Blending Satellite and In Situ Snow Observations for Streamflow Prediction in Snow-Impacted River Basins

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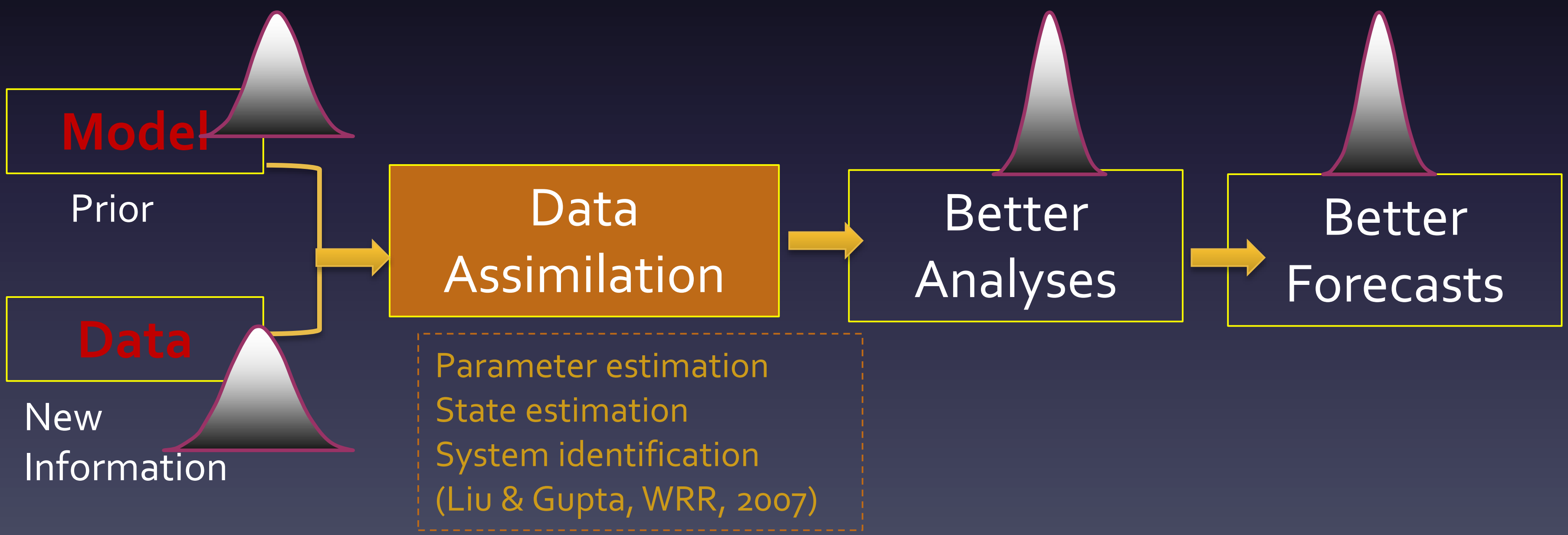
H-SAF and HEPEX Workshops on Coupled Hydrology
ECMWF, Reading UK, November, 3-7, 2014

Why Data Assimilation?

"Essentially, all **models** are wrong, but some are useful." – George E. P. Box

The same applies to **data**



Developing Synergism with Operational Hydrology

Land & Atmo DA Community	Hydrologic DA Community
Satellite DA	Hydrologic forecasting
Research-based DA	Operational DA
Automatic DA	Manual DA

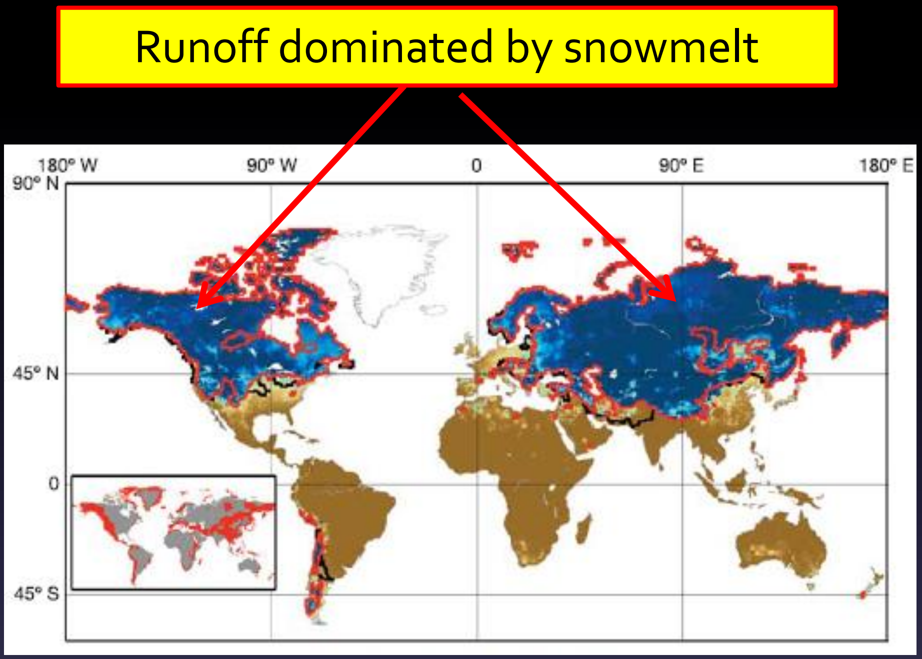
Advancing data assimilation in operational hydrologic forecasting: progresses, challenges, and emerging opportunities HESS 2012

Y. Liu[1,2], A. H. Weerts[3], M. Clark[4], H.-J. Hendricks Franssen[5], S. Kumar[6,2], H. Moradkhani[7], D.-J. Seo[8], D. Schwanenberg[3], P. Smith[9], A. I. J. M. van Dijk[10], N. van Velzen[11], M. He[12,13], H. Lee[12,14], S. J. Noh[15], O. Rakovec[16], and P. Restrepo[12]

* Discussions at HEPEX -DAFOH III (Data Assimilation for Operational Hydrology and Water Management) , Austin, TX, Sep 2014

Importance of Snow

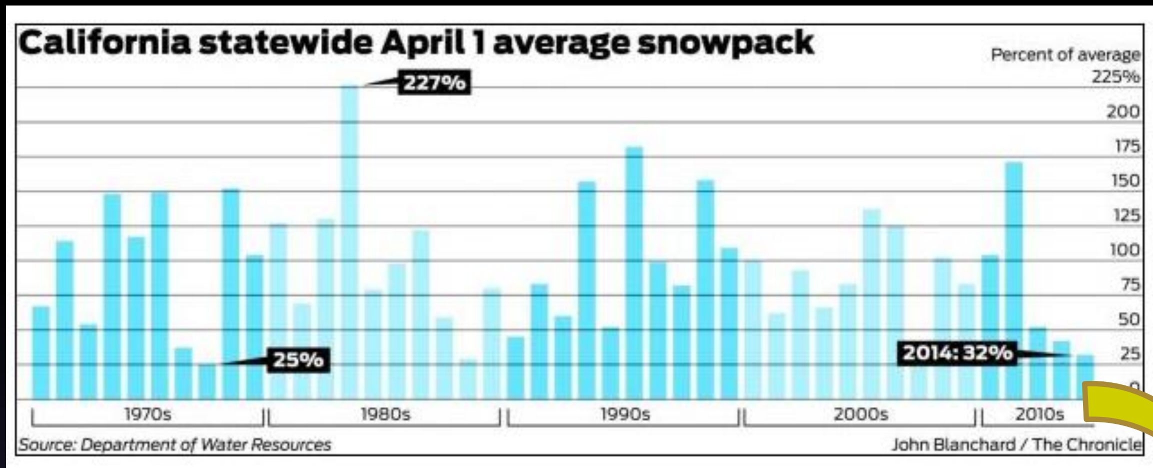
- 1/6 of world's population depends on snowmelt runoff for water supply
- Snow is a critical element of the hydrologic cycle
- Snow is a sensitive indicator of climate change
- Snow is an important initial condition for flow forecasting and weather/climate prediction



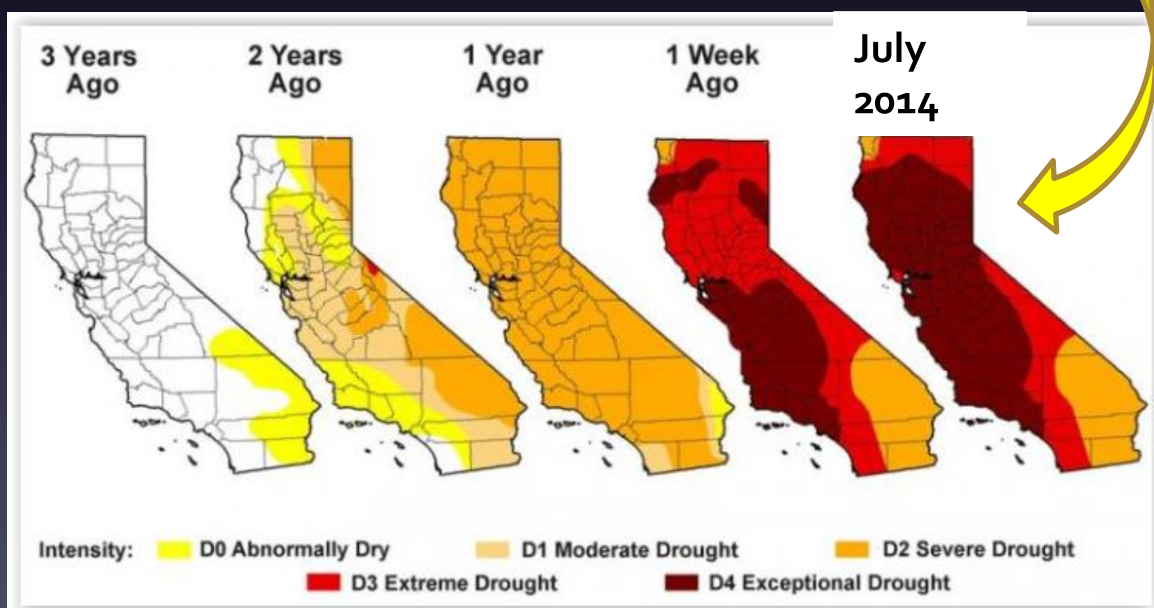
Barnett et al., Nature, 2005

Snow & Drought

The California example



Snow



Drought

Colorado River Basin Drought

Since 2004, the snowmelt-driven Colorado River Basin (which feeds California and six other states) lost nearly 53 million acre feet of freshwater. That's enough to submerge New York City beneath 344 feet of water.

(source: bloomberg.com)

Lake Mead

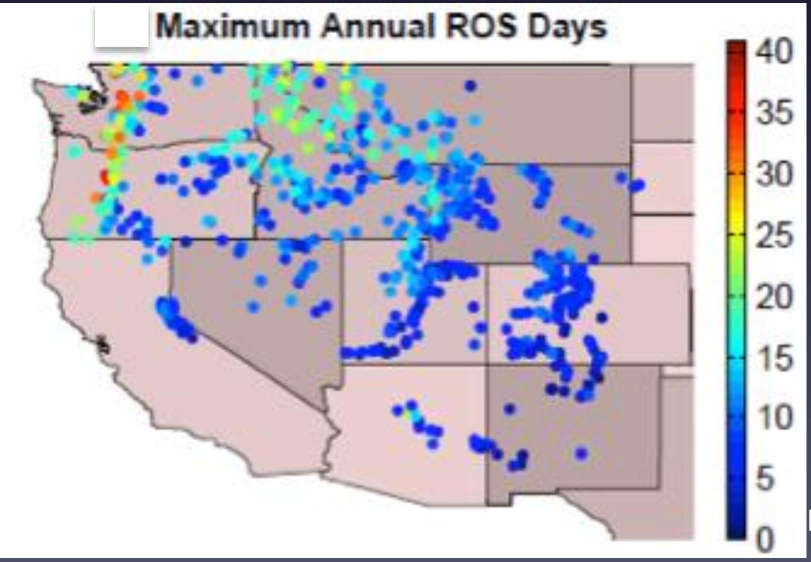
Photo: USBR

Snow & Flooding

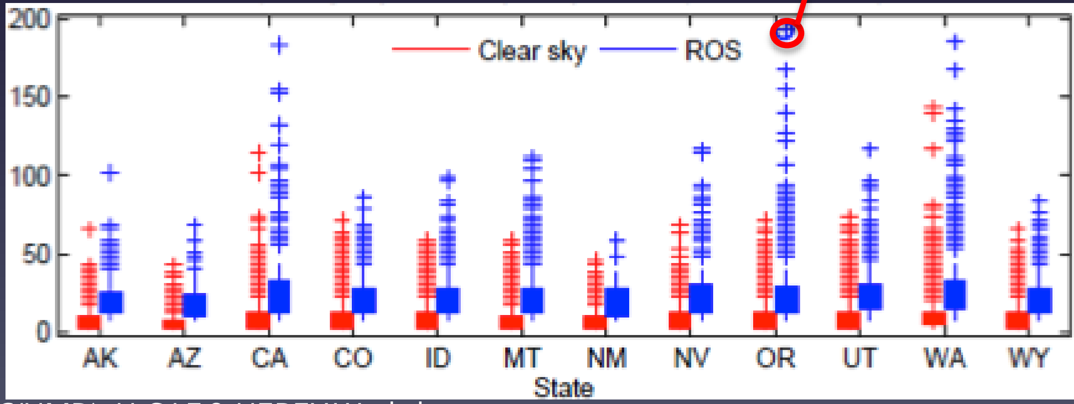
In snow-dominated basins, heavy rainfall accompanied by rapid snowmelt (rain on snow – ROS) can cause severe/dangerous flooding in winter or spring!

(Liu & Peters-Lidard, JHM, submitted)

Willamette River flooding Oregon City, Oregon, photos courtesy Lew Scholl

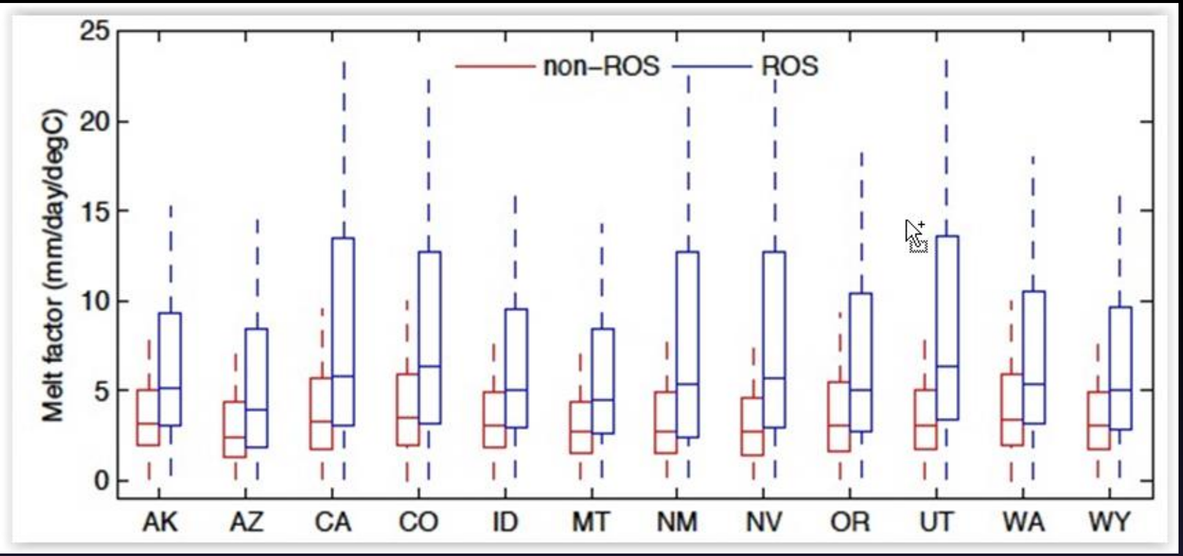


Daily rainfall + snowmelt (mm) at SNOTEL sites

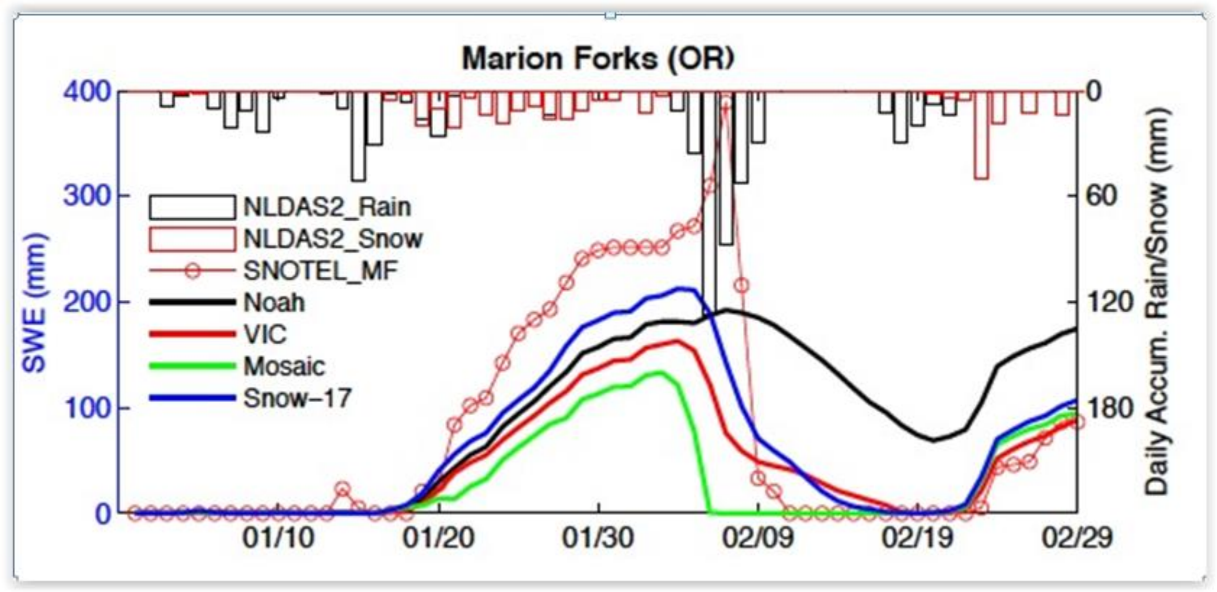


Enhanced Melt From ROS Events

Melt at SNOTEL sites



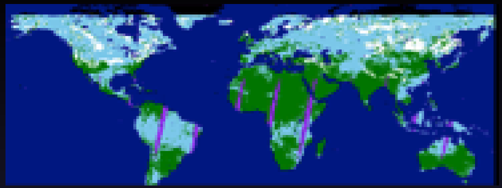
Melt by models
(1996 ROS in Northwest)



Existing snow information

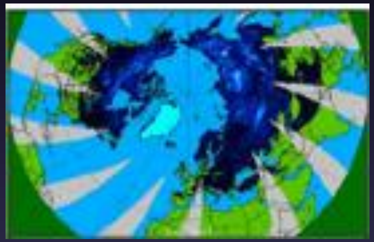
✧Remote sensing products

- MODIS, Landsat, VIIRS, SMMR, SSMI, AMSR-E, AMSR-2, AVHRR, GRACE, GPS, Airborne snow observatory



✧Operational analysis products

- IMS, CMC, SNODAS, GlobSnow

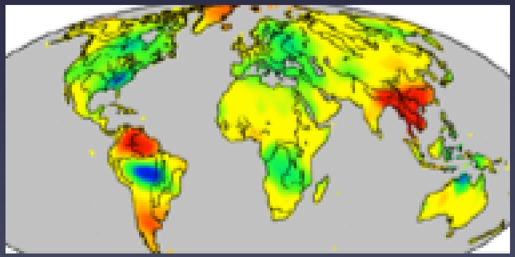


✧Model-based reanalyses

- ERA interim, MERRA-Land, GLDAS, NLDAS

✧Reconstruction products

- Liston and Hiemstra, 2011; Girotto et al., 2014



✧In-situ data

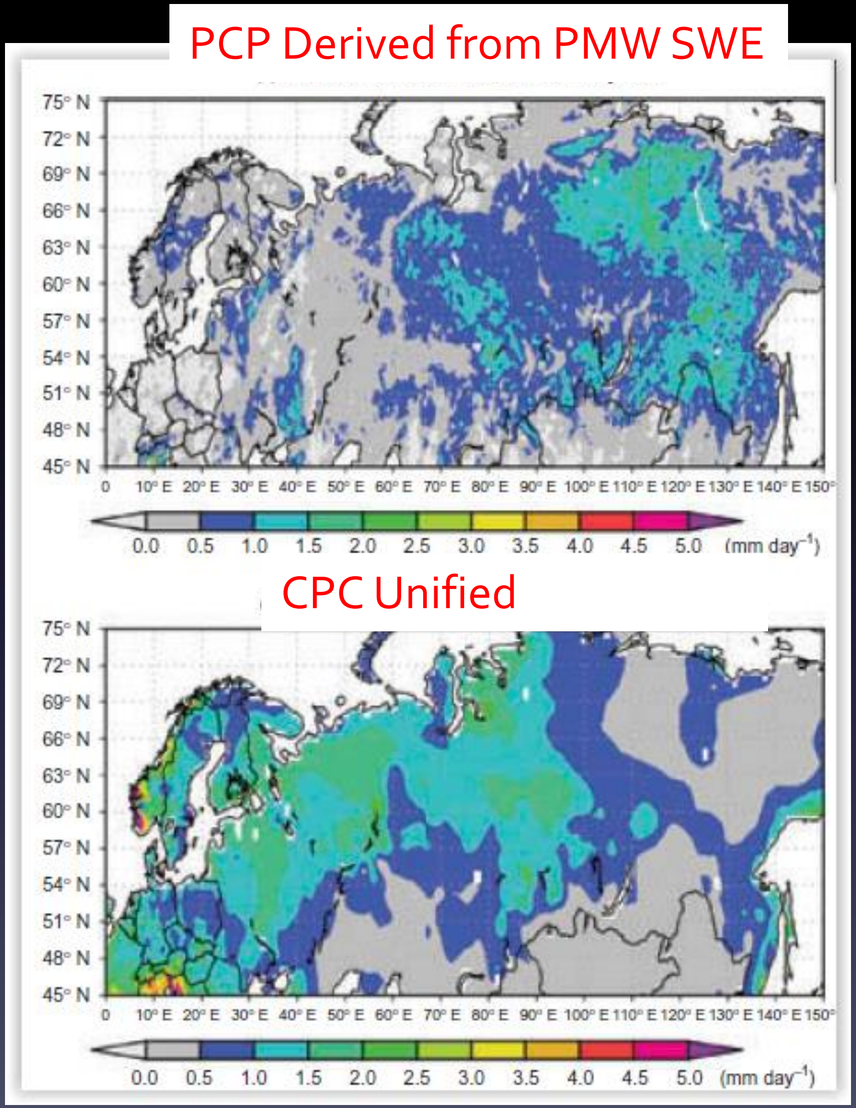
- SNOTEL, GHCN, snow course,
  field campaigns (CLPX, C3VP, GCPEX)

Doing Hydrology Backwards with Snow

Estimating precipitation over snow-covered area from PMW-based SWE retrievals:

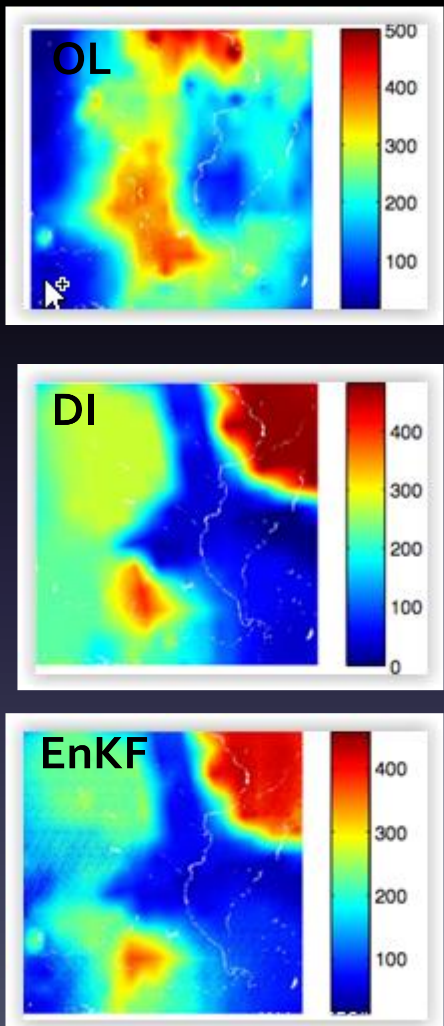
$$P = Q + \Delta S + \Delta(\text{SWE})$$

Tian, Y., Y. Liu, K. Arsenault, and A. Behrangi, 2014: A new approach to satellite-based estimation of precipitation over snow cover, *IJRS*

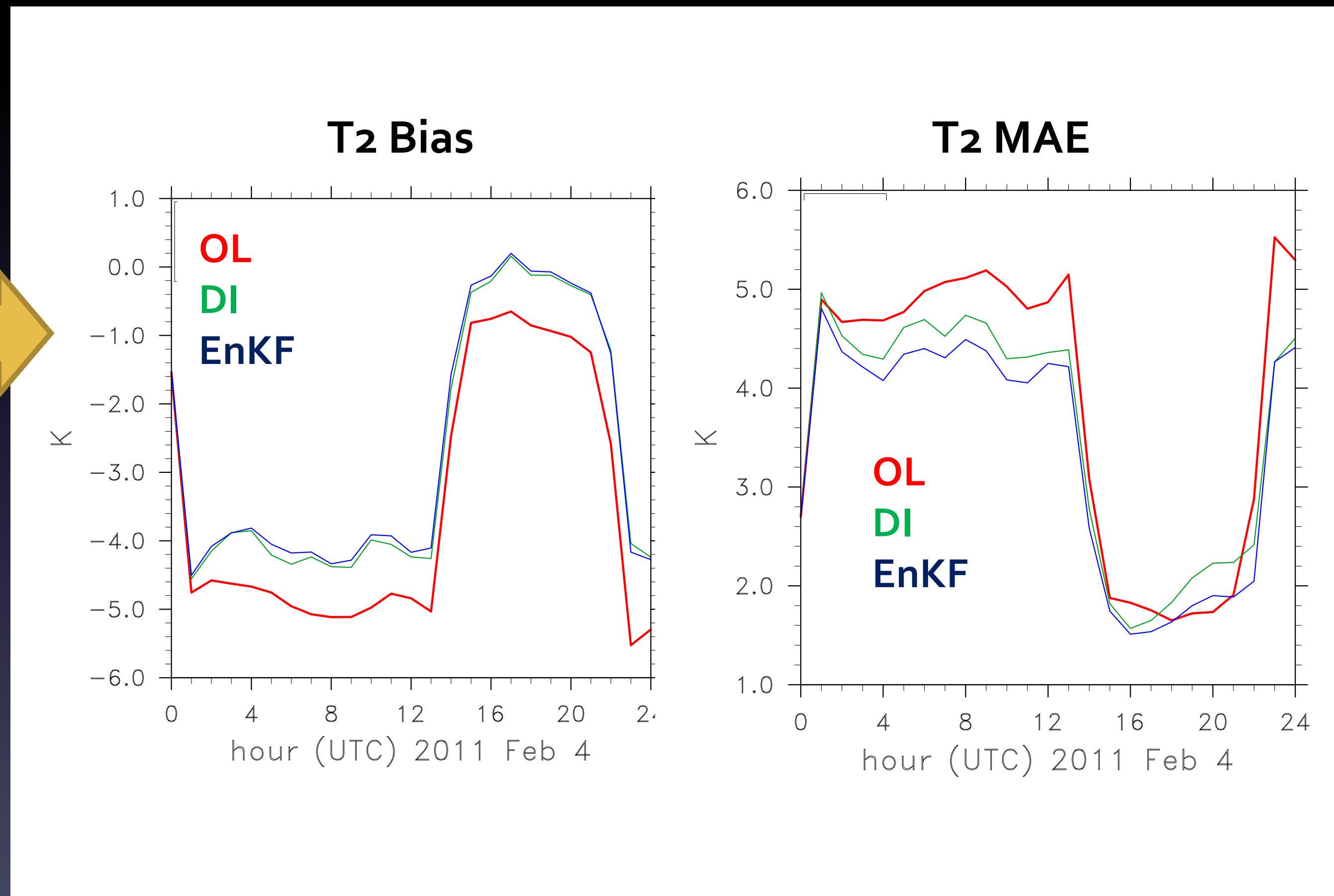


Impact of snow initialization on NWP

SWE Analysis



WRF 2m Temperature Forecast



Snowmelt-driven flow forecasting

Challenges

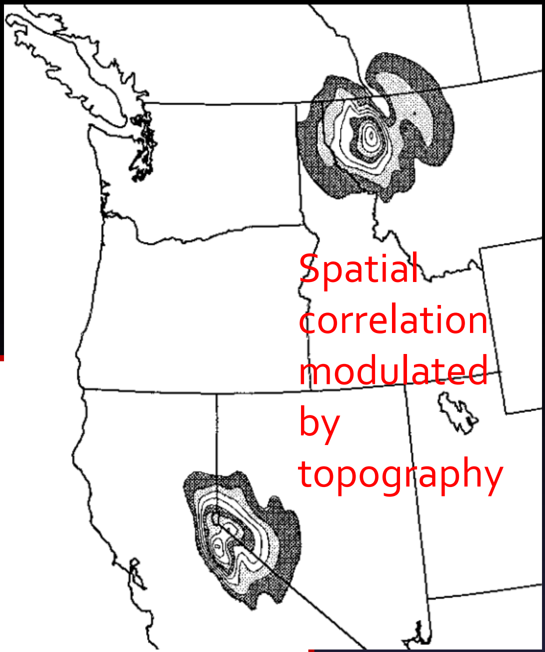
- Sparse in-situ snow observation network
- Large uncertainty snow models
- Improvement in snow does not always translate into improvement in flow
- Remote sensing measurements subject to large bias and data gaps

Opportunities

- Scale satellite products to model climatology and only assimilate anomalies
- Conduct radiance-based assimilation
- Assimilate integrated or multi-sensor products (e.g., PMW + VIS)
- Blending satellite SWE products with in-situ observations to reduce bias prior to assimilation

Satellite-Station Blending Algorithm
– Optimal Interpolation

$$x_g^a = x_g^b + \sum_{i=1}^{N} \boxed{w_i} (o_i - x_i^b)$$



Weight Calculation (Brasnett 1999)

$$W = (P + O)^{-1} q$$

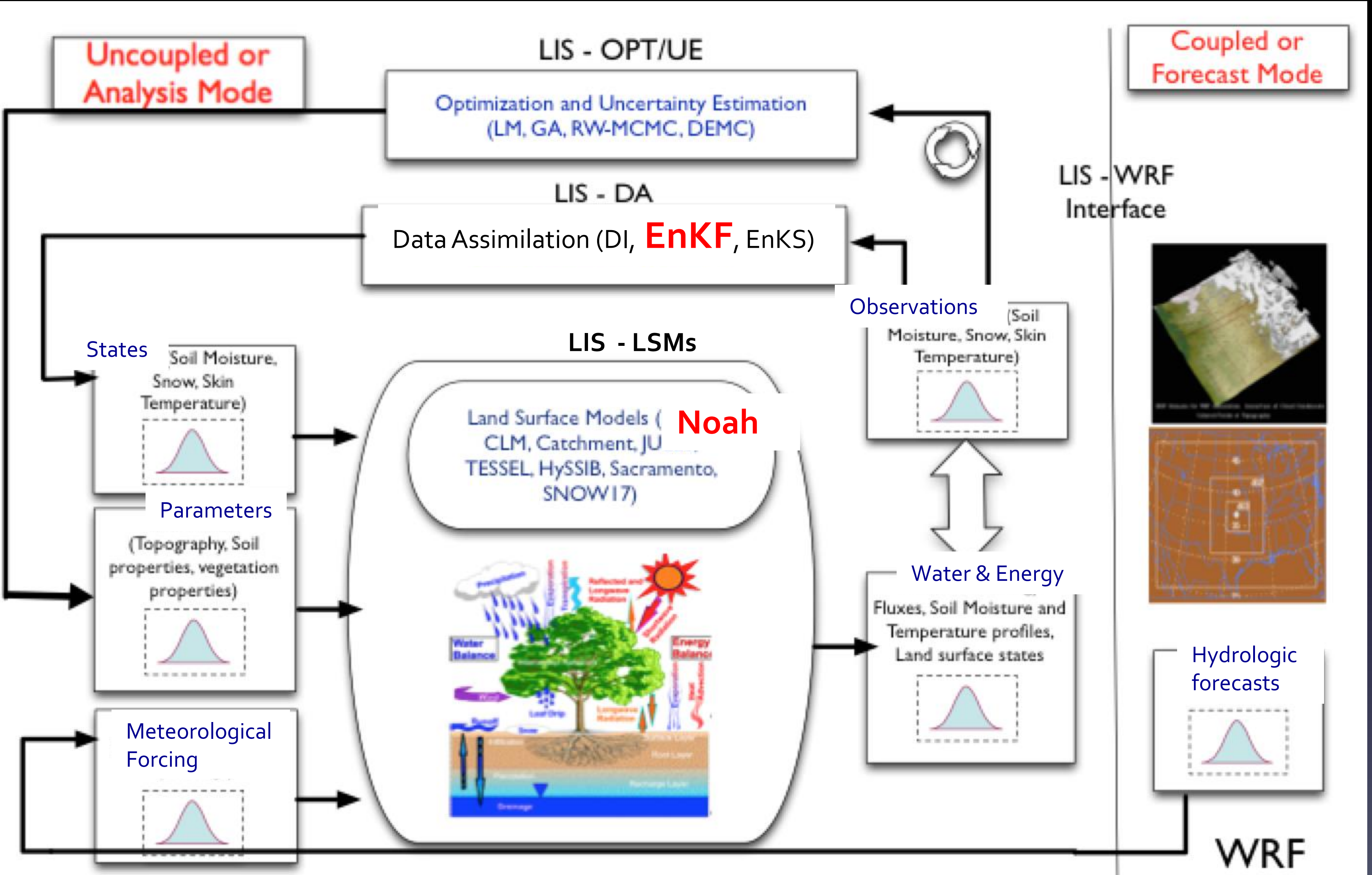
P: correlation of background error at obs. locations
q: correlation of background error between grid cell & observation
O: obs. error variance normalized by background error variance

Calculation of P and q: $\mu_{ij} = \alpha(r_{ij})\beta(\Delta z_{ij})$

$$\alpha(r_{ij}) = (1 + cr_{ij}) \exp(-cr_{ij})$$

$$\beta(\Delta z_{ij}) = \exp\left[-\left(\frac{\Delta z_{ij}}{h}\right)^2\right]$$

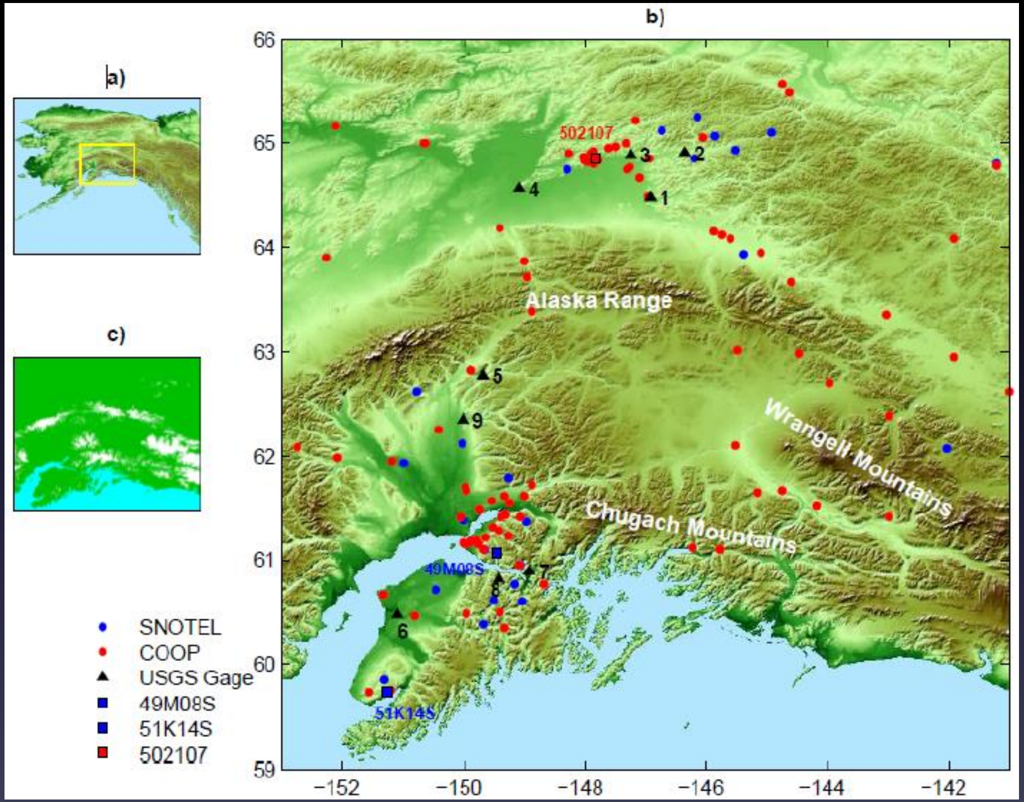
NASA Land Information System (LIS)



Initial Study on Snow/Streamflow Estimation for Alaska

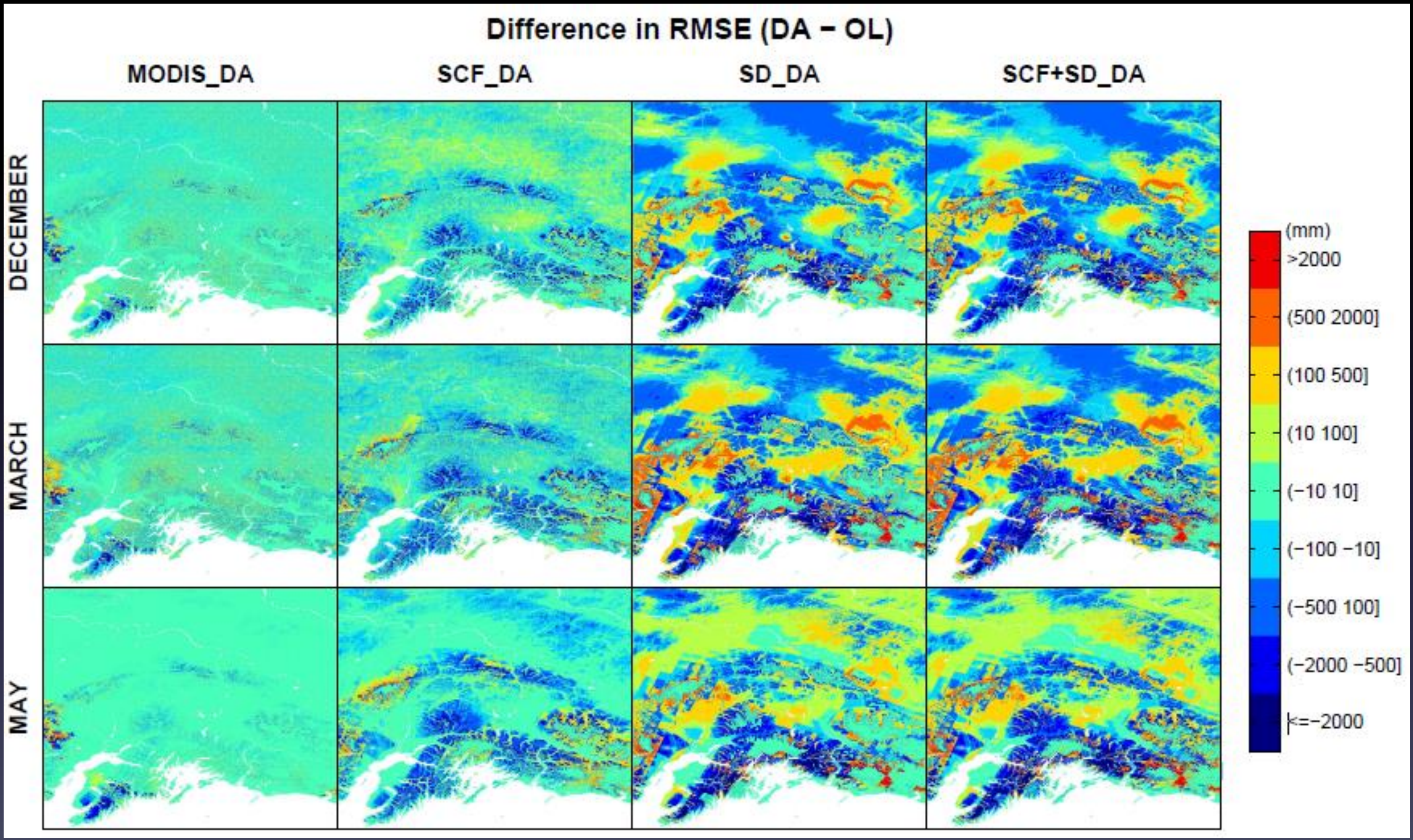
- Elevation: 0-6000 m
- Complex mountainous areas, discontinuous permafrost, seasonally frozen soils, extensive glaciation, distinctive climate zones
- Huge spatial variability in snow distribution, diverse snow classes
- 1-km spatial resolution (700*1200)
- Analysis period: 2002-2011
- Assimilate MODIS snow cover and AMSR-E snow depth
- 27 SNOTELs, 90 COOPs

$7^{o} \times 12^{o}$

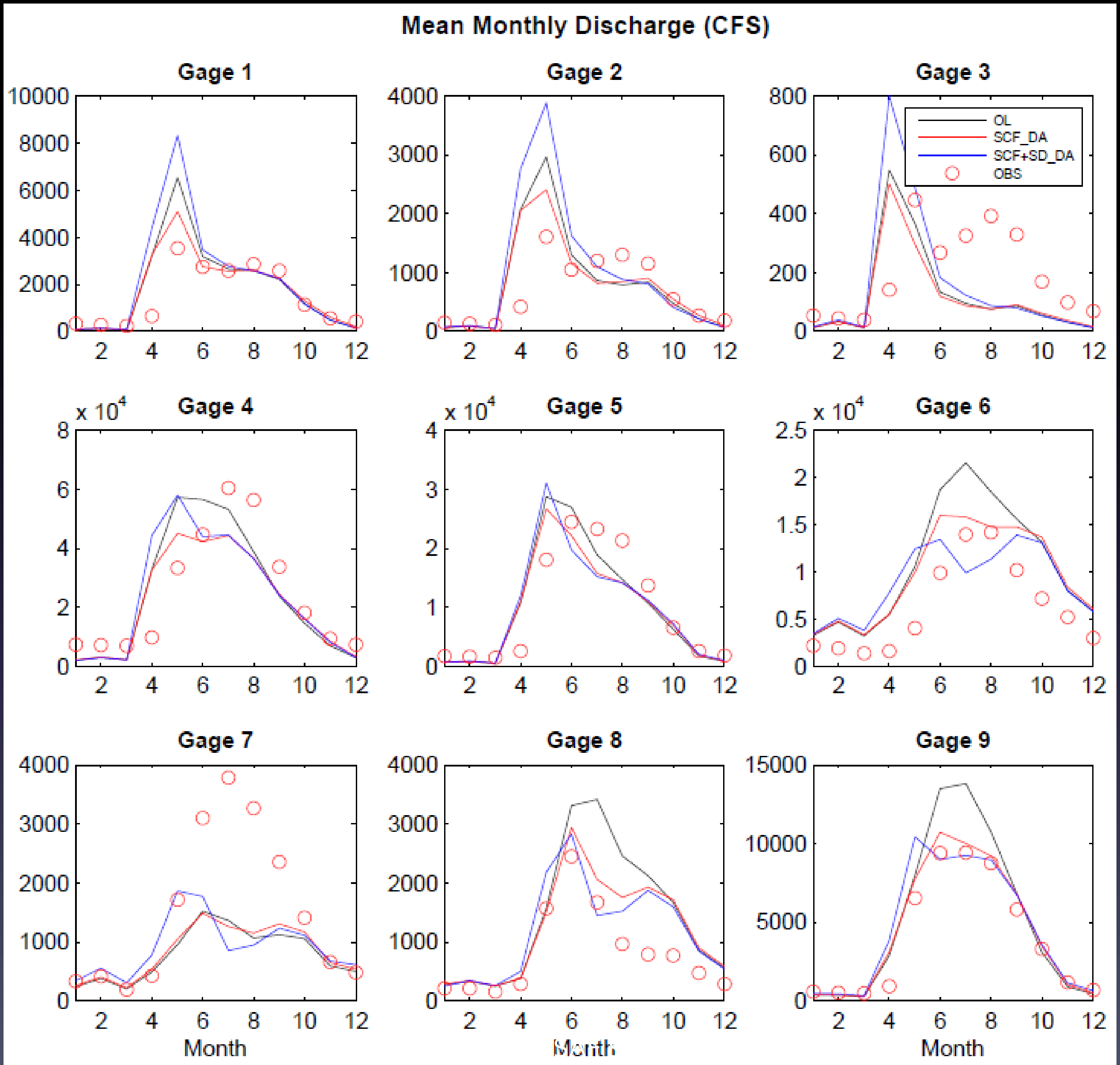


Liu et al., Advances in Water Resources, 2013

Evaluation Against CMC Daily SD - **RMSE**



Evaluation Against USGS Streamflow



Basin area ranges from 140 to 25600 square miles

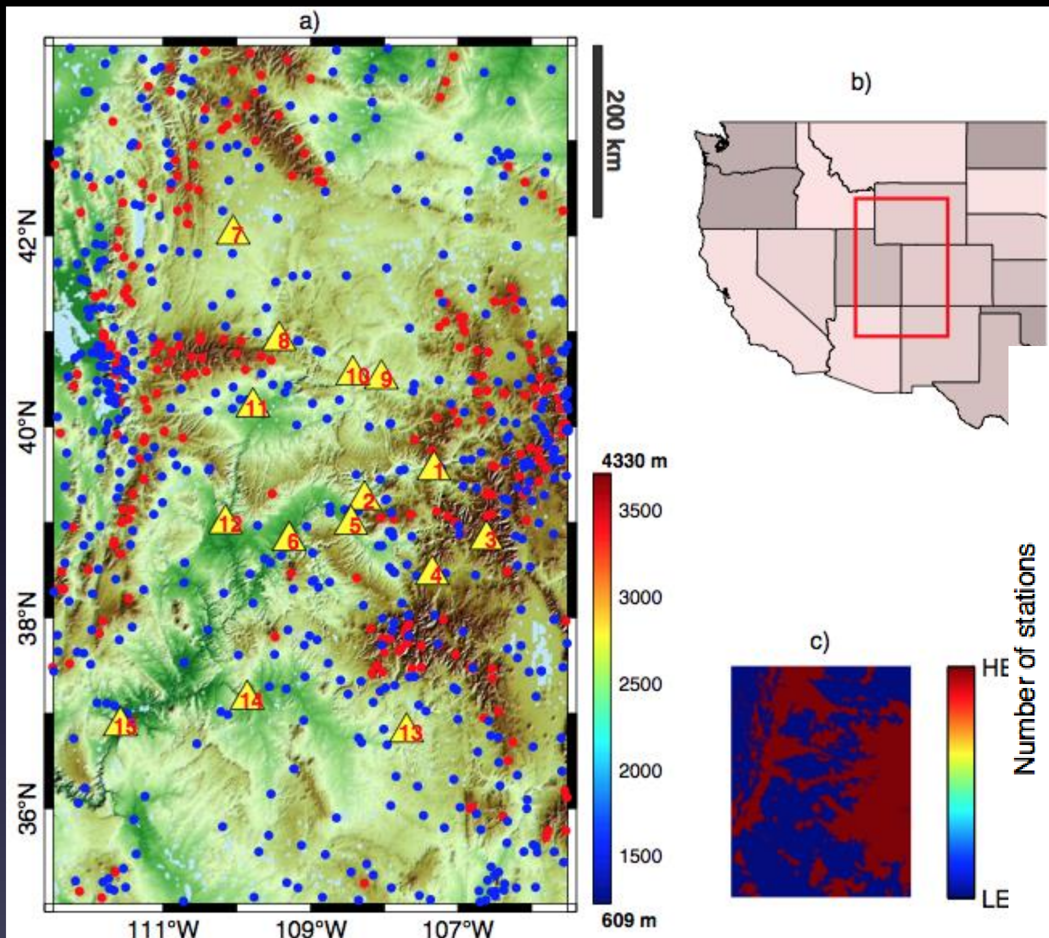
Improving Bias Correction of PMW Snow

- Incorporating terrain aspect information
- Integrating MODIS snow cover for additional quality control
- Tuning algorithm parameters
- Using station data strategically
- Enabling spatial variability in PMW errors based on land cover
- Examining roles of spatial resolution
- Using additional quality checks and flags

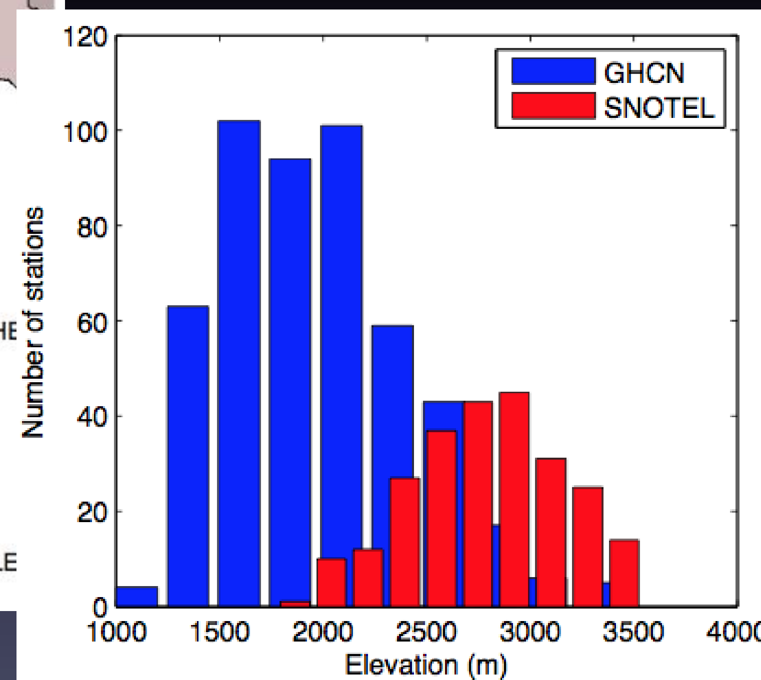
Case Study in Upper Colorado River Basin

(Liu et al., WRR, submitted)

DEM



Elevation distribution of stations

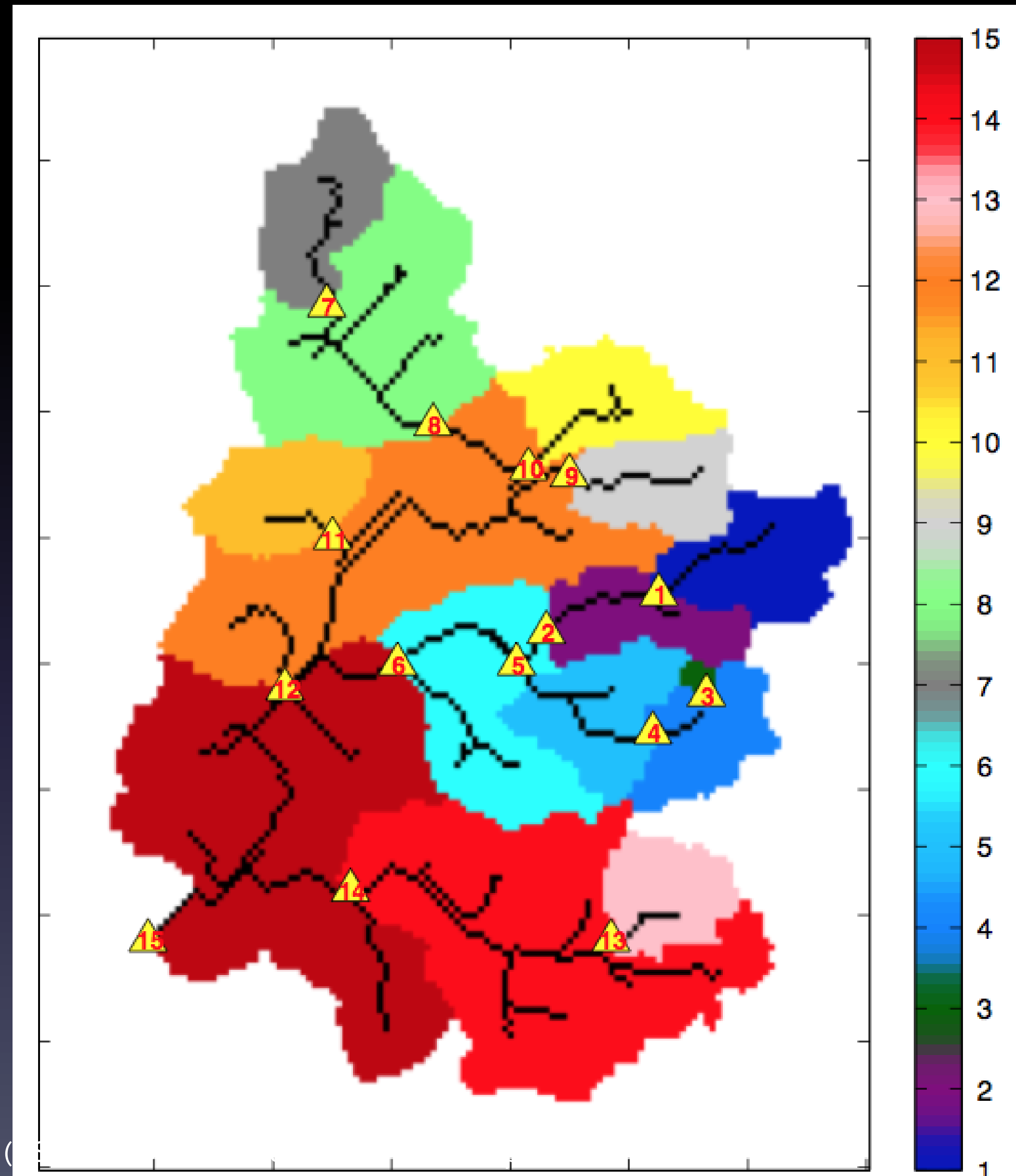


7^{o} x 9^{o}

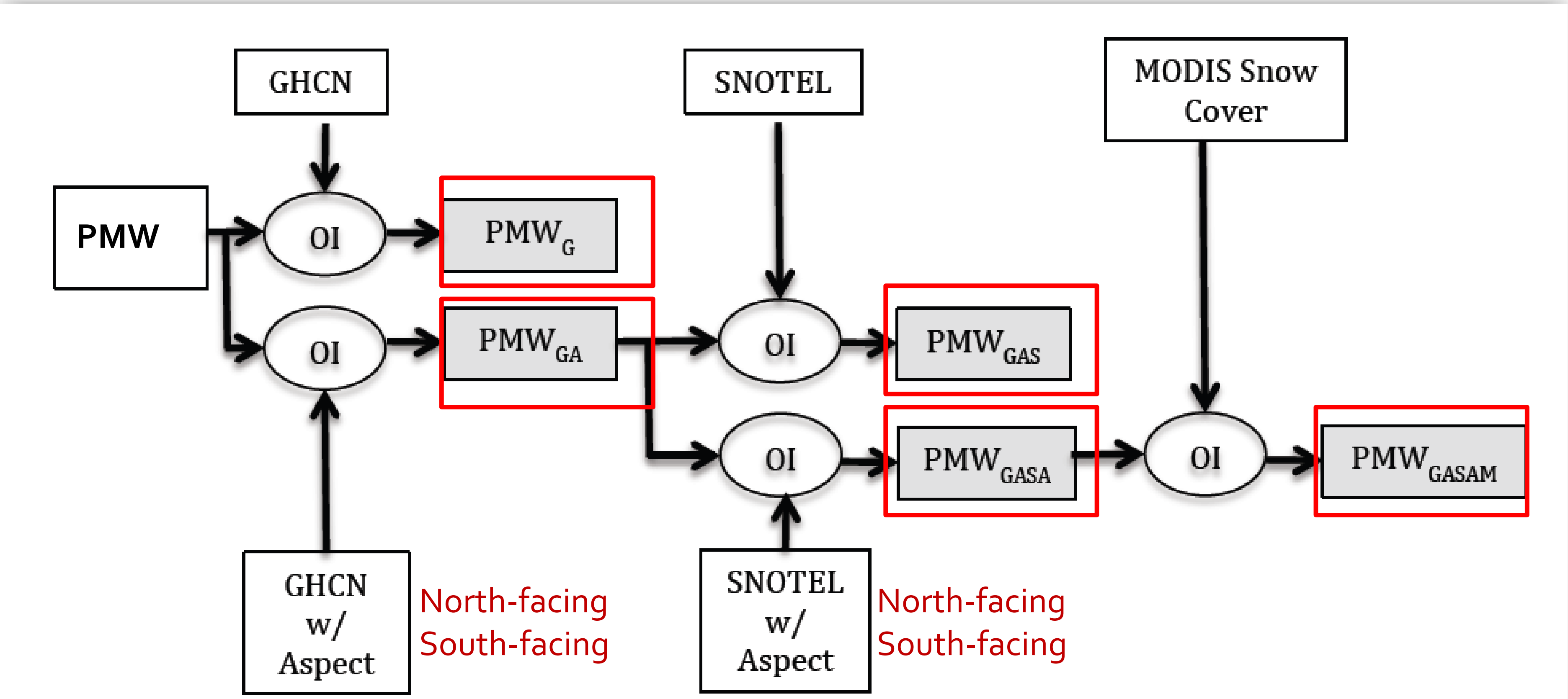
245 SNOTELs
494 GHCNs

Experimental Setup

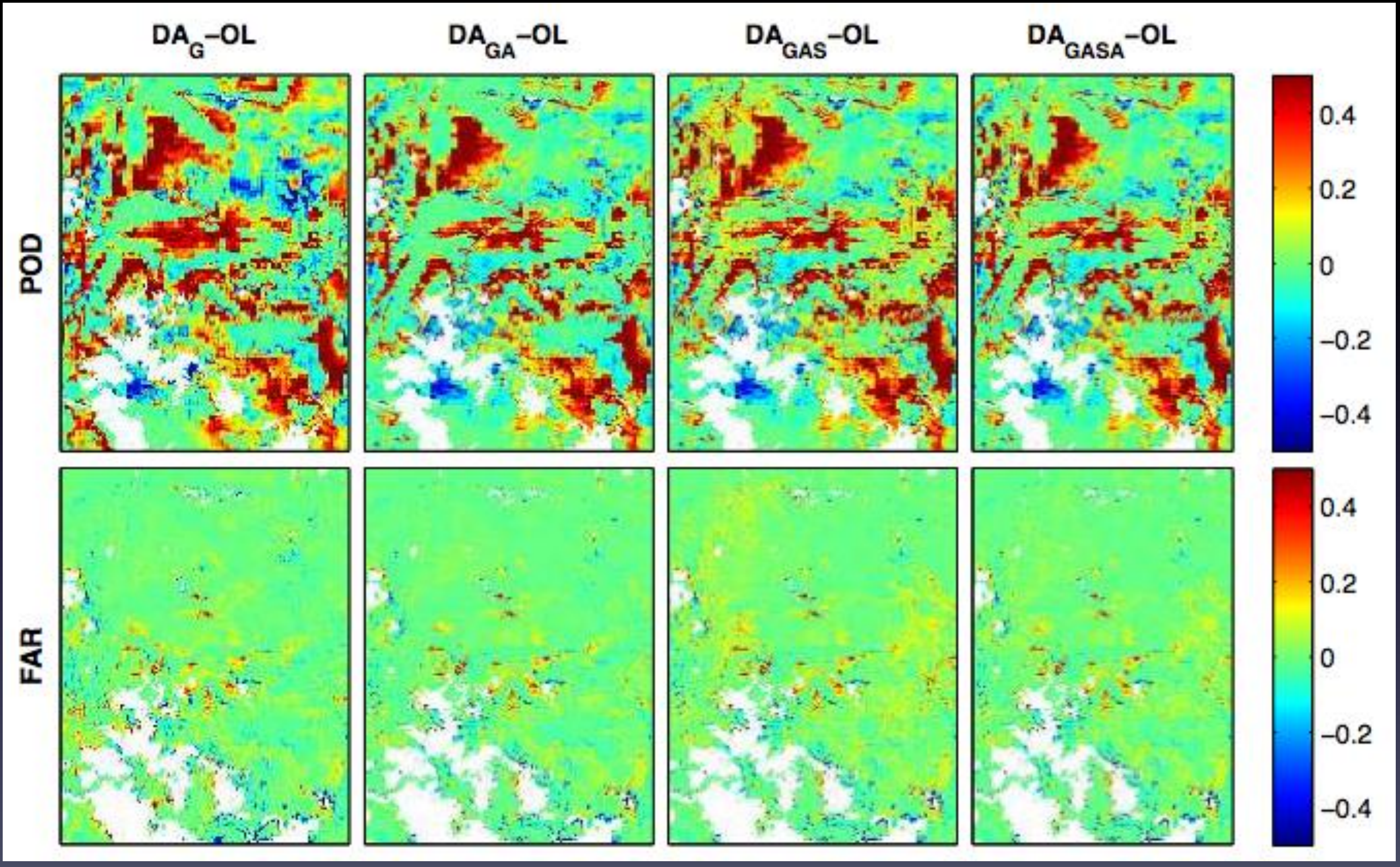
- Multiple DA runs assimilating different PMW-Station blended snow depth datasets
- 5-km, 2002-2011
- 15 large sub-basins in the Upper Colorado Basin, ranging from 254 to 111800 square miles
- Monthly natural streamflow data from BOR



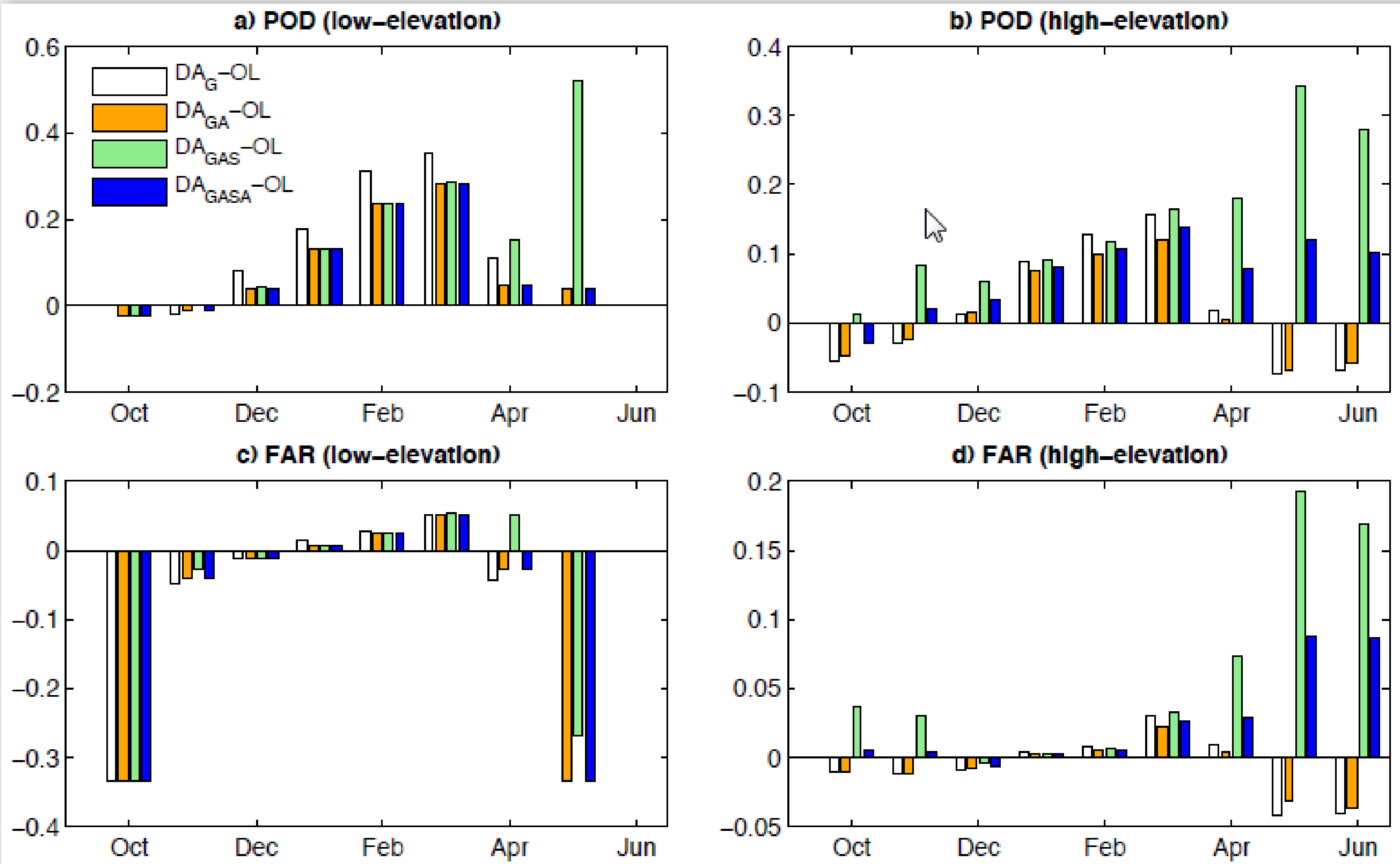
Blending Satellite (PMW) and In Situ Snow Observations



POD & FAR Against MODIS (DA – OL)



Seasonal Cycle of POD & FAR



Streamflow Evaluation: Metrics

Normalized Information Contribution (NIC)

$$NIC_{RMSE} = (RMSE_{OL} - RMSE_{DA}) / RMSE_{OL}$$

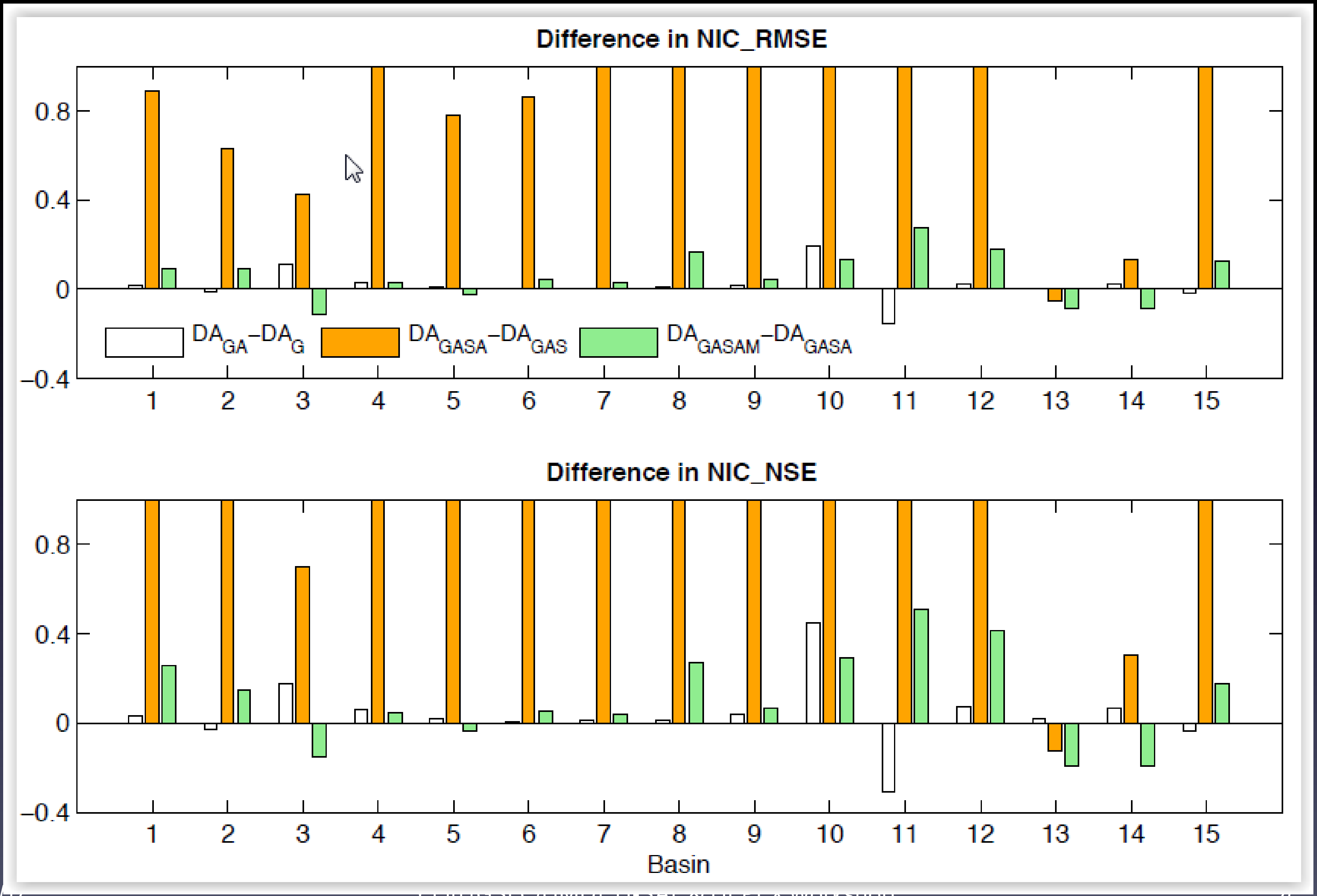
$$NIC_{R} = (R_{DA} - R_{OL}) / (1 - R_{OL})$$

$$NIC_{NSE} = (NSE_{DA} - NSE_{OL}) / (1 - NSE_{OL})$$

(Kumar et al., 2009, 2014)

NIC =0, no impact from DA
NIC>0, positive impact from DA
NIC=1, maximum positive impact from DA
NIC<0, negative impact from DA

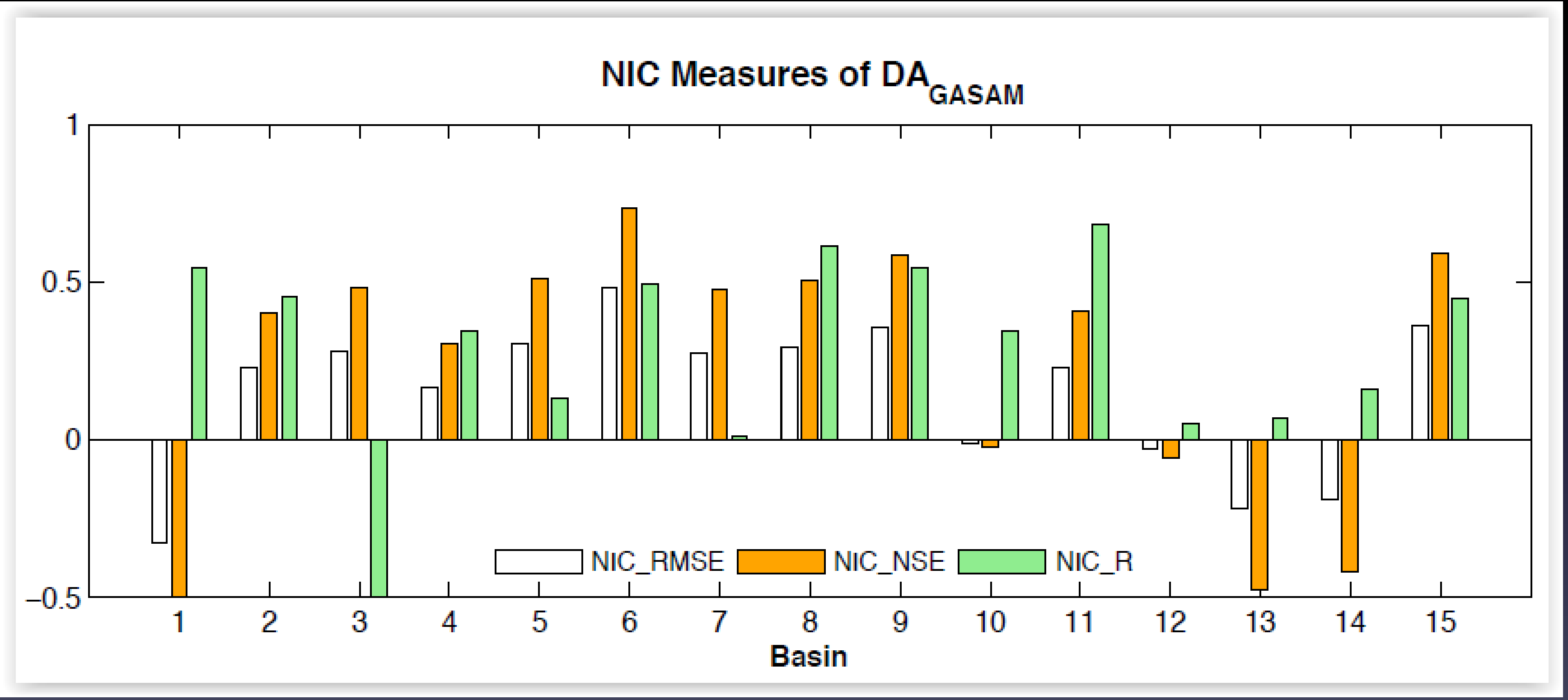
Impact of terrain aspect and MOIDS snow cover



Evaluation Against Monthly Natural Flows

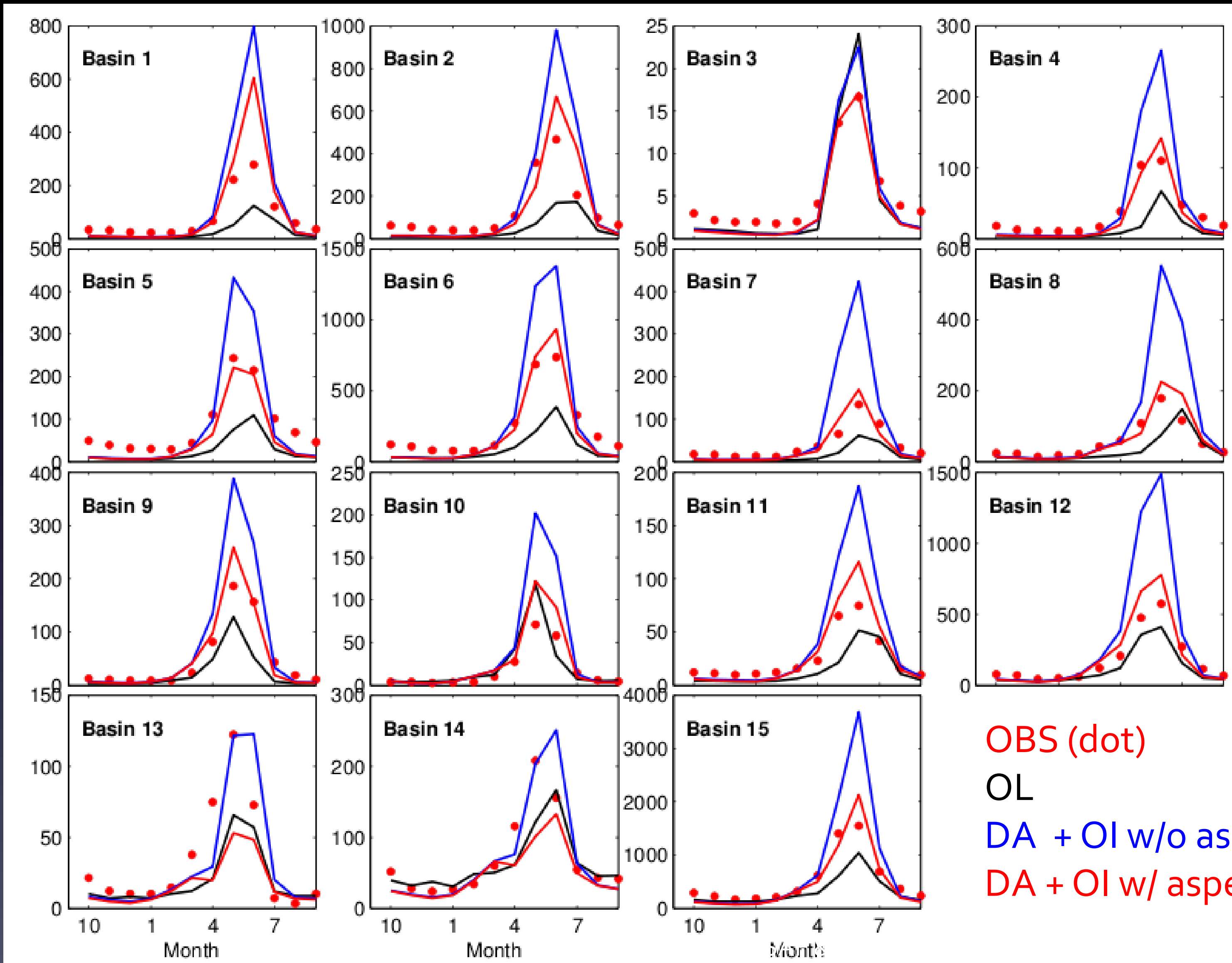
Best results are obtained from assimilating PMW_{GASAM}

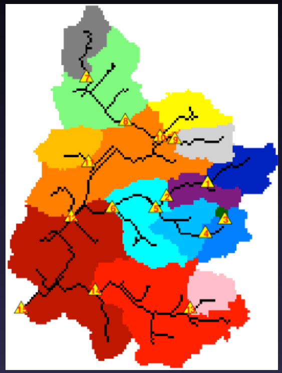
(PMW snow depth + GHCN w/ aspect + SNOTEL w/ aspect + MODIS snow cover)



Evaluation Against Monthly Natural Flows

Mean monthly flow (cms)





OBS (dot)

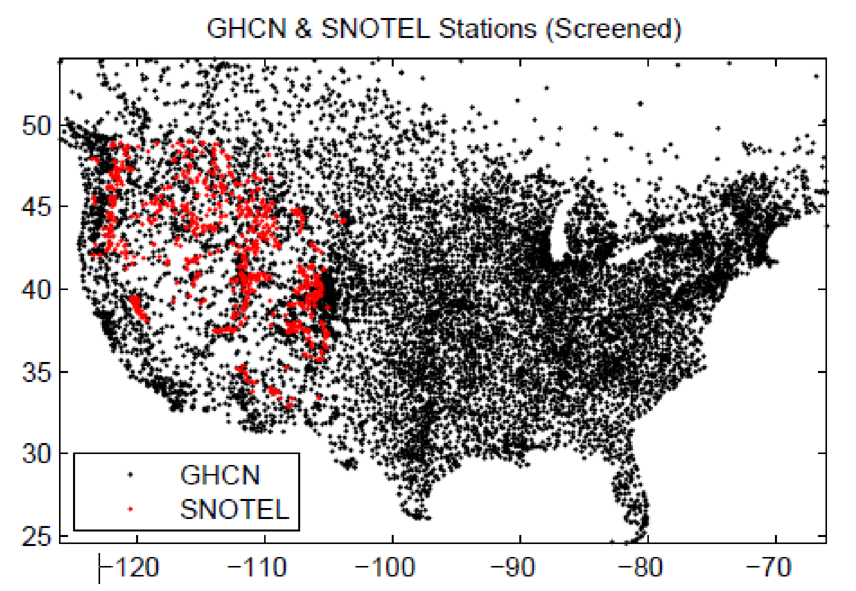
OL

DA + OI w/o aspect (DA_{GAS})

DA + OI w/ aspect (DA_{GASA})

Ongoing Work over CONUS

- 12.5km (NLDAS2 domain)
- 1980-2011 (31 years)
- Producing and assimilating PMW-station blended snow products
  - SMMR (1980-1987)
  - SSMI (1987-2002)
  - AMSR-E (2002-2011)
- Streamflow evaluation
  - USGS daily streamflow for NLDAS2 small headwater basins (946)
  - Monthly natural flow



9106 GHCN stations
669 SNOTEL stations

Concluding Remarks

- Successful data assimilation requires good model and good data
- Blending satellite snow data with in-situ observations shows potential for streamflow prediction in snow-driven basins
  - Critical to have station representation in both high and low elevations
  - Important to consider terrain aspect , especially in high elevations
  - MODIS snow cover can provide additional value
- Ongoing/future work
  - Continental/global applications
  - Implementation and verification in operational hydrologic ensemble forecasting

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