

Near real time data assimilation and uncertainties for hydrological forecasting

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Data Assimilation and Uncertainties

Ensemble Weather
Forecast pre-processor

- Ensemble calibration
- Met input errors

VIC hydrology model
+
Routing model

Data Assimilation

- Met input errors
- SWE: snow model errors (in situ SWE obs)
- SM: model structure, model parameterization (previous days river flow conditions)

Ensemble Flow Forecast
“post-processor”

- Melting-pot (everything)

Outline

- ▶ Snow Water Equivalent (SWE) assimilation
 - Approach
 - Results
 - Conclusions
- ▶ Soil Moisture (SM) assimilation
 - Approach
 - Results
 - Future directions

Approach – snow data assimilation

- SWE assimilation can correct for:
 - Errors in precipitation input leading to errors in model SWE
 - Errors in snow/rain differentiation and spatial distribution over the model grid cell which also lead to model SWE errors
- Point observations vs spatial average model predictions lead to complications

Approach

- ▶ Improve the Wood and Lettenmaier (2006) SWE assimilation for short term flow forecasting:
 - Weighted average between point-based observed and spatially (and vertically) distributed simulated anomalies:
 - Linearly decreasing weights based on distance and elevation:
 - $SWE_{station} \geq 10 \text{ cm}$
 - $W_{distance} = \text{MAX}[0, 1 - \text{distance}(\text{station}, \text{grid cell}) / 50 \text{ km}]$
 - $W_{elevation} = 1 - \text{MAX}[0, |\text{Elev}_{station} - \text{Elev}_{gridcell}| / 2000 \text{ m}]$
 - $W_{total_i} = W_{distance_i} \cdot W_{elevation_i}$

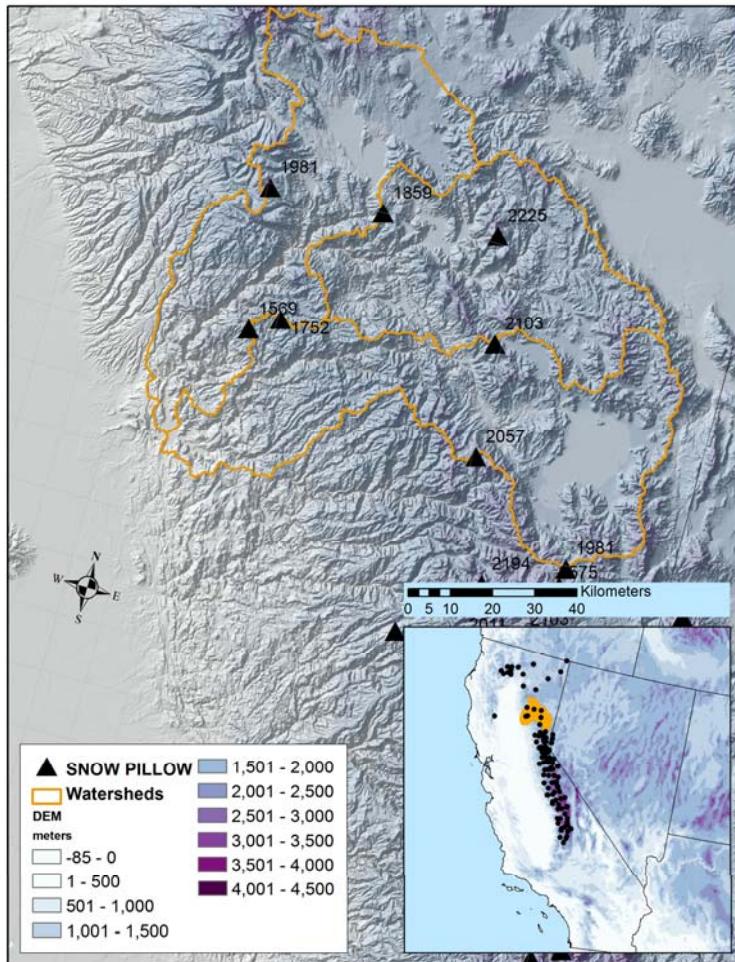
$$SWE_{new} = (1-K)SWE_{VIC} + K \cdot SWE_SIGNAL_{stations}$$

$$SWE_{new} = (1-K)SWE_{VIC} + \sum [W_{total_i} \cdot CDF_{VIC}^{-1}(CDF_{station}(SWE_{station}))]$$

where $\sum W_{total_i} = K$

CDF_{VIC} and $CDF_{station}$ based on 1990-2005 daily SWE

Feather River Basin, California



Snowmelt driven basin

13 000 km²

~3 day concentration time

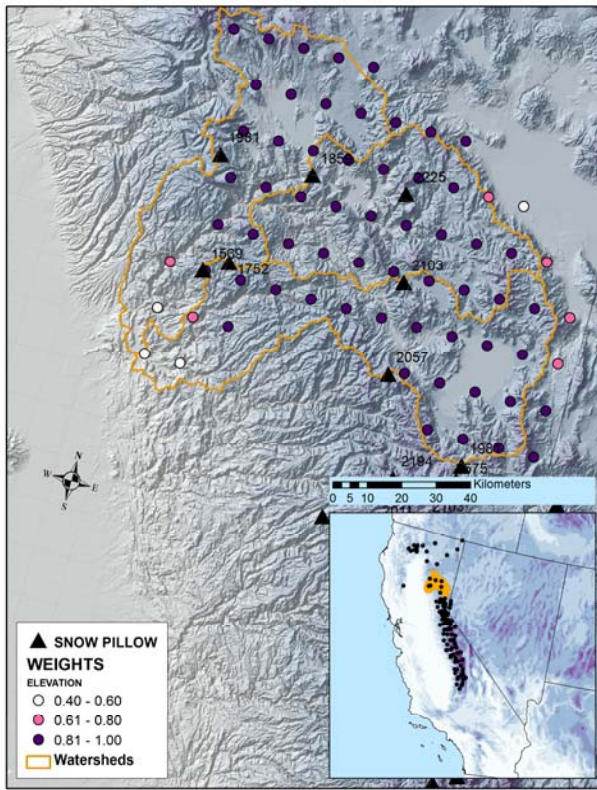
Up to 15 SNOTEL stations influencing each
VIC grid cell (50 km radius)

SNOTEL influence on simulated SWE

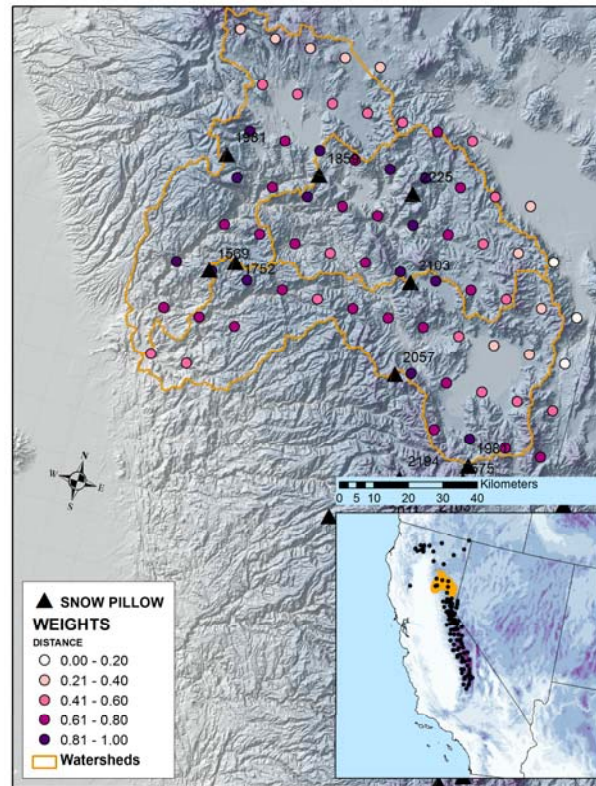
Elevation-based

Distance-based

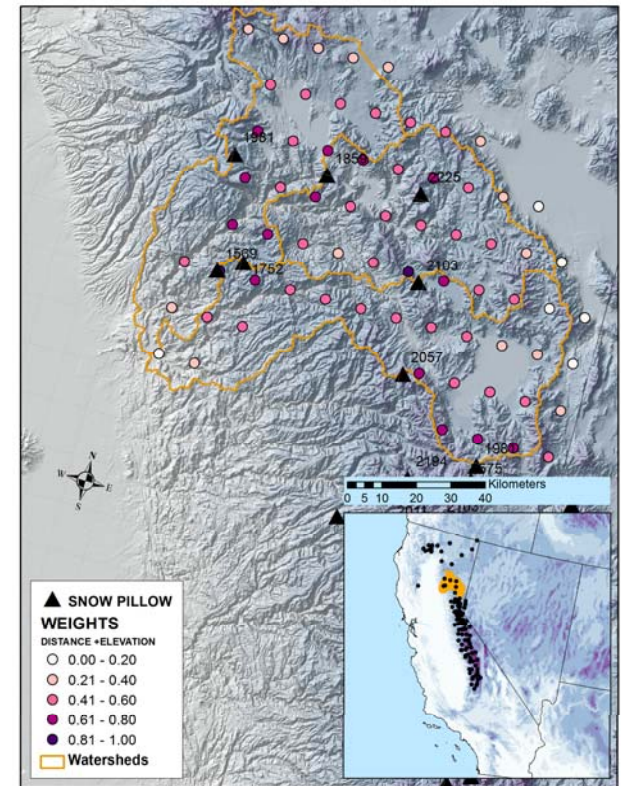
Distance and
Elevation-based



(0.8-0.9)



(0.2-0.8)



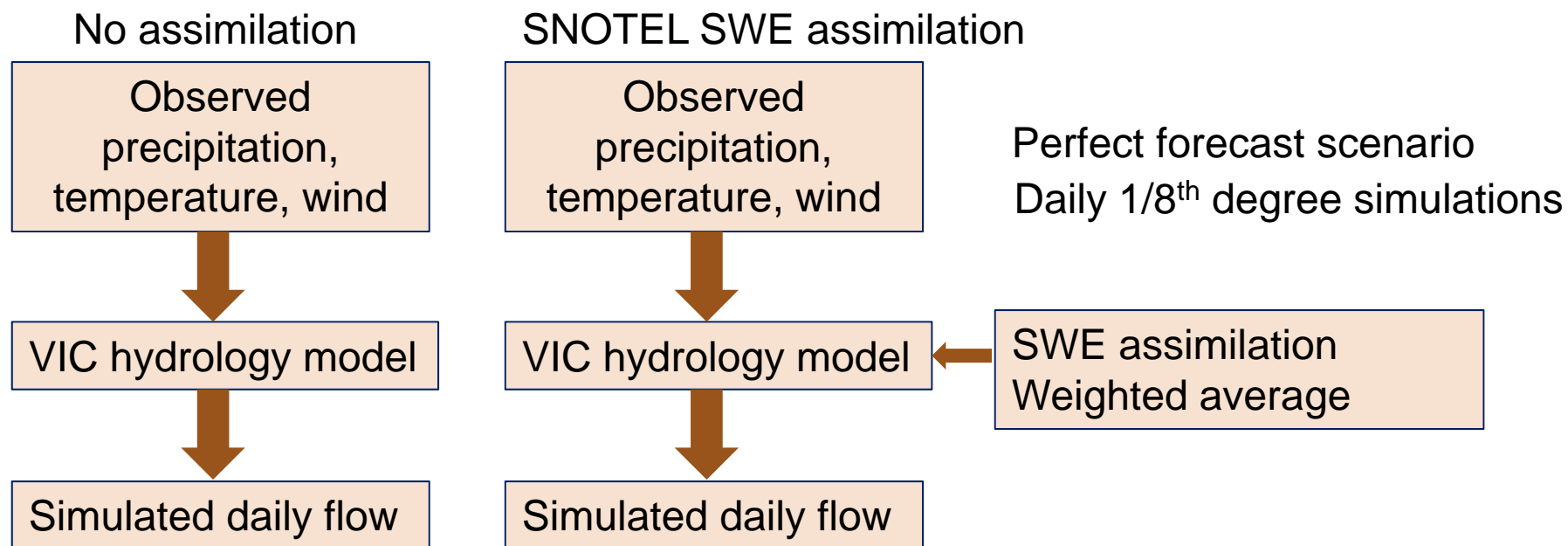
(0.1-0.8)

Weights decrease

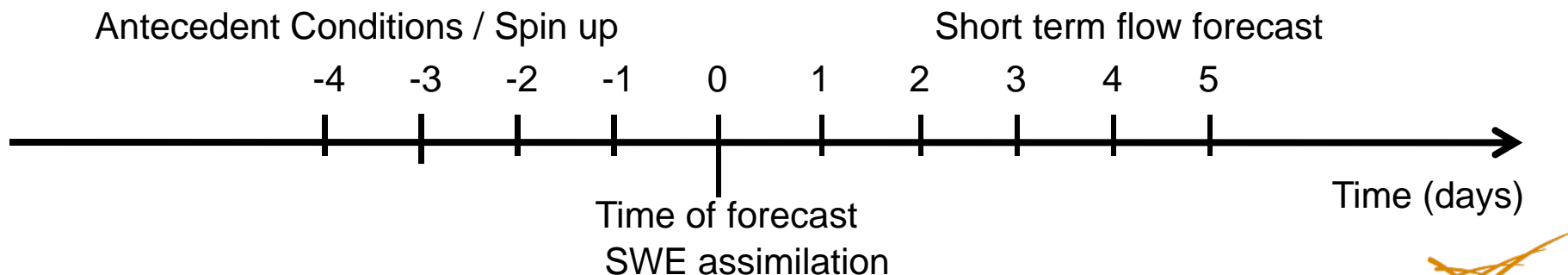
Science Questions

- ▶ Can SNOTEL SWE assimilation improve short term flow forecasts?
- ▶ What is the uncertainty in the flow forecasts due to uncertainties in the SWE assimilation ?
 - Different weights
 - Uncertainty in spatial and vertical disaggregation of the point-based SWE information
- ▶ How significant is the uncertainty in the spatial disaggregation of observed SWE information with respect to model parameterization uncertainty?

Approach



Flow forecast verification with respect to observed daily (naturalized) flow



Approach

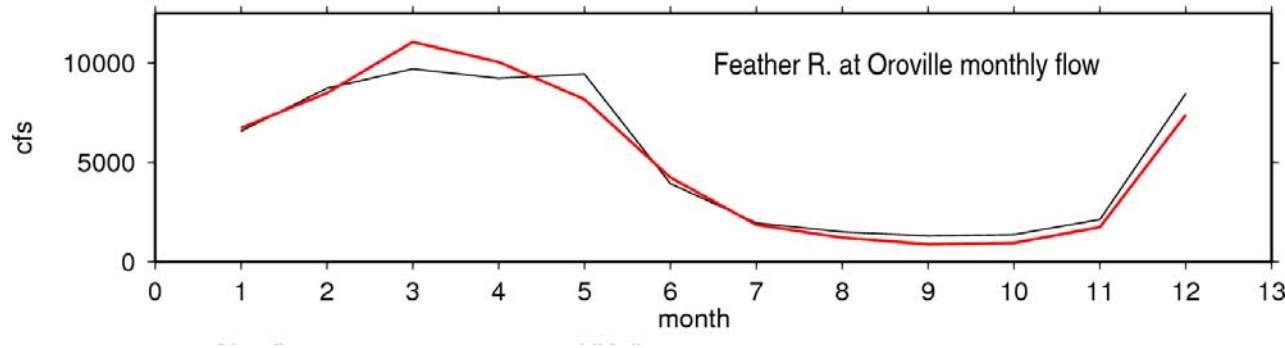
► Experiments:

- “Perfect forecast” scenario; estimate only assimilation
- For different weights between simulated and observed SWE anomalies: uncertainties due to the static weights

► Analysis

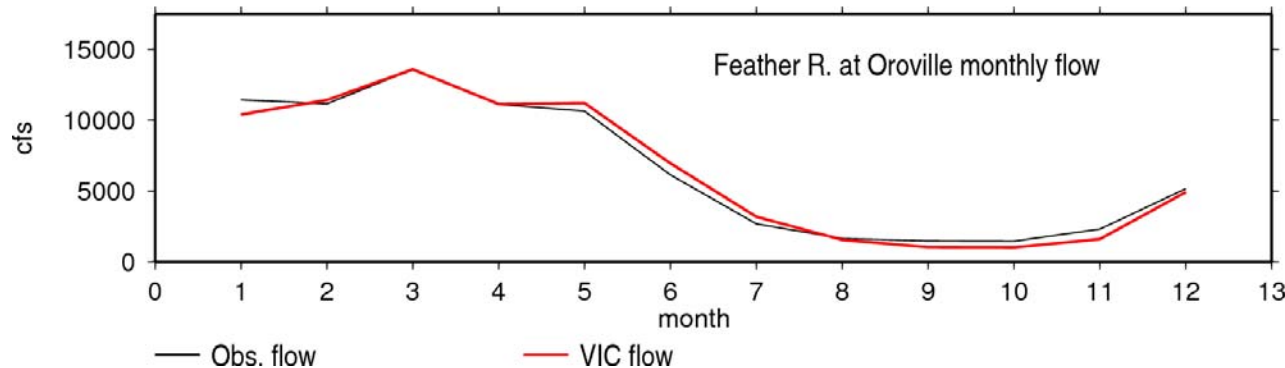
- Daily streamflow forecast verification for the 1990-2005 period
- For different months: accumulation vs ablation period
- Streamflow forecast categories based on observations
- Accuracy skills assessment: biases, RMSE, correlation

Feather – VIC calibration



Mean monthly flow
Calibration period
2000-2005

Daily NSE: 0.81
Annual bias: 0



Mean monthly flow
Validation period
1990-2000

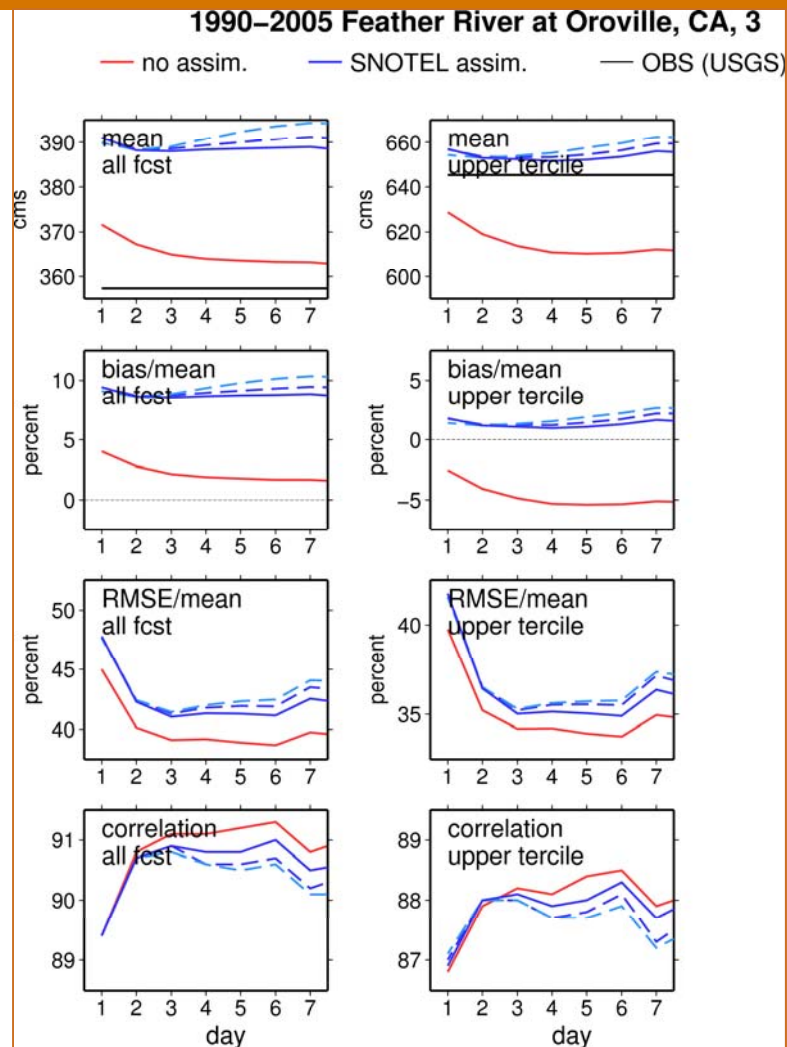
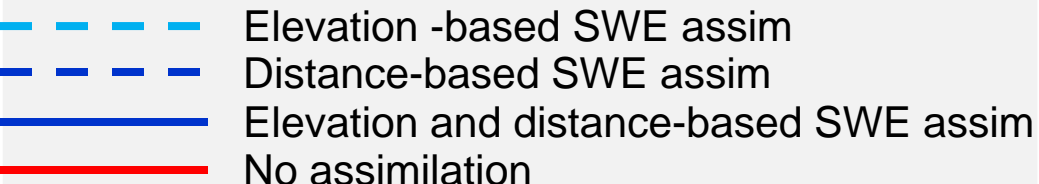
Daily NSE: 0.84
Annual Bias: 0

Results - March

1990-2005 period
496 forecasts
Observed flow categories

For all lead times:

- Overall higher bias and RMSEs, decreased bias during high flows
- Status quo

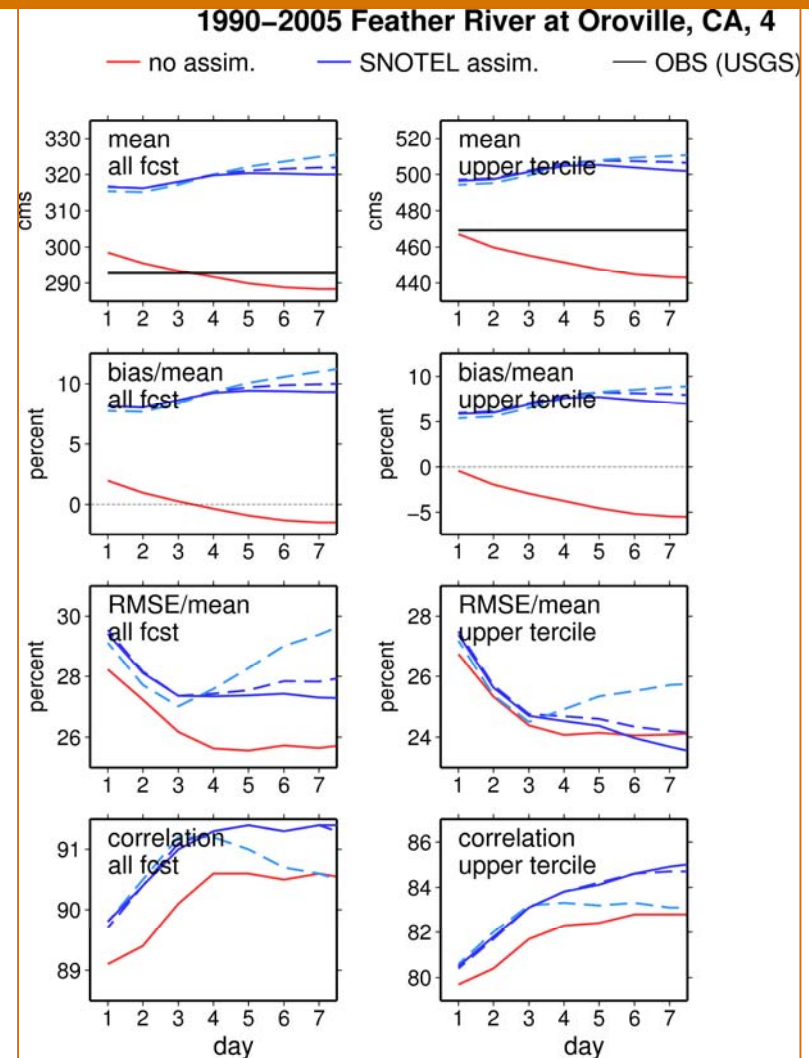
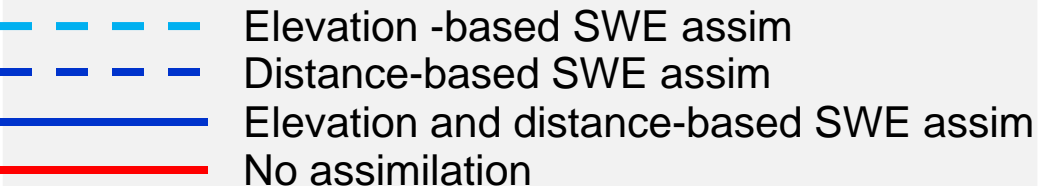


Results - April

1990-2005 period
480 forecasts
Observed flow categories

For all lead times:

- Increased bias and RMSE
- Status quo



Results - May

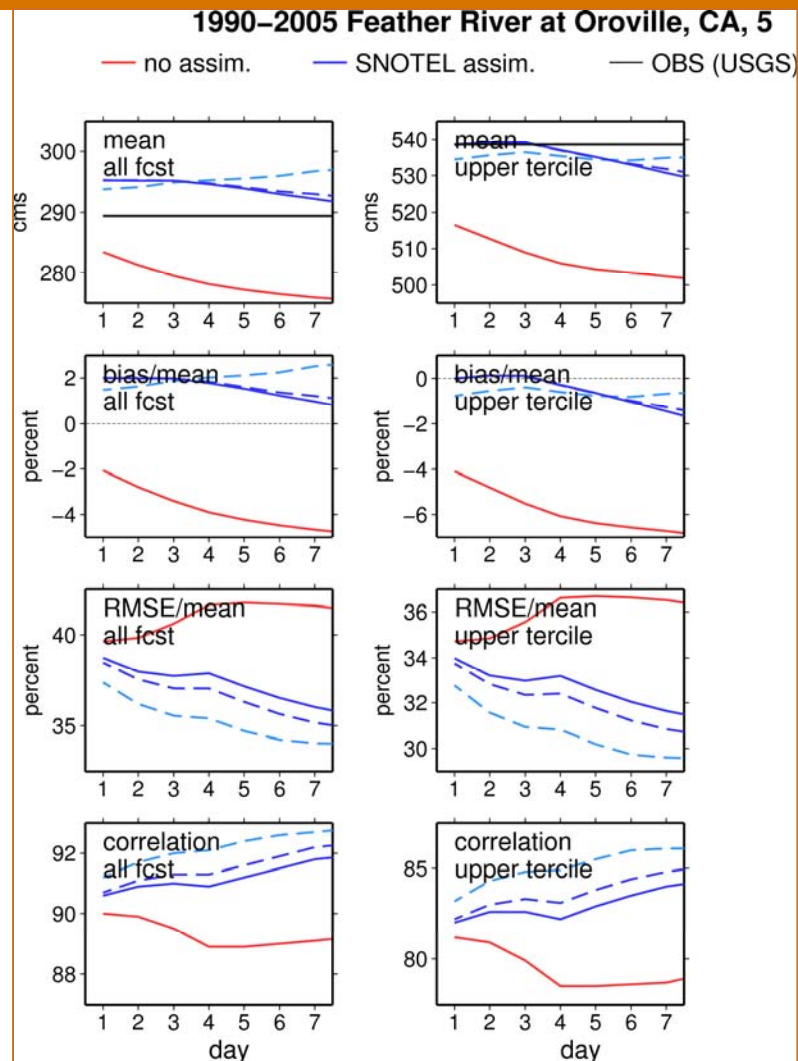
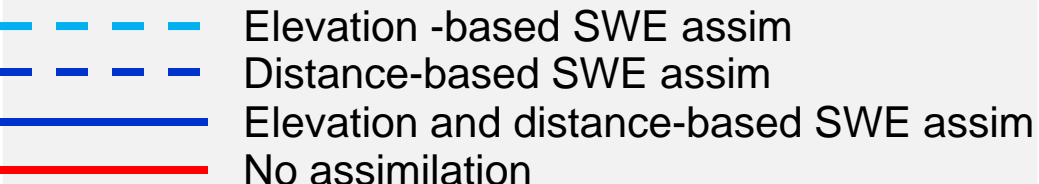
1990-2005 period

496 forecasts

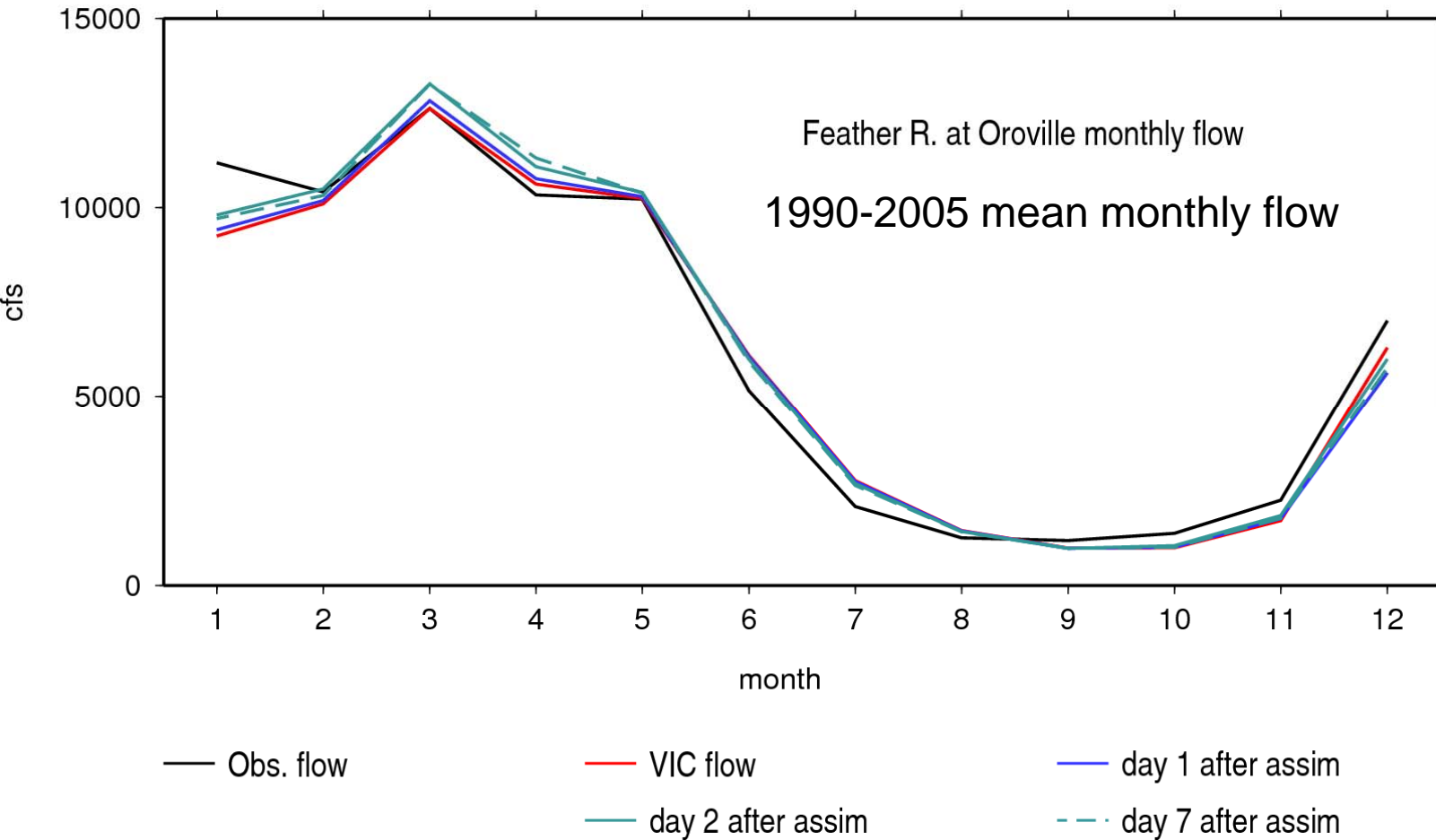
Observed flow categories

For all lead times:

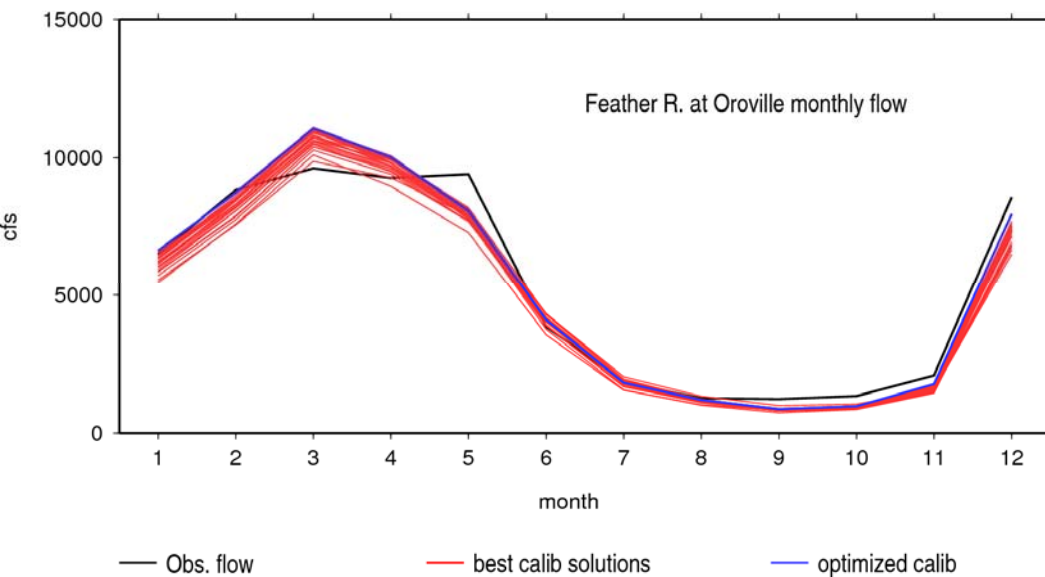
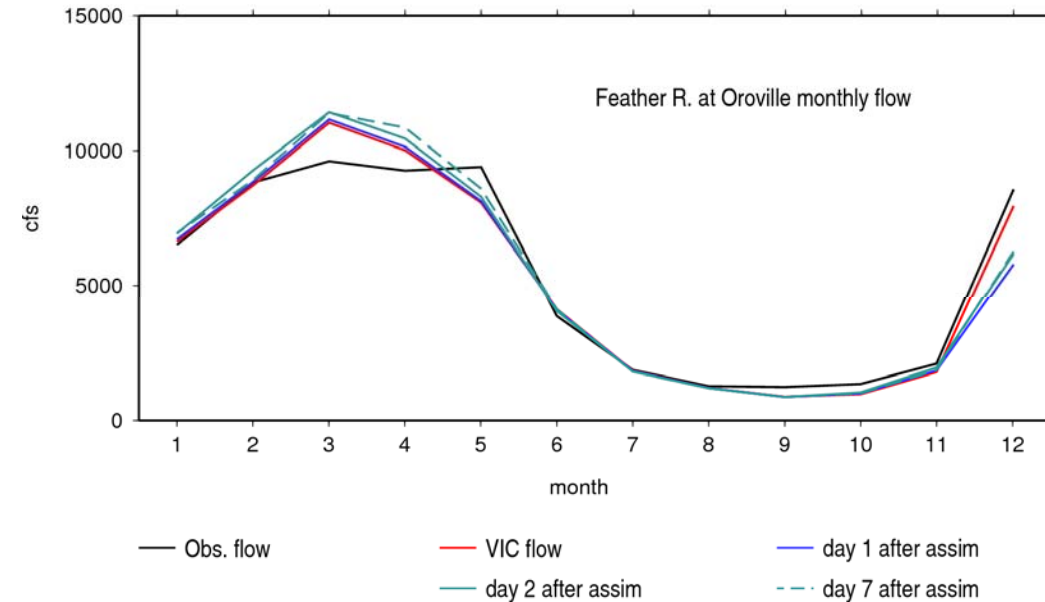
- Decreased RMSE
- Decreased bias for high flows
- Increased correlation
- Increased sensitivity to weights: largest at end of snowmelt period
- Not shown: both high and low flow improved by SWE DA



Effect of SWE assim. on the calibrated water balance (model parameterization)



SWE uncertainty vs model uncertainty



- i) Uncertainty in precipitation forcing
- ii) (not shown) small differences between different weight scenarios – small uncertainty due to different weighting scenarios

Parameter uncertainty:

Best 25 parameterization solutions for the VIC-routing model.

- Annual bias varies 0-12%.
- For equivalent NSE values

Conclusions

- ▶ SWE assimilation can improve short term flow forecasts volume during ablation period.
- ▶ Largest improvement for lead times longer than time of concentration.
- ▶ Uncertainties related to elevation-based and distance-based weights increased at the end of the snowmelt period.
 - Need to calibrate the weights – calibrate the spatial disaggregation of the SNOTEL SWE for basins with different hydro-climatic conditions
- ▶ Over the Feather RB: parameterization uncertainties larger than the precipitation forcing uncertainty.

Future direction

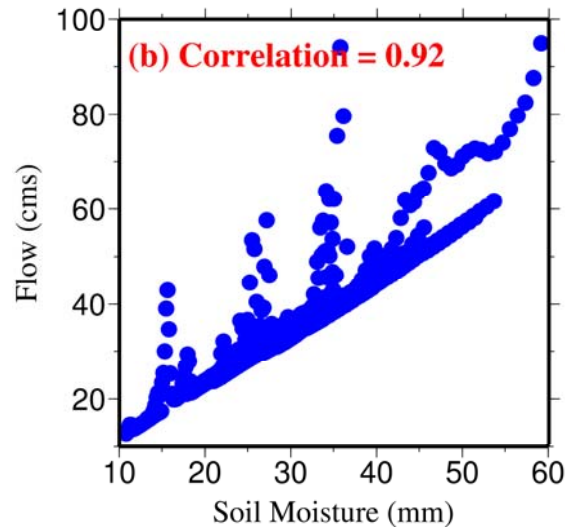
- ▶ Future direction: merge a pre-processor with a SWE DA.
 - Should we also calibrate the SWE DA for probabilistic forecast?
 - How to merge it with the pre-processor.

River flow – Soil Moisture Assimilation Approach

- ▶ Direct insertion of soil moisture initial state information
- ▶ Initial state information was obtained from relationship between weekly mean soil moisture and flow differences through an empirical relationship
 - High flow period (Oct-June) -- SM (LYR1+LYR2)
 - Low flow period (July-September) -- SM (LYR3)

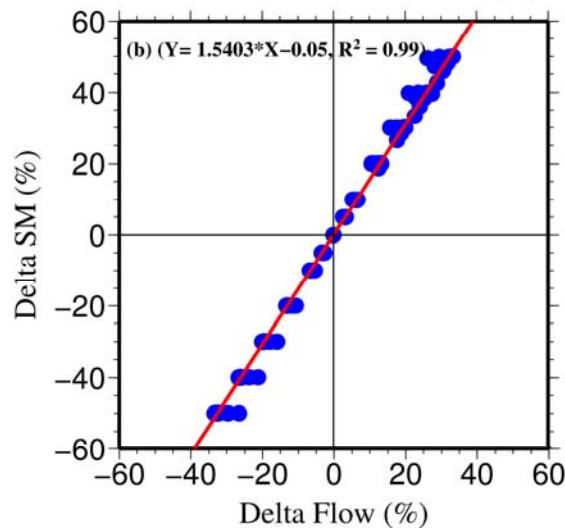
River flow – Soil Moisture Assimilation Approach

Flow–Soil Moisture Relationship (August)



- Developed relationship between change in weekly flow and weekly soil moisture (layer 3)
- Linear relationship was found suitable for August

Flow–Soil Moisture Relationship (August)



River flow – Soil Moisture Assimilation Results

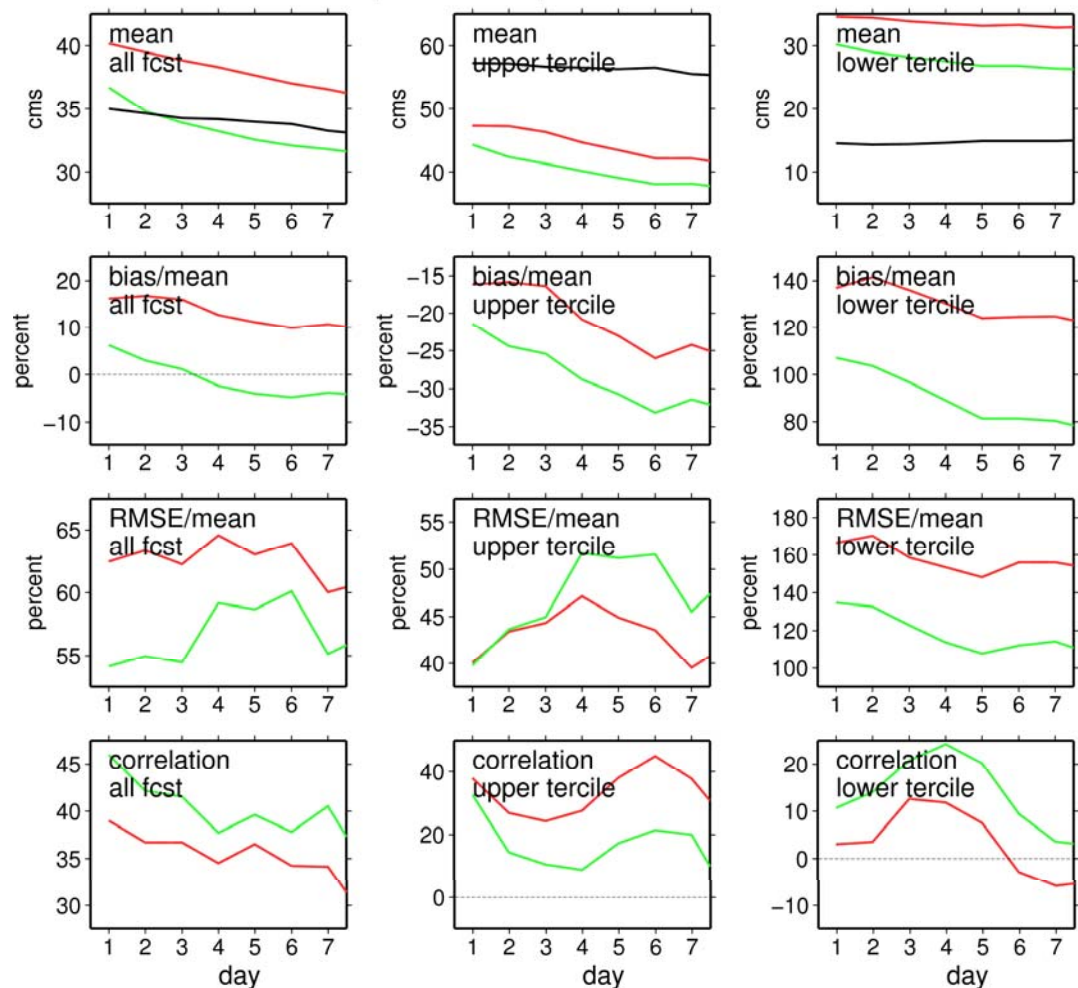
AUGUST

1990-2005 period

400 forecasts

Observed flow categories

- overall improvement
- slow flow sensitive to DA



Soil Moisture Assimilation – Bottom Soil Layer
No assimilation

River flow – Soil Moisture Assimilation

Future work

- ▶ Improve results for high flows: use a shorter spatial window of previous observed flow conditions for assimilation
- ▶ Apply assimilation over several soil layers depending on previous flow conditions
- ▶ Merge SWE and soil moisture assimilation using an ensemble Kalman Filter.

Thank you!

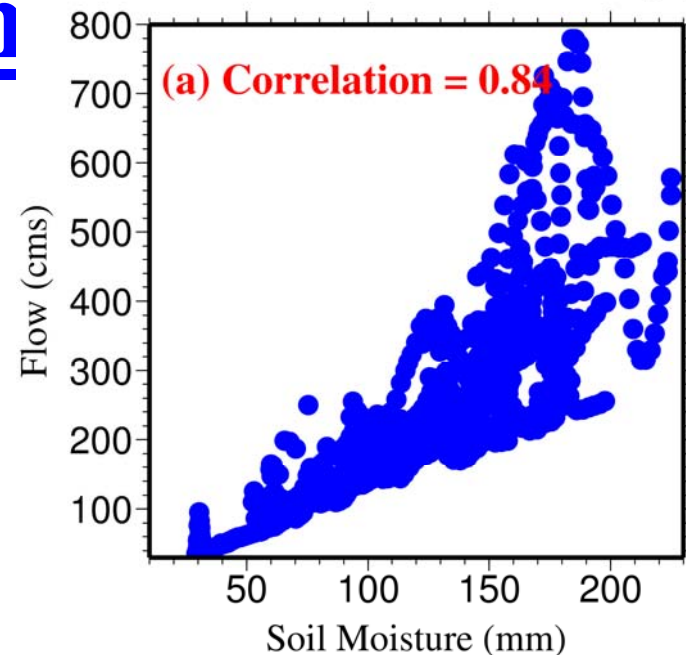
Extra slides

Assimilation Approach

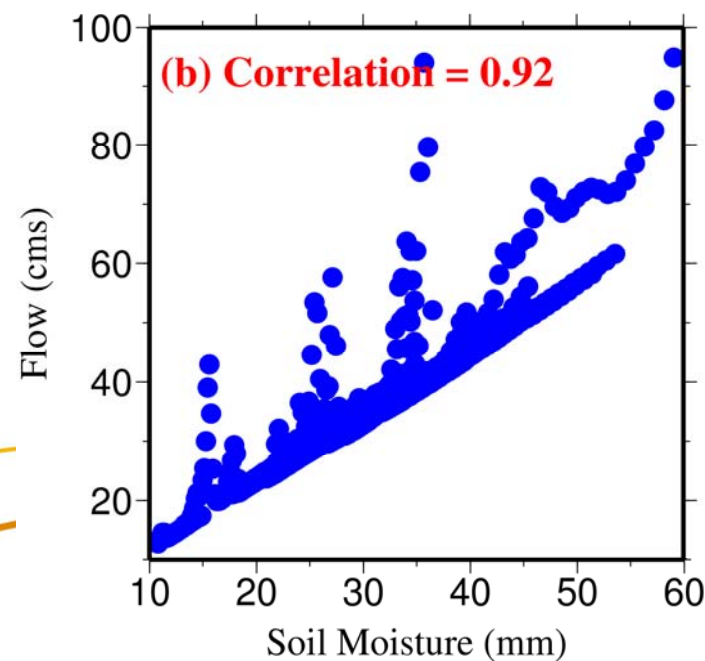
Period : 1961 -1990

- Soil moisture (Layer 3) – May flow correlation **0.84**
- Soil moisture (Layer 3) – August correlation **0.92**
- Tested relationship for other layers but moisture from layer 3 provided best skill for flow prediction

Flow–Soil Moisture Relationship (May)



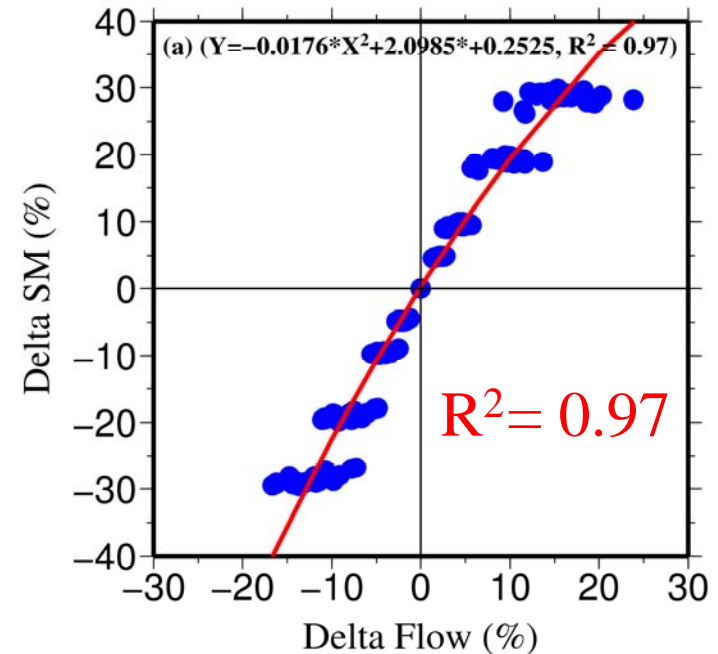
Flow–Soil Moisture Relationship (August)



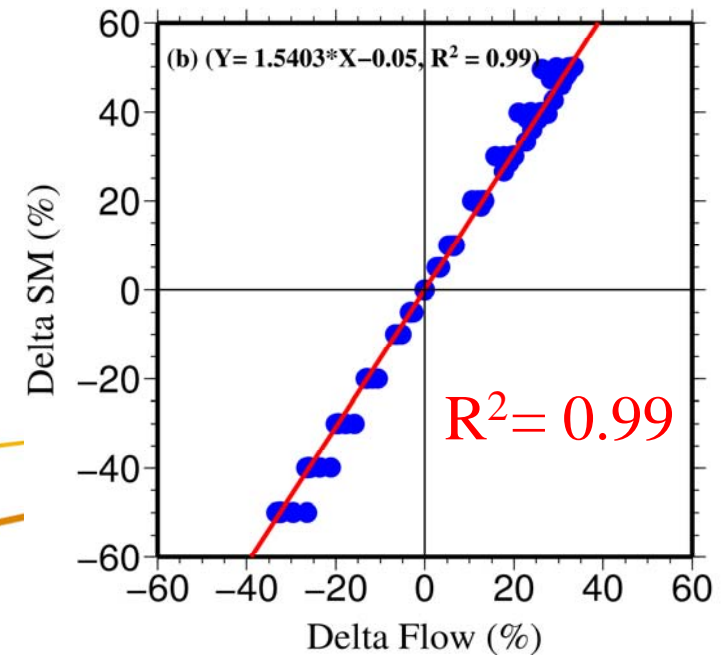
Assimilation Approach

- Developed relationship between change in weekly flow and weekly soil moisture (layer 3)
- Second order polynomial was used to estimated change in soil moisture state for May
- Linear relationship was found suitable for August

Flow–Soil Moisture Relationship (May)

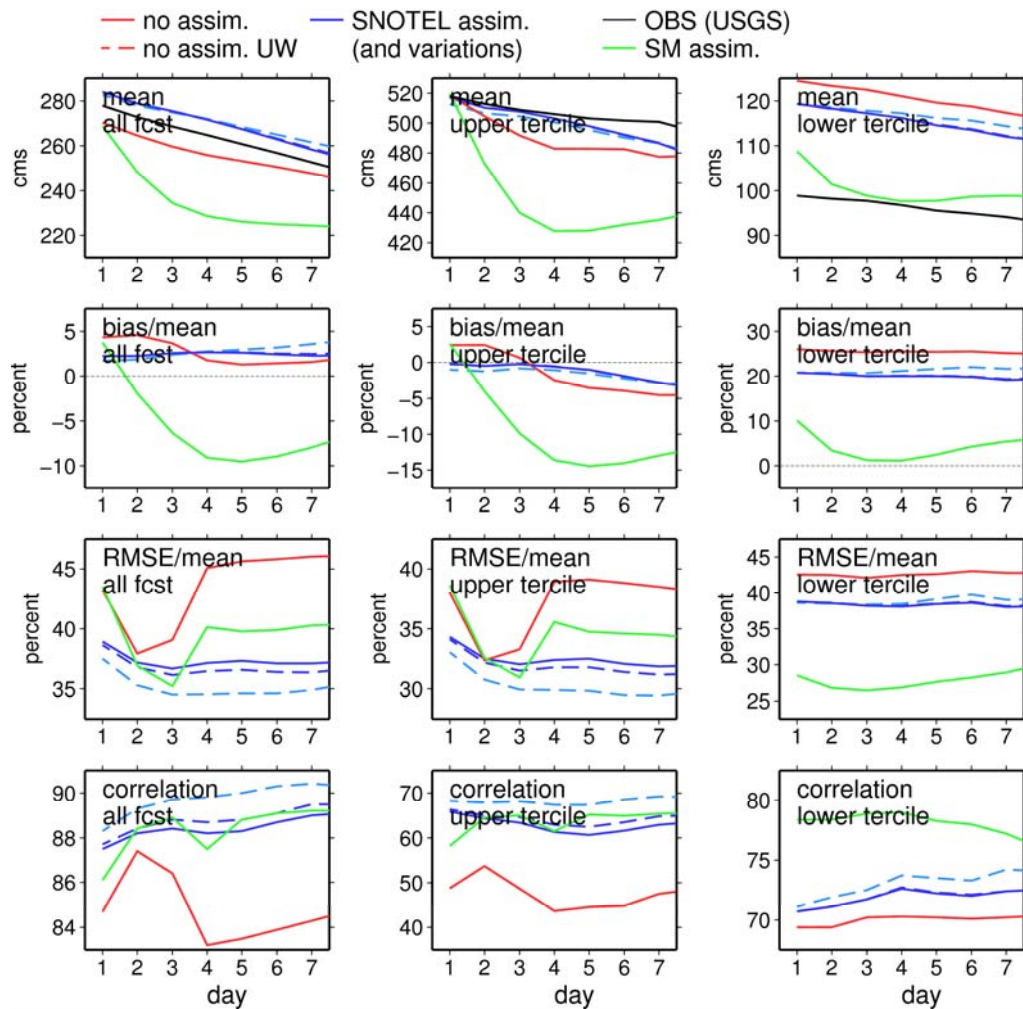


Flow–Soil Moisture Relationship (August)



SWE DA - May

1990–2005 Feather River at Oroville, CA, 5



Approach – SWE assimilation

▶ Direct insertion

- SNODAS: direct insertion of SWE observation at the discretion of the forecaster (SNTHERM high spatial resolution snow model)
- Incoherency between assimilated SWE and subsequent hydrologic model

▶ Assimilation

- Weighted average of spatially distributed simulated and point-based observed anomalies (Wood and Lettenmaier 2006)
- Ensemble Kalman Filter of simulated and interpolated SWE anomalies (Z-score, Slater and Clark 2006)

Coherent with hydrologic model parameterization and structure.

Background – snow data assimilation

Snow Water Equivalent (SWE) or Snow Coverage (SCA)?

- SCA assimilation has shown some ability to reduce weekly and seasonal streamflow forecast errors in previous work (Clark and Slater 2006, Tang et al. 2010, McGuire et al. 2006, Andreadis et al. 2006, etc)
 - Not a model state variable, SWE (reflects water storage) may be weakly linked to SCA
 - Uncertainties in cloud-no cloud conditions
- SWE assimilation can correct for:
 - Errors in precipitation input leading to errors in model SWE
 - Errors in snow/rain differentiation and spatial distribution over the model grid cell which also lead to model SWE errors
- Point observations vs spatial average model predictions lead to complications

Background – SWE assimilation

▶ Direct insertion

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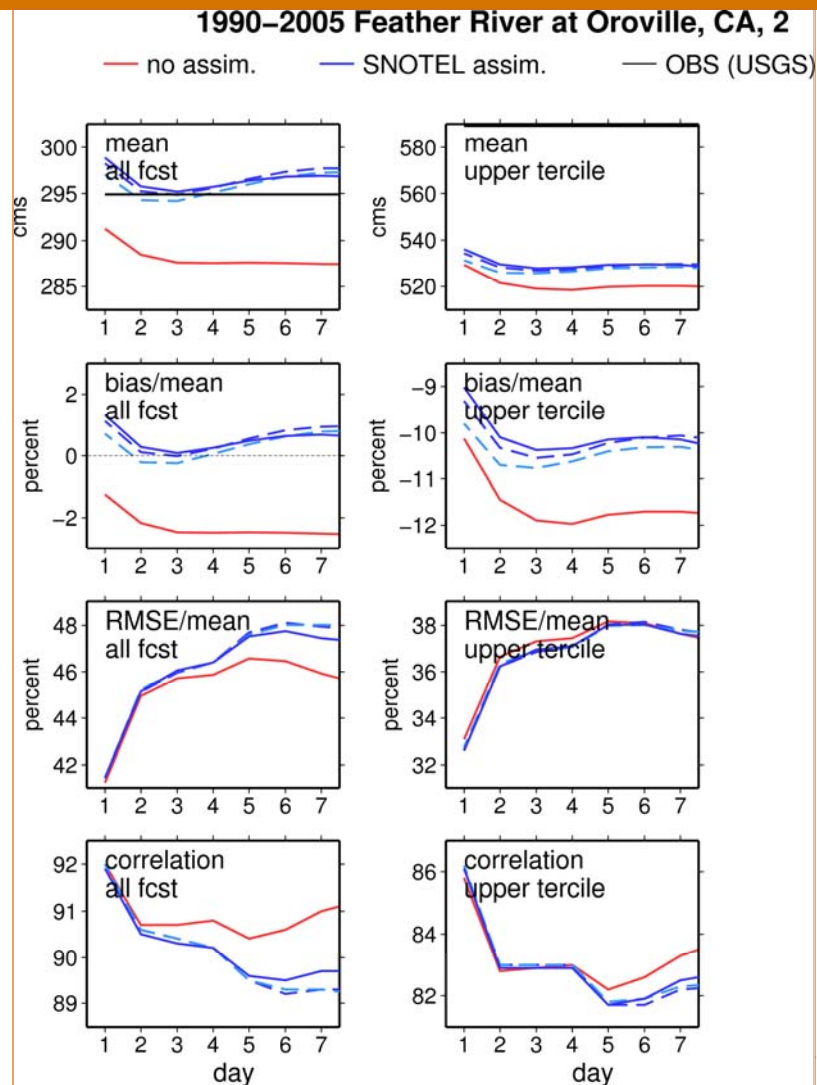
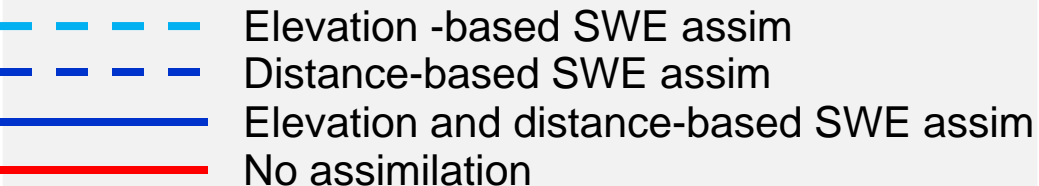
Coherent with hydrologic model parameterization and structure.

Results - February

1990-2005 period
452 forecasts
Observed flow categories

Status quo

Note: no improvement during
accumulation period



Status quo