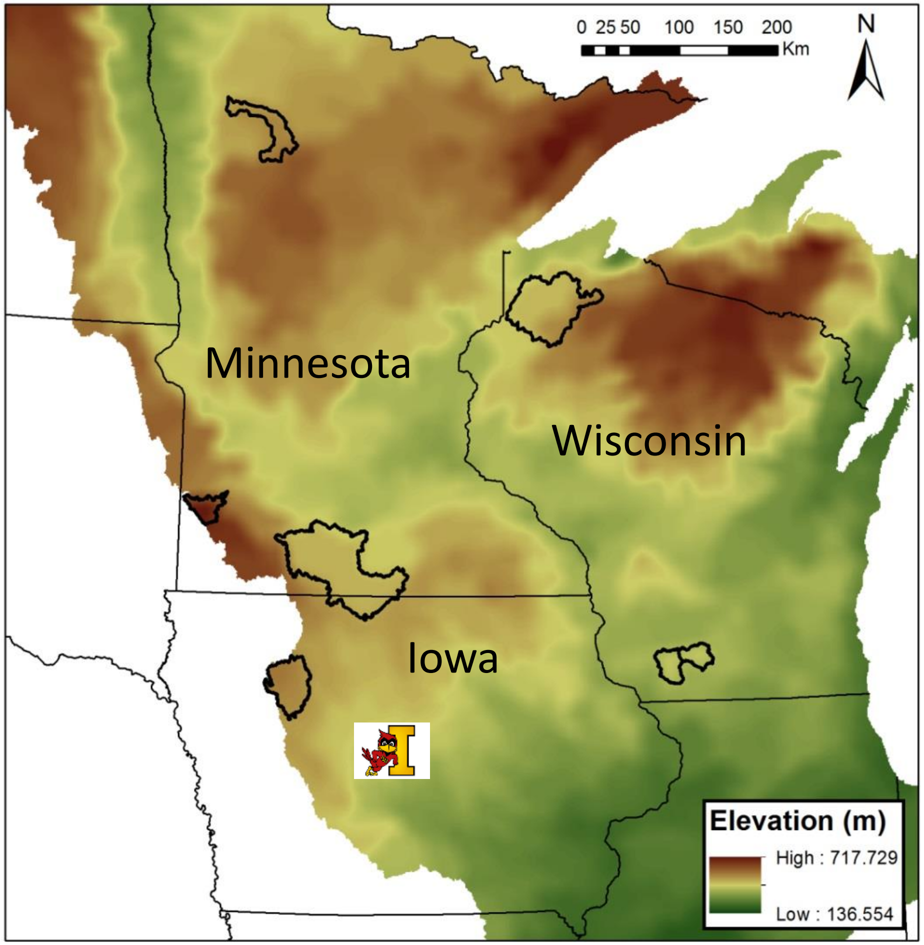
Test: Assimilation of SWE data AMSR-E

Data Period: 2006-2011

Snow: persistent to north, transient and thin to south

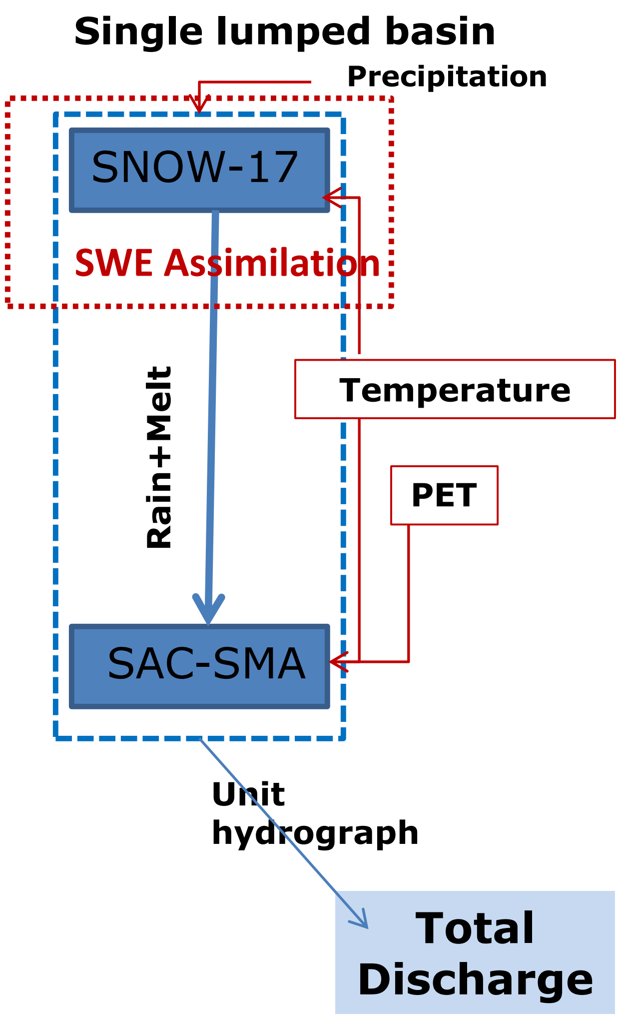
Land Use: North to south – forests/some wetlands to predominantly row crop

Area: 572 - 6330 km^2
Annual Avg. Ppt: 846 mm
Annual Avg. Runoff: 217 mm



Dziubanski and Franz, in prep.

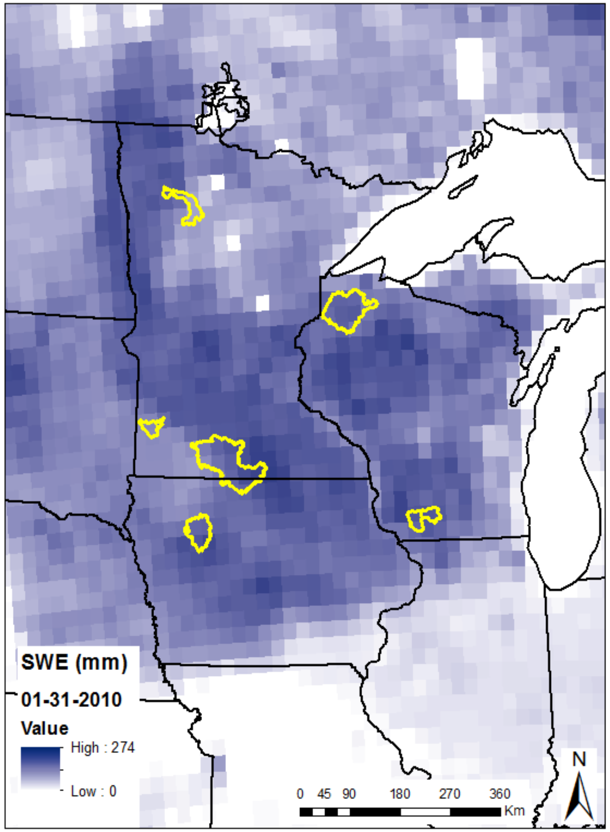
Model & Assimilation Setup



- Single, lumped basin
- SWE assimilation
  - Updating daily, when data available
  - Forcing uncertainty
    Precip: lognormal, mean 1 and SD 25 mm
    Temp: gaussian, mean 0 and SD 0.5°C
  - NWS RFC model parameters

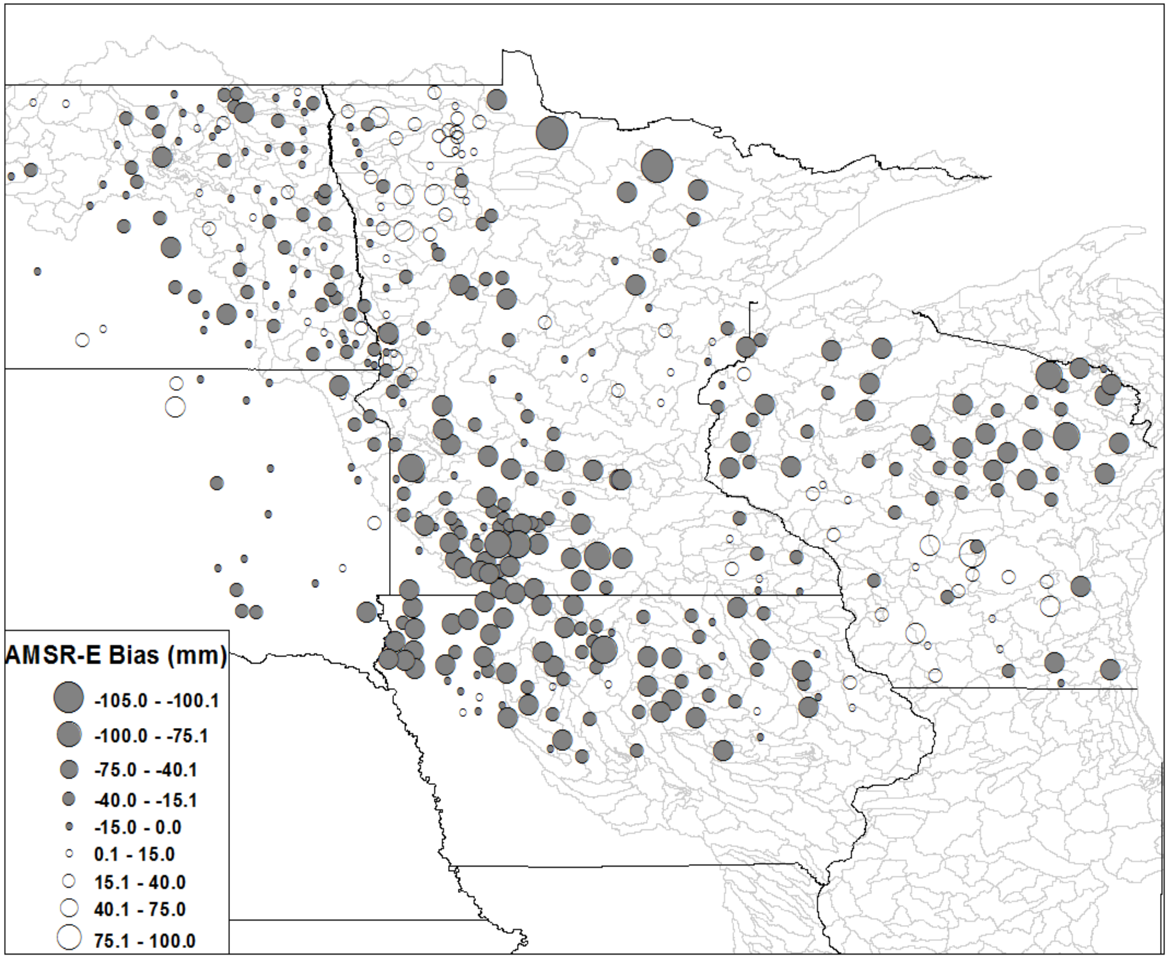
Data

- AMSR-E Snow Water Equivalent (SWE).
  - 25 km resolution, daily
  - Microwave brightness temperature to calculate snow depth. Climatological, regional snow density to get SWE.
  - Error of 10-50 mm. (Tong and Velicogna, 2010; Kelly et al. 2003; Foster et al., 2005)
  - Factors affecting detection: size and number of snow grains, snow density, ice or free water, forest cover.



AMSR-E Bias Correction

- Bias evaluation using 1500 NOHRSC airborne observations (gamma radiation sensor)

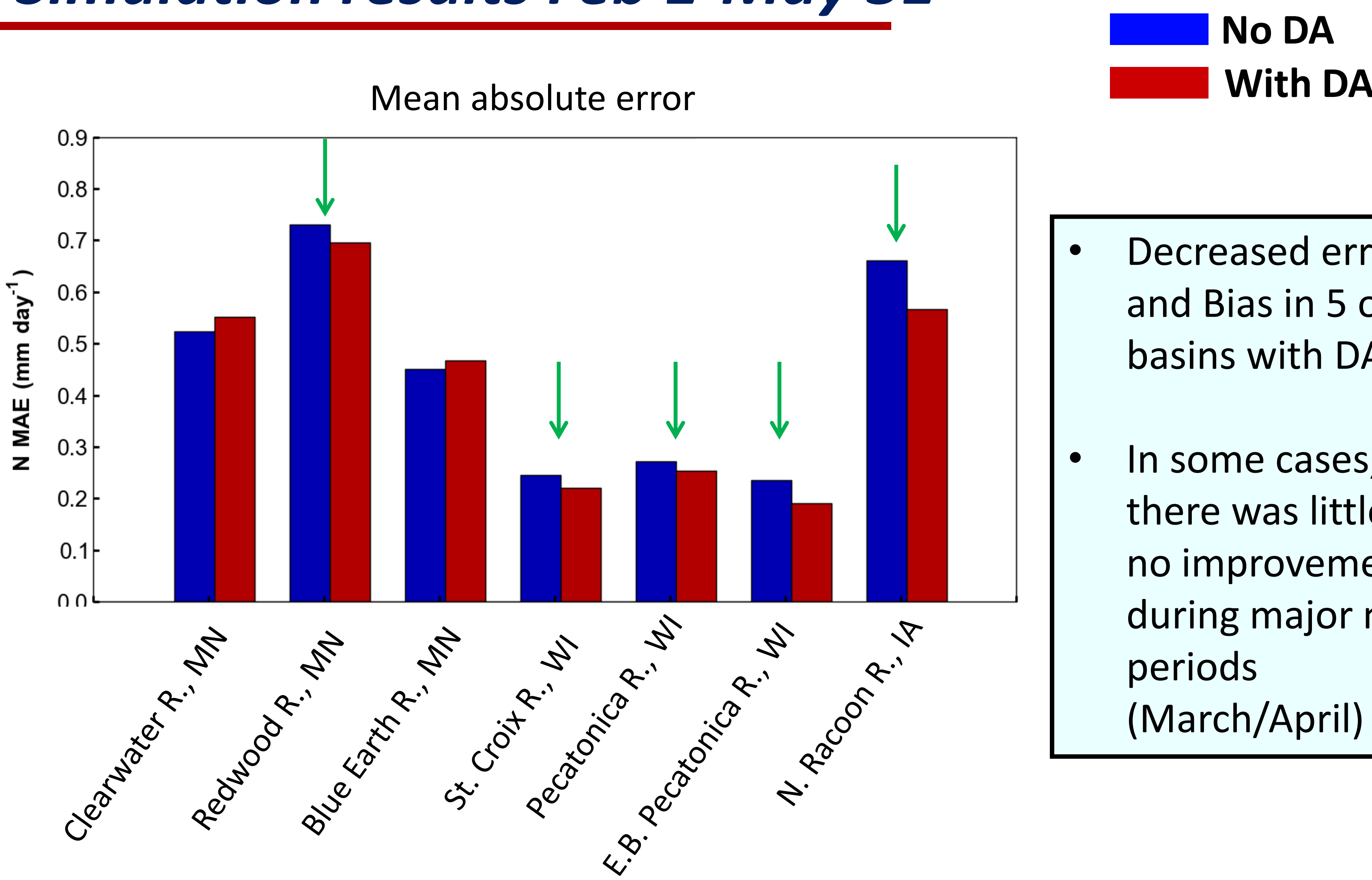


- Removed outliers based on the modified Z score method (Iglewicz and Hoaglin, 1993).
    - NOHRSC SWE
    - AMSR-E SWE
    - Bias
- Bias correction and standard deviation of bias.
    - Avg. Bias: -17.91 mm
    - SD: 29.73 mm (uncertainty)

- Forecasts 1st and 15th from January to April
  - 90 day outlooks

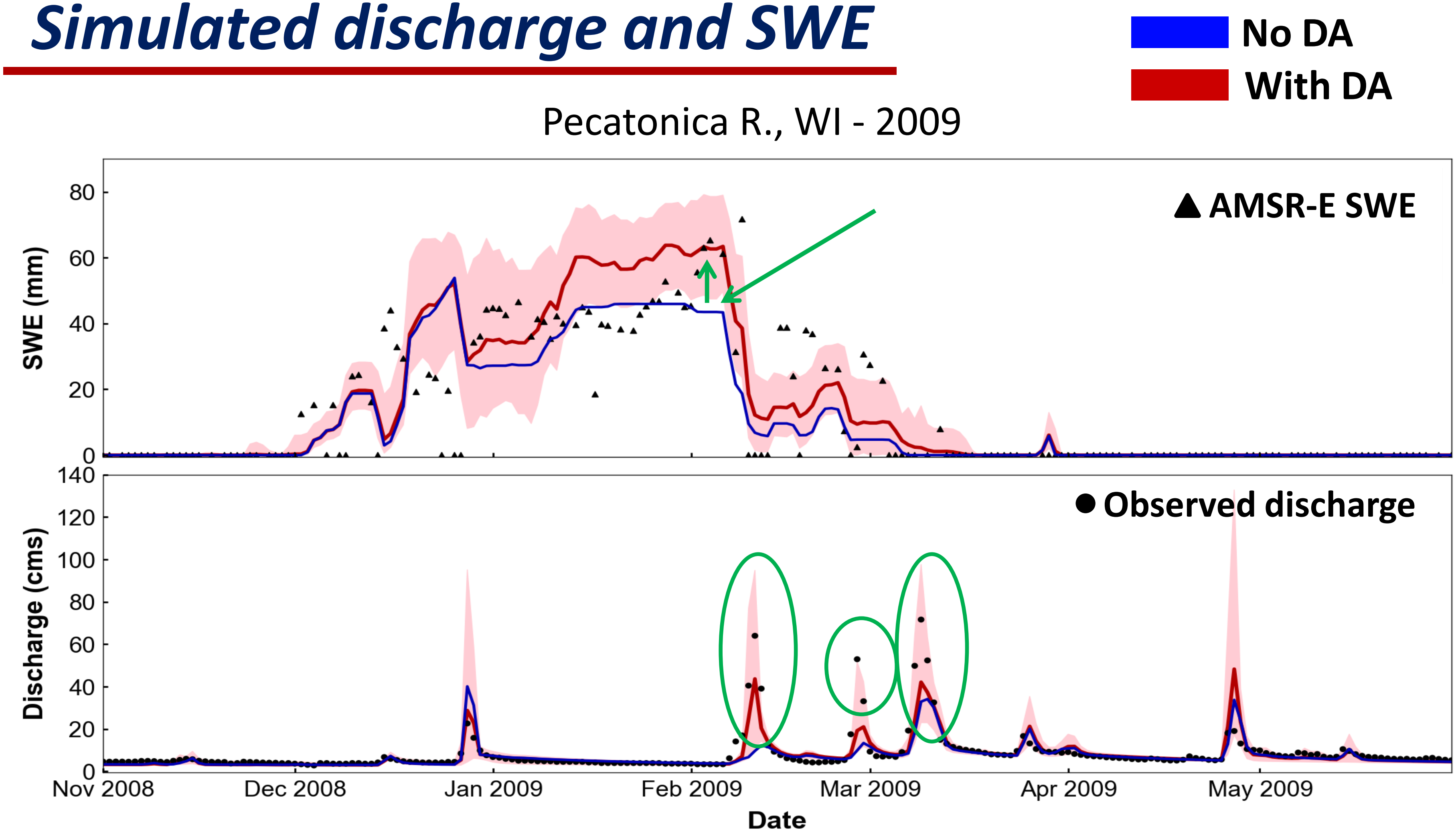
- Only 6 hindcast samples for each forecast date
  - Non-DA: 61 member ensemble
  - DA: 6100 member ensemble - 61 climatologic scenarios x 100 replicate states

Simulation results Feb 1-May 31



- Decreased errors and Bias in 5 of 7 basins with DA
- In some cases, there was little or no improvement during major melt periods (March/April)

Simulated discharge and SWE

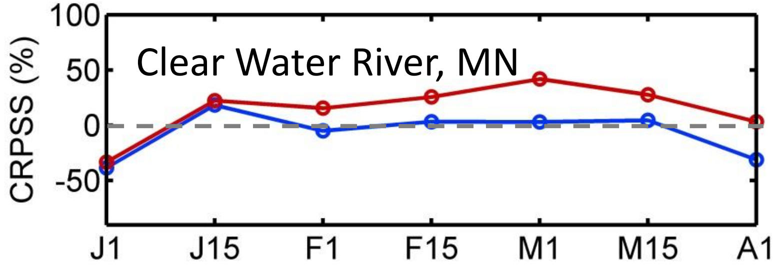


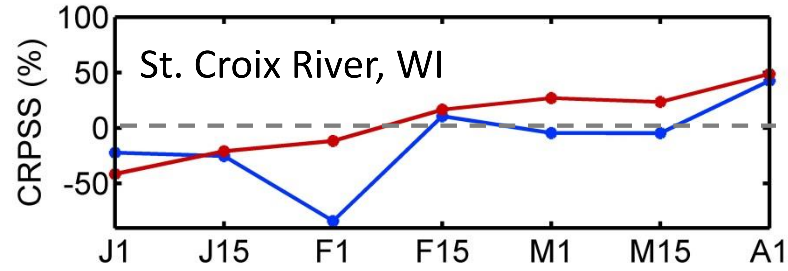
- Observed low bias in SNOW17, generally corrected through DA
- SNOW17 has slow melt compared to AMSR-E (sensor data errors in melt periods)

Hindcasts: CRPSS 90-day maximum flow

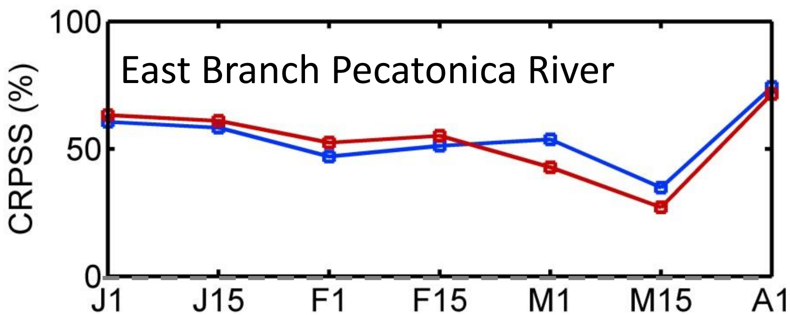
No DA
With DA

- Some improvement with DA in a few basins

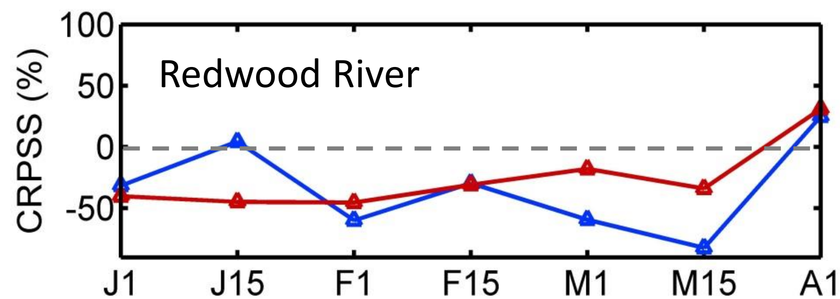




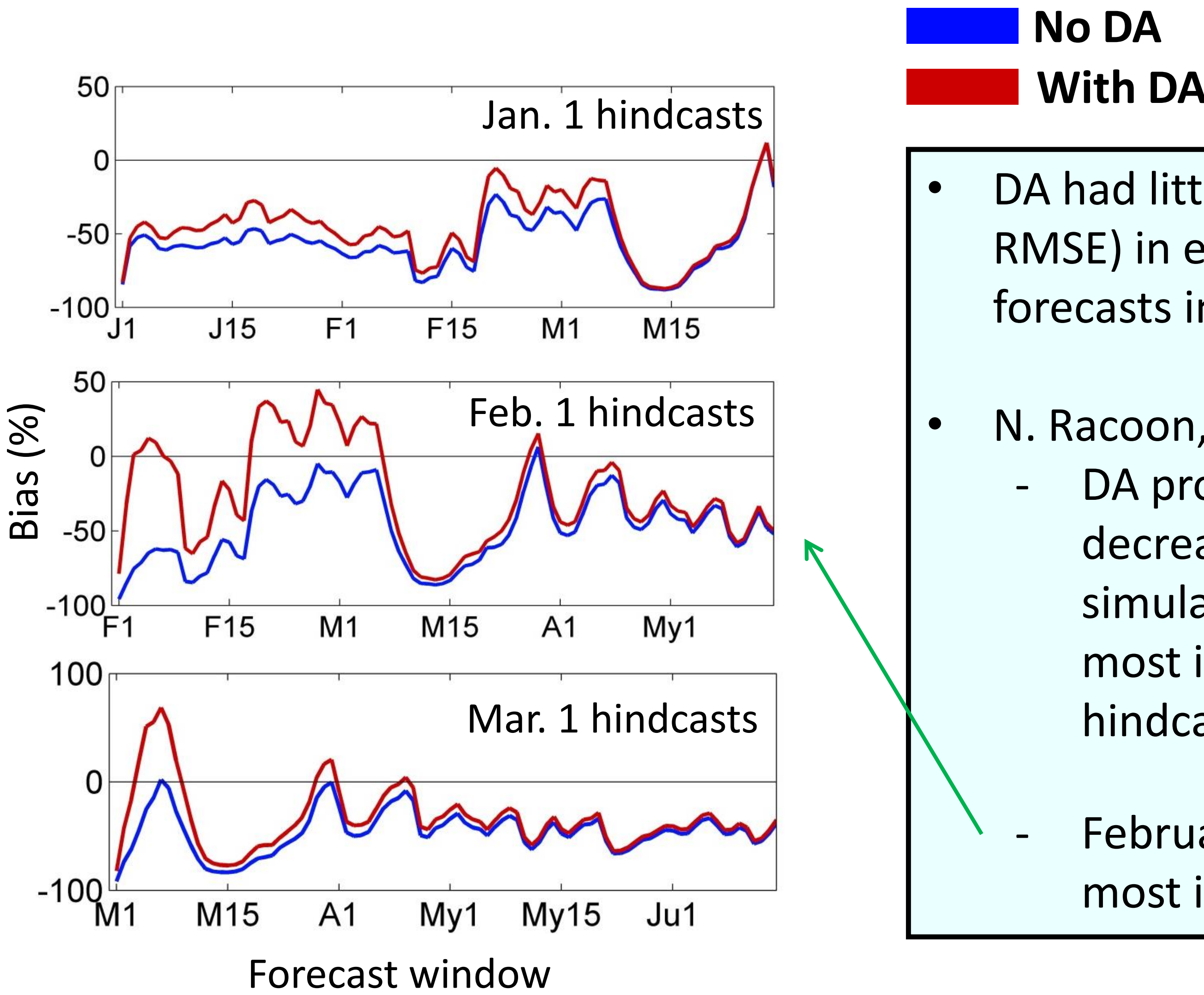
- No difference with DA
- Skillful forecasts
- Well-modeled basin



- Low skill
- Poorly modeled basin



Ensemble mean hindcasts: Bias in daily flow



- DA had little impact on Bias (or RMSE) in ensemble mean forecasts in most basins
- N. Racoon, IA shown
  - DA produced greatest decrease in Bias for simulated daily flows & most impact on Bias in hindcasts
  - February 1 hindcasts had most improvement

Summary Remarks

- **Improvements in simulated discharge observed in both DA studies.**
  - Apparent low SWE bias in SNOW17 for north-central US improved through assimilation of AMSR-E data
  - Additional work to consider AMSR-E errors needed
- **Few examples of improved hindcast performance when DA is applied compared to no DA**
  - Climate uncertainty likely dominates in these examples (i.e. long-term forecasts)
  - Testing on short-term forecasts needed
  - Mismatch in evaluation of simulations with DA versus hindcasts with DA (e.g. daily flow versus seasonal volume)

Summary Remarks

Common assumption …

- Application of new hydrologic methods will give better modeling results and lead to better forecasts.

…difficult to prove, why?
…how do we prove this and move operations forward?

Questions?

Acknowledgements

- Mike DeWeese (NCRFC), Pedro Restrepo (NCRFC)
- Rob Hartman (CNRFC)
- NASA New Investigator Program grant #NNX10AQ77G
- NOAA National Weather Service grant # NA07NWS4620013
- UCAR COMET grant

UCAR University Corporation for Atmospheric Research