

# Understanding Groundwater Hydrological Coupling in a Land Surface Model based on Multi-sensor Satellite Data Assimilation

**Zong-Liang Yang**

Long Zhao, Yongfei Zhang, Yonghwan Kwon, Peirong Lin, Wen-Ying Wu, and more

<http://www.geo.utexas.edu/climate>

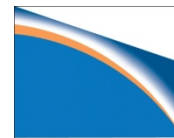
<http://www.jsg.utexas.edu/ciess>



THE UNIVERSITY OF TEXAS AT AUSTIN

**CIESS**

CENTER FOR INTEGRATED EARTH SYSTEM SCIENCE



**NCAR**

NATIONAL CENTER FOR ATMOSPHERIC RESEARCH



**TEXAS** Geosciences

The University of Texas at Austin

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WHAT STARTS HERE CHANGES THE WORLD

THE UNIVERSITY OF TEXAS AT AUSTIN

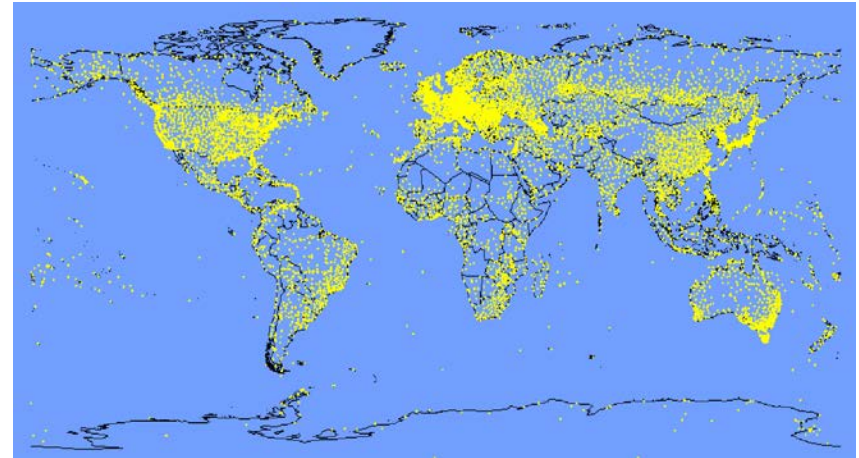
# Key Points

- Land state variables (soil moisture, snow mass, groundwater, vegetation phenology) have value in predicting
  - Climate
  - Runoff and streamflow
  - Extreme events (floods and droughts)
- High-quality land state datasets are lacking
- Our collaborative efforts in
  - Developing a multivariate global land data assimilation framework
  - Quantifying uncertainties
  - Delivering high-quality datasets & products
  - Applications

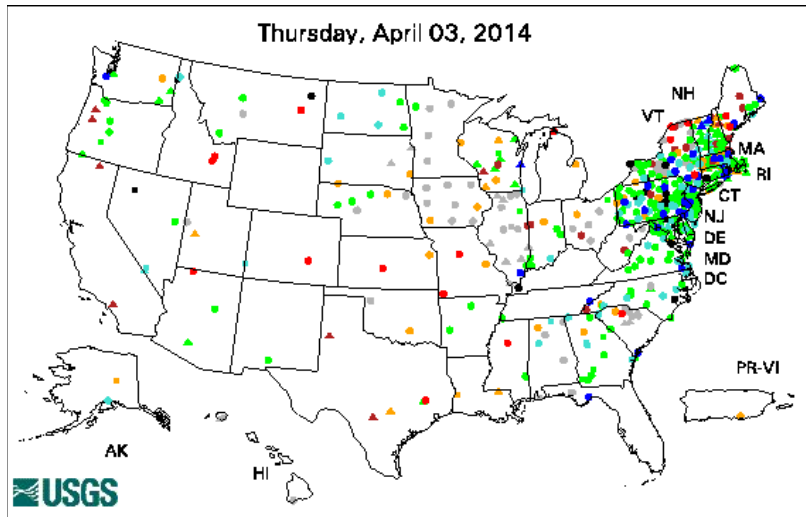
# Inadequacy of Surface Observations

## Issues:

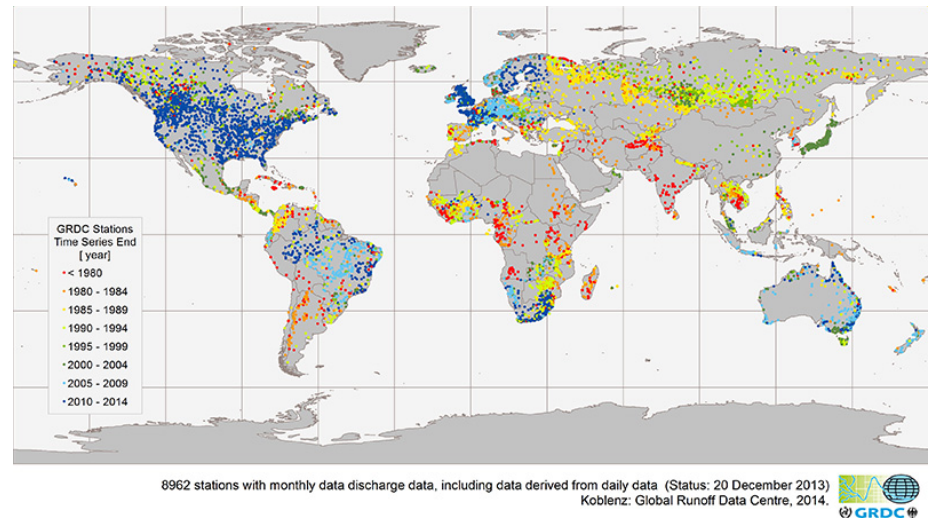
- Spatial coverage of existing stations
- **Temporal gaps and delays**
- **Many governments unwilling to share**
- Measurement inconsistencies
- Quality control
- **(Un)Representativeness of point obs**



Global Telecommunication System meteorological stations. Air temperature, precipitation, solar radiation, wind speed, and humidity only.

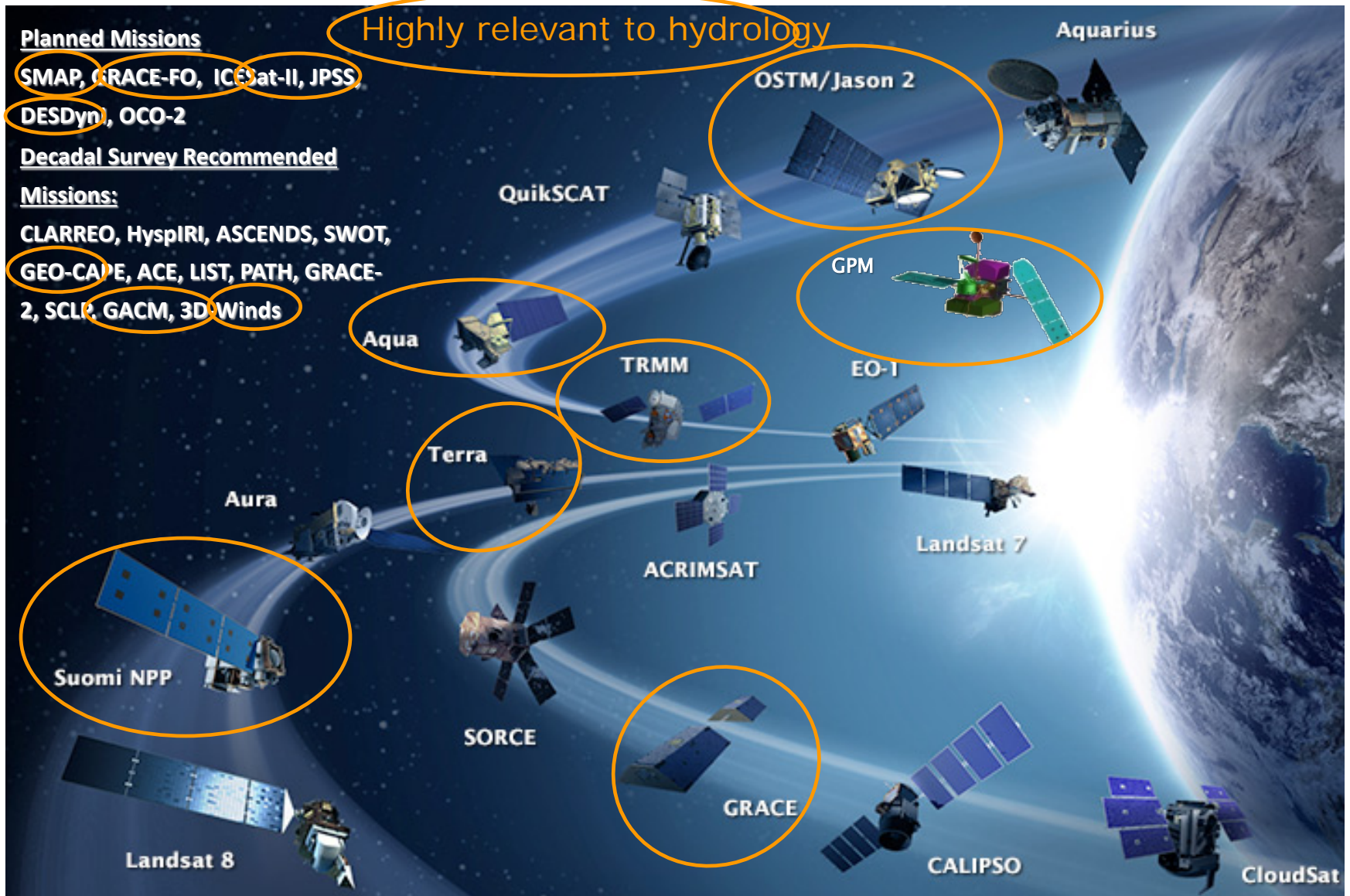


USGS Groundwater Climate Response Network.  
**Very few** groundwater records available **outside of**  
the U.S.



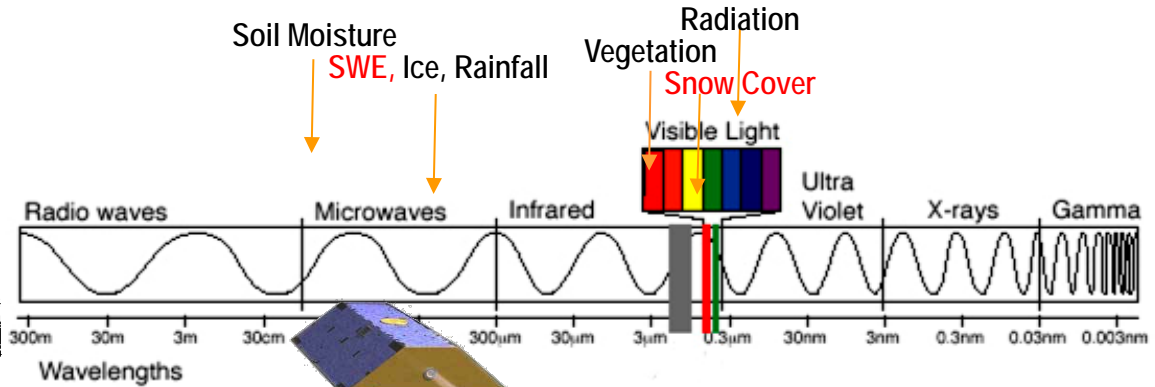
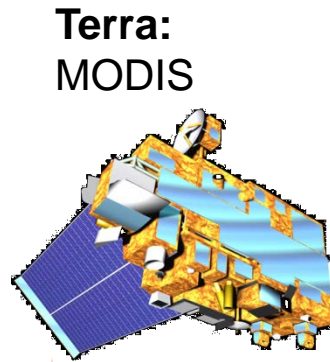
River flow observations from the Global Runoff Data Centre.  
**Warmer colors indicate greater latency in the data record.**

# Present and Future NASA Earth Science Missions





# Complementary Information from Different Satellites



## GRACE

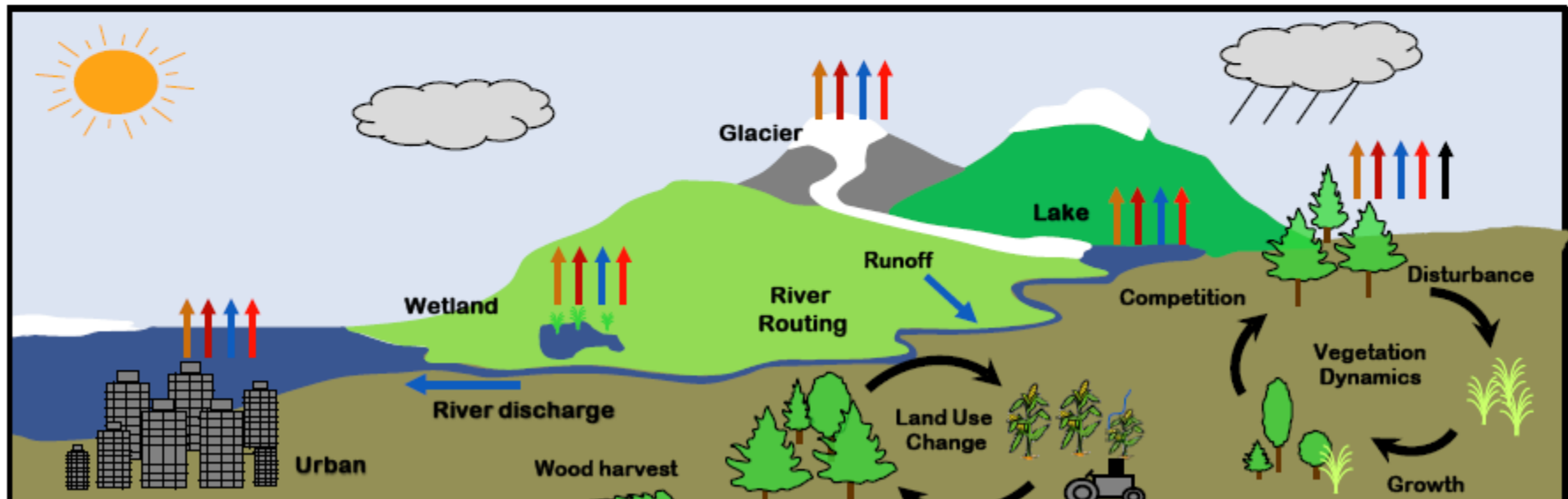
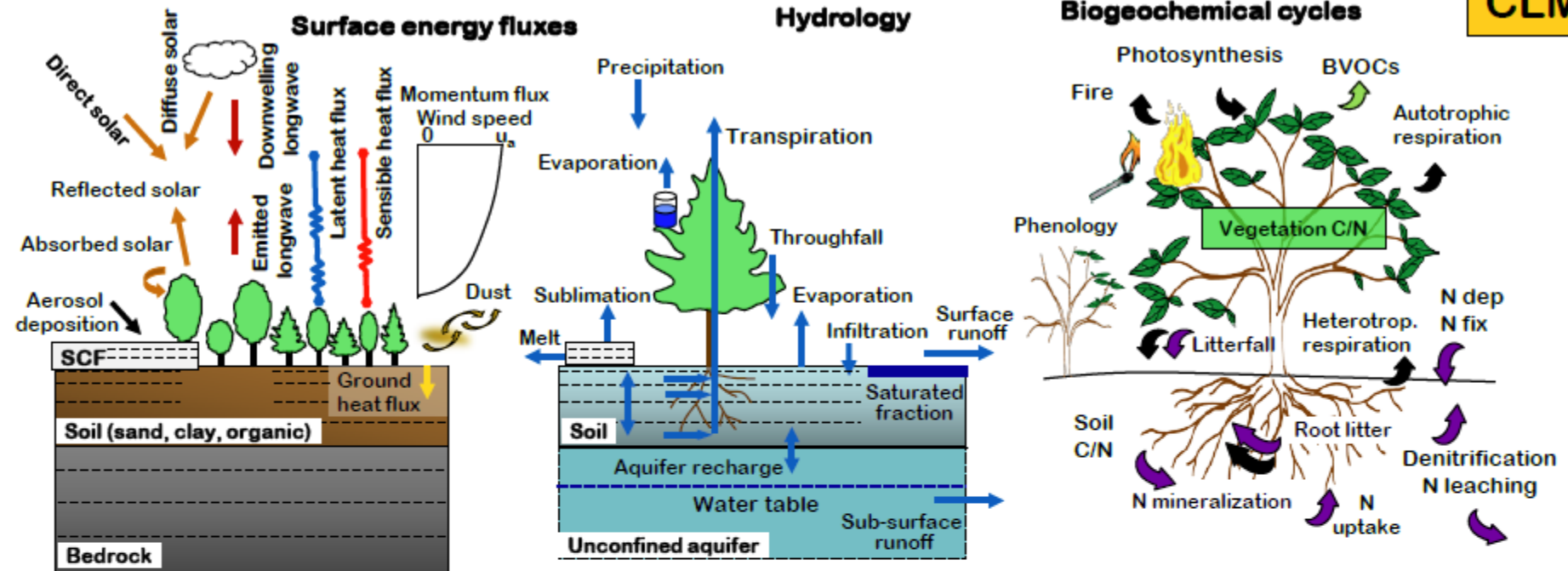
GRACE provides changes in total water storage but not high resolution snow cover data which are dominated by SWE. AMSR-E provides SWE data at high latitudes and altitudes, and provides soil moisture changes elsewhere, but at very coarse resolution

# Grand Objective

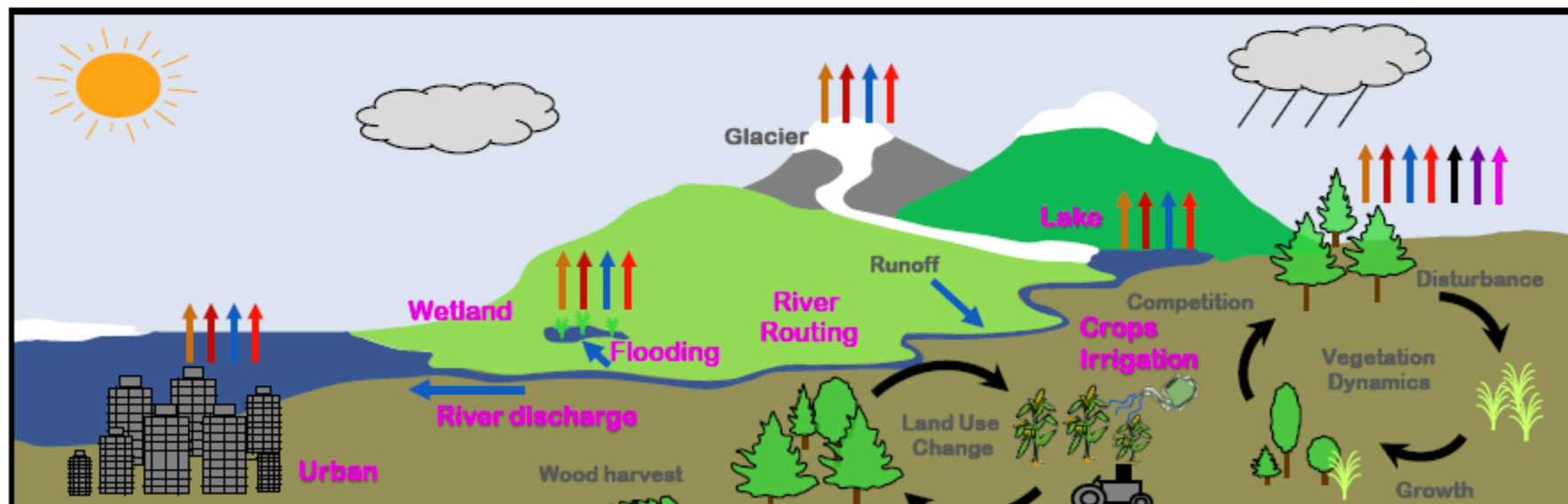
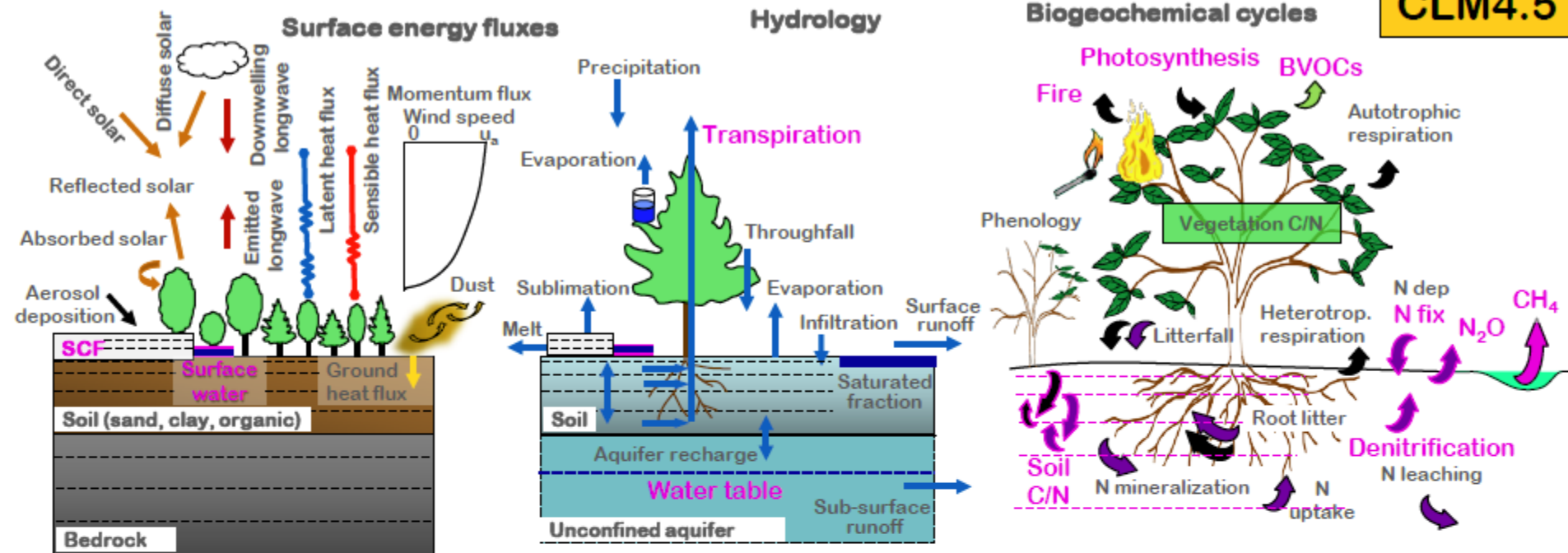
- Develop a multi-mission, multi-platform, multi-source, and multi-scale global land data assimilation system
- Why CLM?
- Why DART?
- Initial Results
- Recent Results

# Community Land Model version 4

- Evolved from CLM3.5 (released in 2008). CLM3.5 improves over CLM3 (released in 2004)
  - Surface runoff (Yang and Niu, 2003; Niu, Yang et al., 2005)
  - Groundwater (Niu, Yang, et al., 2007)
  - Frozen soil (Niu and Yang, 2006)
  - Canopy integration, canopy interception scaling, and pft-dependency of the soil stress function
- CLM4 (released in 2010) improves over CLM3.5
  - Prognostic in carbon and nitrogen (CN) as well as vegetation phenology; the dynamic global vegetation model is merged with CN
  - Transient landcover and land use change capability
  - Urban component
  - BVOC component (MEGAN2)
  - Dust emissions
  - Updated hydrology and ground evaporation
  - New density-based snow cover fraction (Niu and Yang, 2007), snow burial fraction, snow compaction
  - Improved permafrost scheme: organic soils, 50-m depth (5 bedrock layers)
  - Conserving global energy by separating river discharge into liquid and ice water streams







# Land Data Assimilation at UT-Austin (1)

## CLM2 with hardwired EnKF

- Su, H., **Z.-L. Yang**, G.-Y. Niu, and R. E. Dickinson, [2008](#): Enhancing the estimation of continental-scale snow water equivalent by assimilating MODIS snow cover with the ensemble Kalman filter, *J. Geophys. Res.*, 113, D08120, doi:10.1029/2007JD009232.
- Su, H., **Z.-L. Yang**, R. E. Dickinson, C. R. Wilson, and G.-Y. Niu, [2010](#): Multisensor snow data assimilation at the continental scale: The value of Gravity Recovery and Climate Experiment terrestrial water storage information, *J. Geophys. Res.*, 115, D10104, DOI: 10.1029/2009JD013035.
- Su, H., **Z.-L. Yang**, G.-Y. Niu, and C. R. Wilson, [2011](#): Parameter estimation in ensemble based snow data assimilation: A Synthetic study, *Advances in Water Resources*, **34**, 407–416



**Finding Truth** is like playing **DART**



# Data Assimilation Research Testbed (DART)

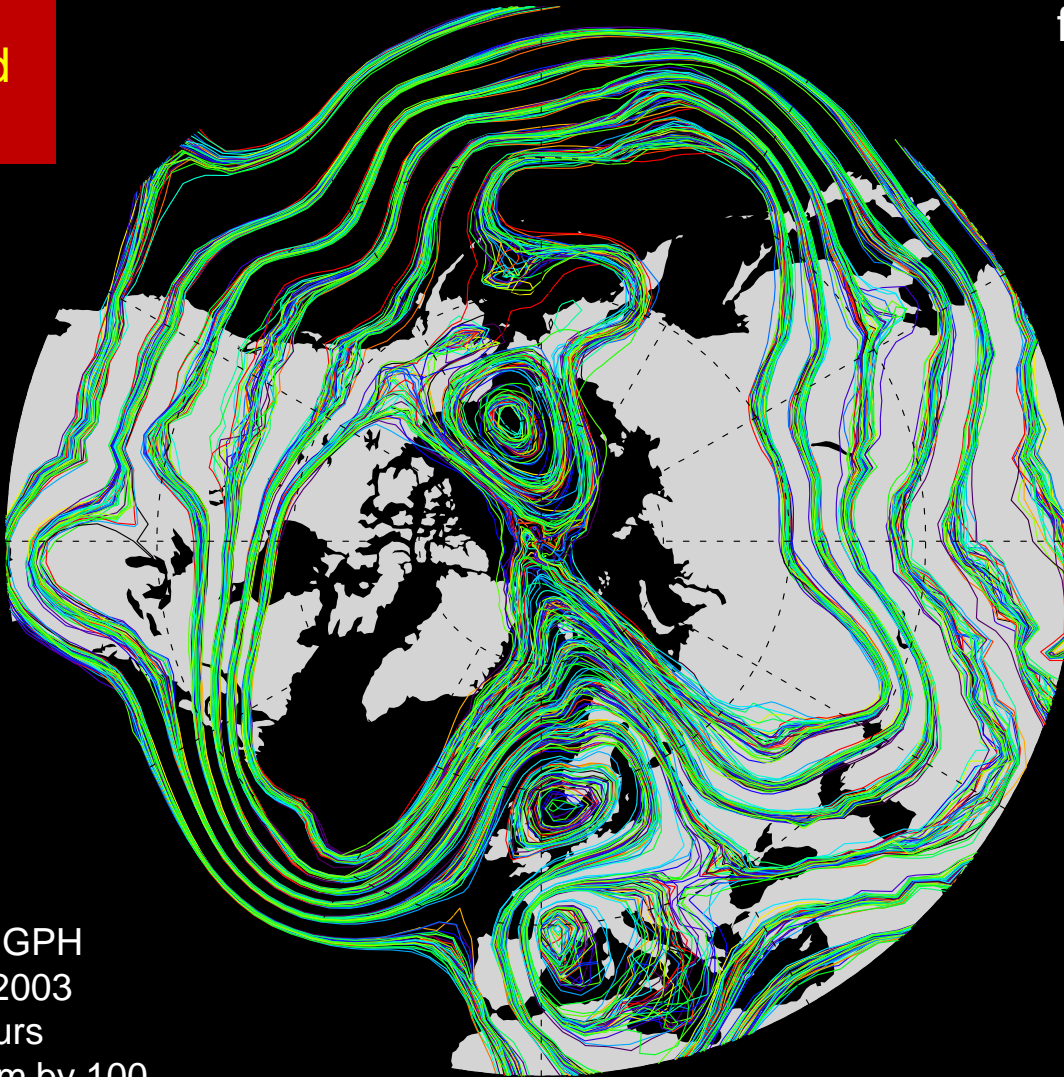
- A comprehensive data assimilation software environment
  - <http://www.image.ucar.edu/DAReS/DART>
  - developed and maintained by Jeff Anderson's group at NCAR
  - used by both modelers and observational scientists to easily explore different data assimilation methods, observations, and models
  - linked to atmospheric models (WRF, CAM4) and oceanic models
  - linked to CLM4 (through UT and NCAR collaboration)
- Community efforts for data assimilation



O(1 million)  
atmo. obs  
are  
assimilated  
every day.

# Atmospheric Reanalysis

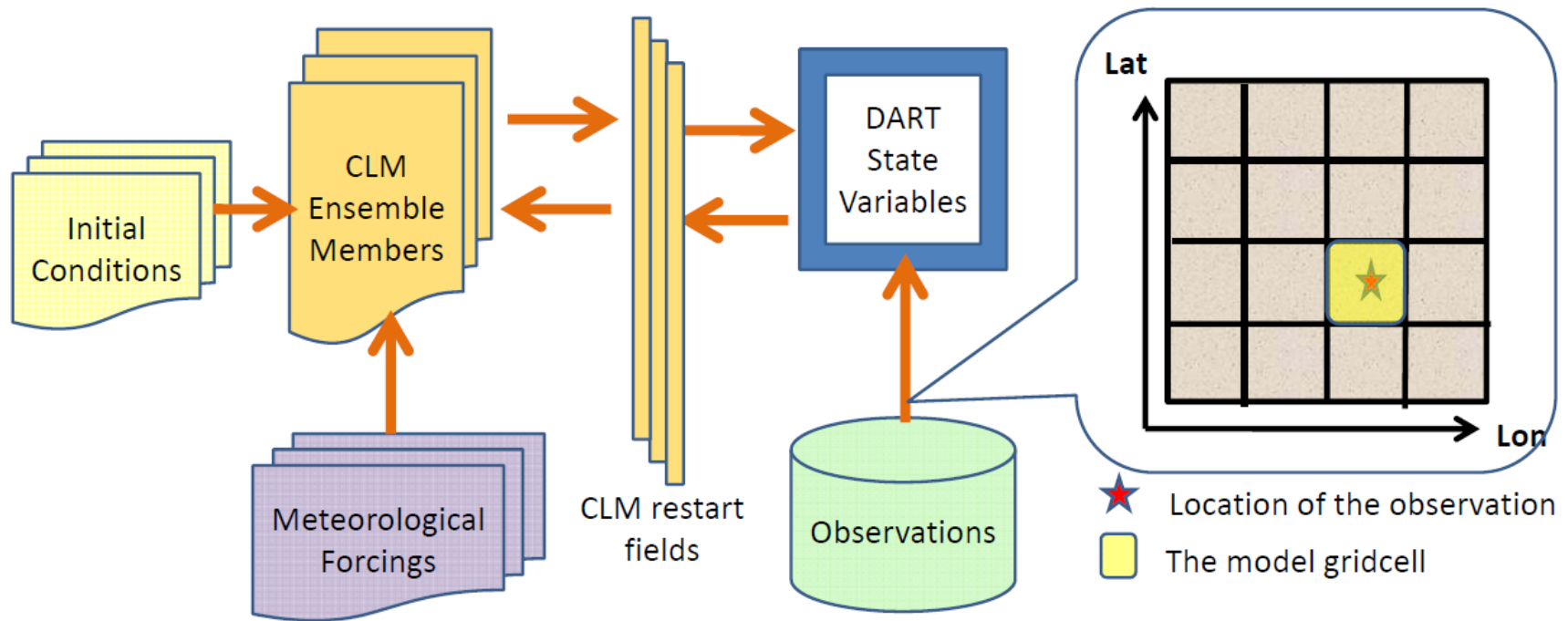
Assimilation uses 80 members of 2° FV CAM forced by a single ocean (Hadley+ NCEP-OI2) and produces a very competitive reanalysis.



500 hPa GPH  
Feb 17 2003  
Contours  
5200m:5700m by 100

1998-2010  
4x daily  
is free and available.  
Contact  
[dart@ucar.edu](mailto:dart@ucar.edu)

# Flowchart of CLM4–DART Coupling



Each CLM member has a distinct meteorological forcing from **CAM reanalysis** and **initial condition**.

When new observations are available, all the members stop and send restart files to DART.

DART updates the modeled state variables with observations and sends back to CLM.

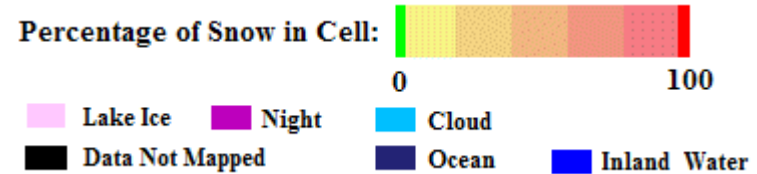
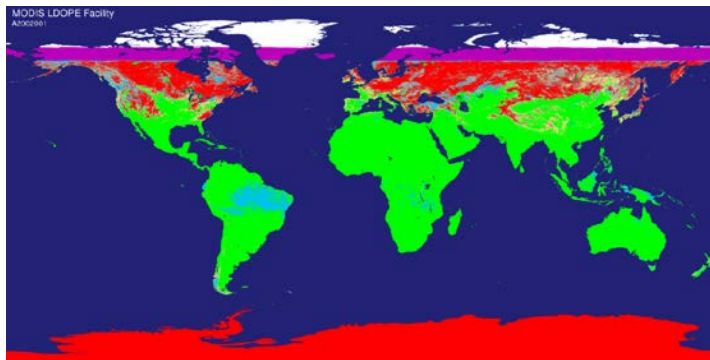
# Land Data Assimilation at UT-Austin (2)

## CLM4 with DART (using restart files)

- Zhang, Y.-F., T. J. Hoar, **Z.-L. Yang**, J. L. Anderson, A. M. Toure, and M. Rodell, [2014](#): Assimilation of MODIS snow cover through the Data Assimilation Research Testbed and the Community Land Model version 4, *J. Geophys. Res. – Atmospheres.*, **119**, 7,091–7,103.
- Zhang, Y.-F. and **Z.-L. Yang**, [2016](#): Estimating uncertainties in the newly developed multi-source land snow data assimilation system, *J. Geophys. Res.–Atmospheres*, **121**, 8254–8268, doi: 10.1002/2015JD024248.
- Kwon, Y.H., A. M. Toure, **Z.-L. Yang**, M. Rodell, and G. Picard, [2015](#): Error characterization of coupled land surface–radiative transfer models for snow microwave radiance assimilation, *IEEE Transactions on Geoscience and Remote Sensing*, **53 (9)**, 5247–5268, DOI: 10.1109/TGRS.2015.2419977.
- Zhao, L., **Z.-L. Yang**, and T. J. Hoar, [2016](#): Global soil moisture estimation by assimilating AMSR-E brightness temperatures in a coupled CLM4-RTM-DART system, *Journal of Hydrometeorology*, doi: 10.1175/JHM-D-15-0218.1.

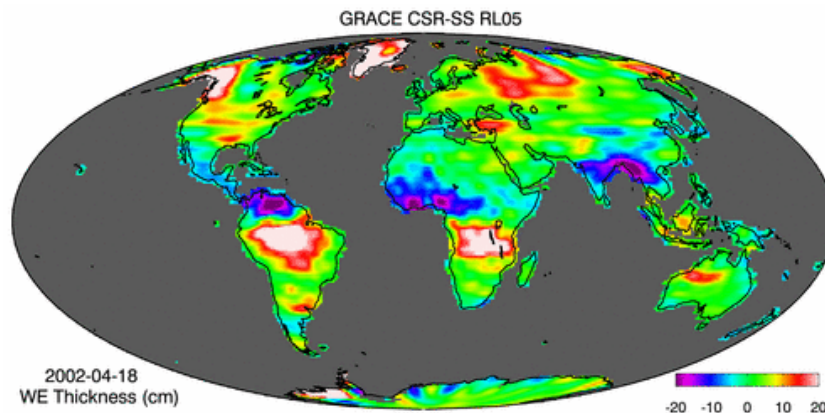
# Available satellite observations of snow

## Daily MODIS snow cover observation



<http://landweb.nascom.nasa.gov/animation/>

## Monthly GRACE terrestrial water storage observation



[ftp://podaac-ftp.jpl.nasa.gov/allData/tellus/L3/land\\_mass/RL05/animation/](ftp://podaac-ftp.jpl.nasa.gov/allData/tellus/L3/land_mass/RL05/animation/)



## RESEARCH ARTICLE

10.1002/2015JD024248

### Key Points:

- Uncertainties from multiple sources are assessed in the land snow data assimilation system
- The atmospheric forcing uncertainty is found to be the largest source
- Model structure and choice of data assimilation technique are also two big sources of uncertainty

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## Estimating uncertainties in the newly developed multi-source land snow data assimilation system

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**Abstract** The snow simulations from the recently developed multivariate land snow data assimilation system (SNODAS) for the Northern Hemisphere are assessed with regard to uncertainties in atmospheric forcing, model structure, data assimilation technique, and satellite remote sensing product. The SNODAS consists of the Data Assimilation Research Testbed (DART) and the Community Land Model version 4 (CLM4). A series of experiments are conducted to estimate each of the above uncertainty sources. The experiments include several open-loop model cases and data assimilation cases that assimilate the snow cover fraction (SCF) data from the Moderate Resolution Imaging Spectroradiometer (MODIS) and the terrestrial water storage (TWS) from the Gravity Recovery and Climate Experiment (GRACE). The atmospheric forcing uncertainty in terms of precipitation and radiation is found to be the largest among the various uncertainty sources examined, especially over the Tibetan Plateau (TP) and most of the mid- and high-latitudes. Model structure and choice of data assimilation technique are also two big sources of uncertainty in SNODAS. The uncertainty of model structure is represented by two different parameterizations of SCF. The density-based SCF scheme (as used in CLM4) generally results in better snow simulations than does the stochastic SCF scheme (as in CLM4.5) within the data assimilation framework. The choice of TWS products retrieved from GRACE has relatively the least impact on the snow data assimilation.

# Question 1: Where and when does assimilating MODIS SCF observations improve snow simulations in the land surface model?

- Snow simulations can be improved mostly at lower-middle latitudes ( $23^{\circ}$ – $45^{\circ}$ )
- Only minimal modifications are made at the higher-middle ( $45^{\circ}$ – $66^{\circ}$ N) and high latitudes
- Results are mixed over densely-forested regions

## Question //: Can GRACE TWS assimilation add value to snow DA?

- Yes.
- While MODIS DA is mainly effective along the snowline, GRACE provides valuable information across all latitudes.
- River discharge is not improved, which is possibly caused by inappropriate updates in groundwater.

## Question III: How does the SNODAS respond to uncertainties from multiple sources?

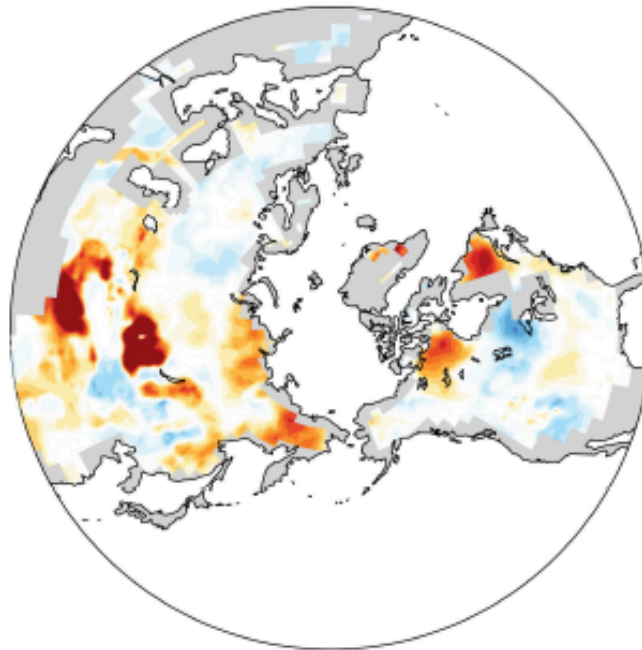
- **The atmospheric forcing** uncertainty is found to be the largest source.
- **Model structure and choice of data assimilation methods** are also two big uncertainty sources.
- Choice of GRACE TWS products has relatively least impacts on snow DA.



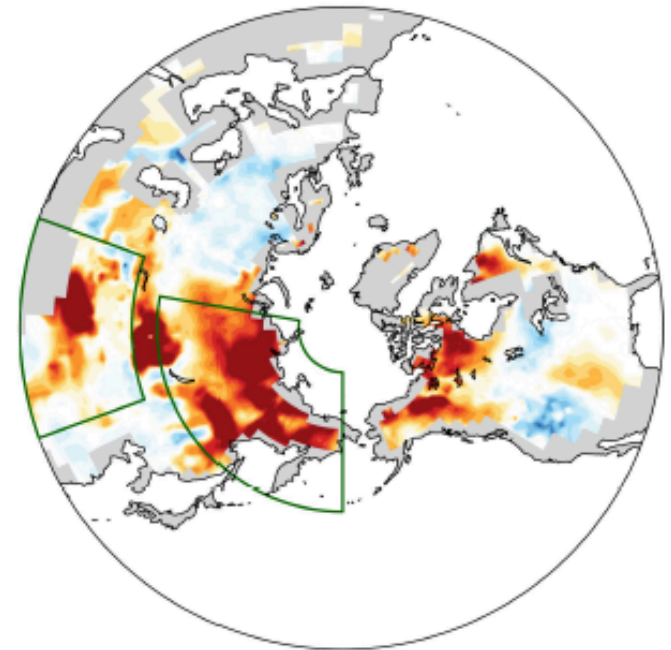
# Improved CESM seasonal temperature prediction in gauge-sparse regions (the TP and Siberia)

- ❖ Cumulative RMSE across MAM
- ❖ The prediction is initialized on March 1<sup>st</sup> of 2003 to 2009
- ❖ **Red colors:** reduced cRMSE by DA and improved temperature prediction

MOD-OL



GRAMOD-OL



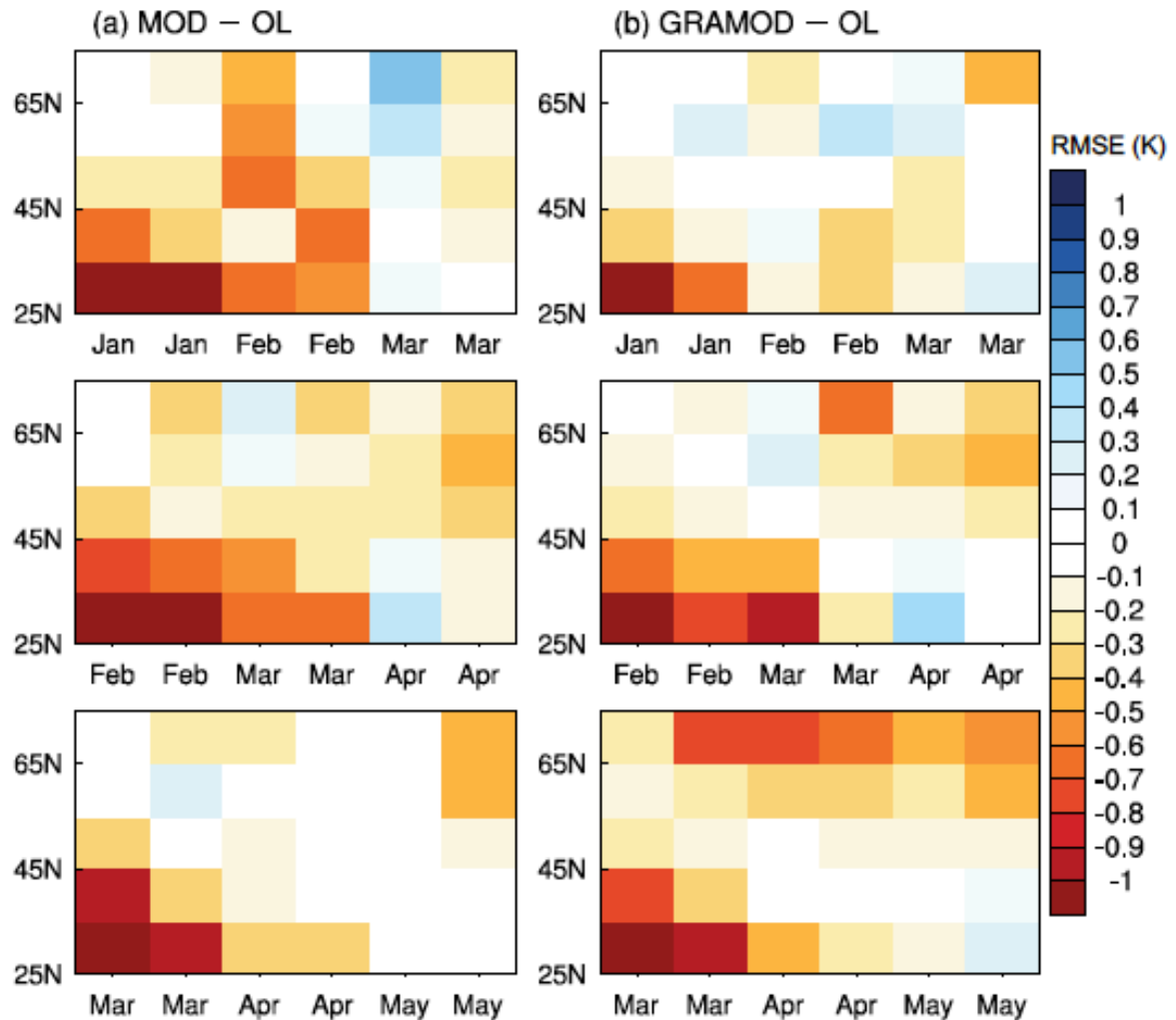
# The improvements are dependent on lead time (x-axis) and latitudes (y-axis)

- ❖ The prediction initialized is on Jan 1<sup>st</sup>, 2003 to 2009

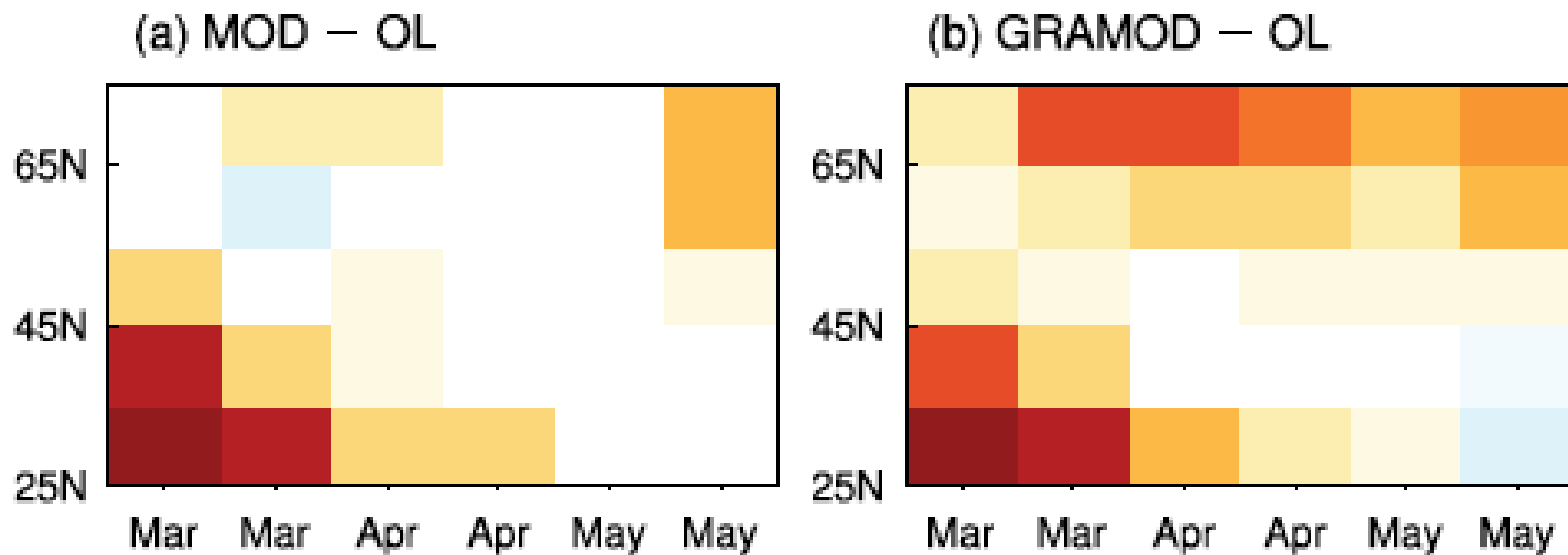
Feb 1<sup>st</sup>

Mar 1<sup>st</sup>

- ❖ **Red colors:** reduced RMSE and improved temperature prediction



(Cont.) The improvements are dependent on lead time (x-axis) and latitudes (y-axis)

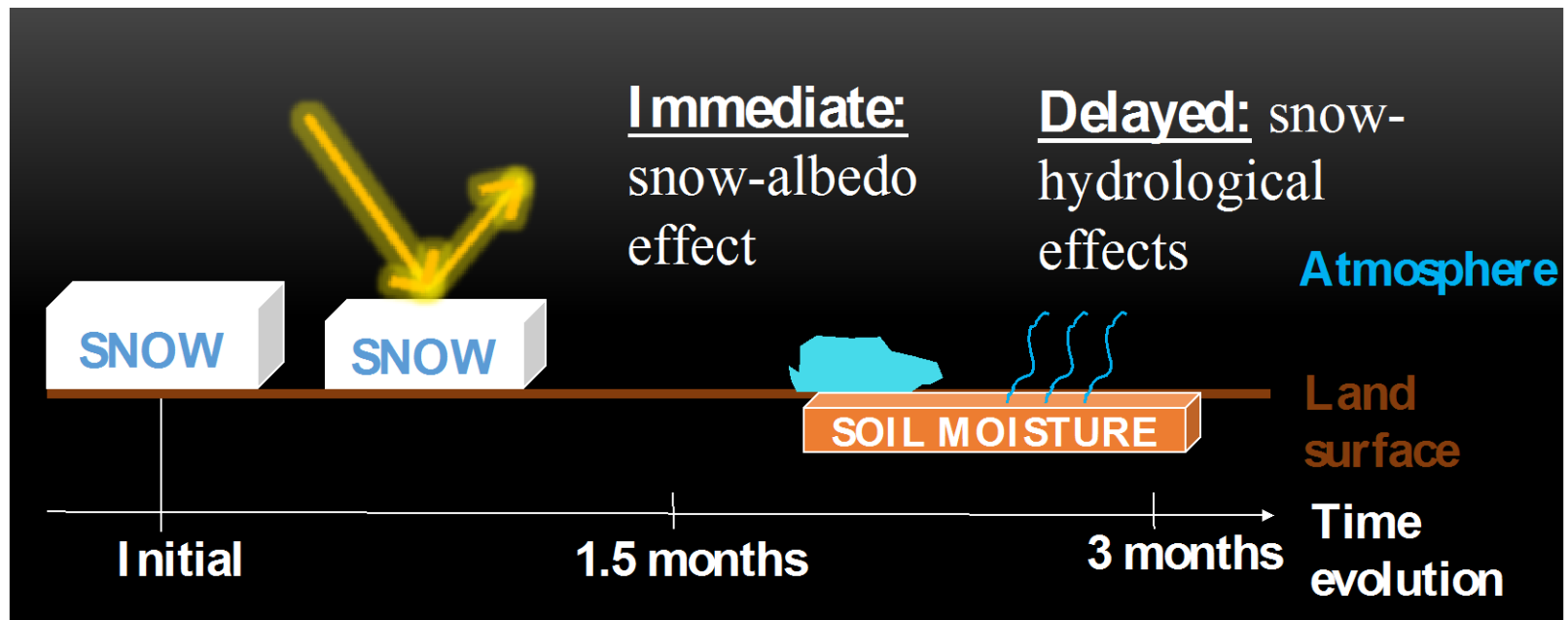


❖ **Summary:**

- ❖ (1) High-latitude improvements: only evident after late March, due to the sufficient incoming solar radiation
- ❖ (2) GRACE DA offers more improvements than MODIS DA only at high latitudes

# Contribution of improved snow initialization to seasonal climate prediction

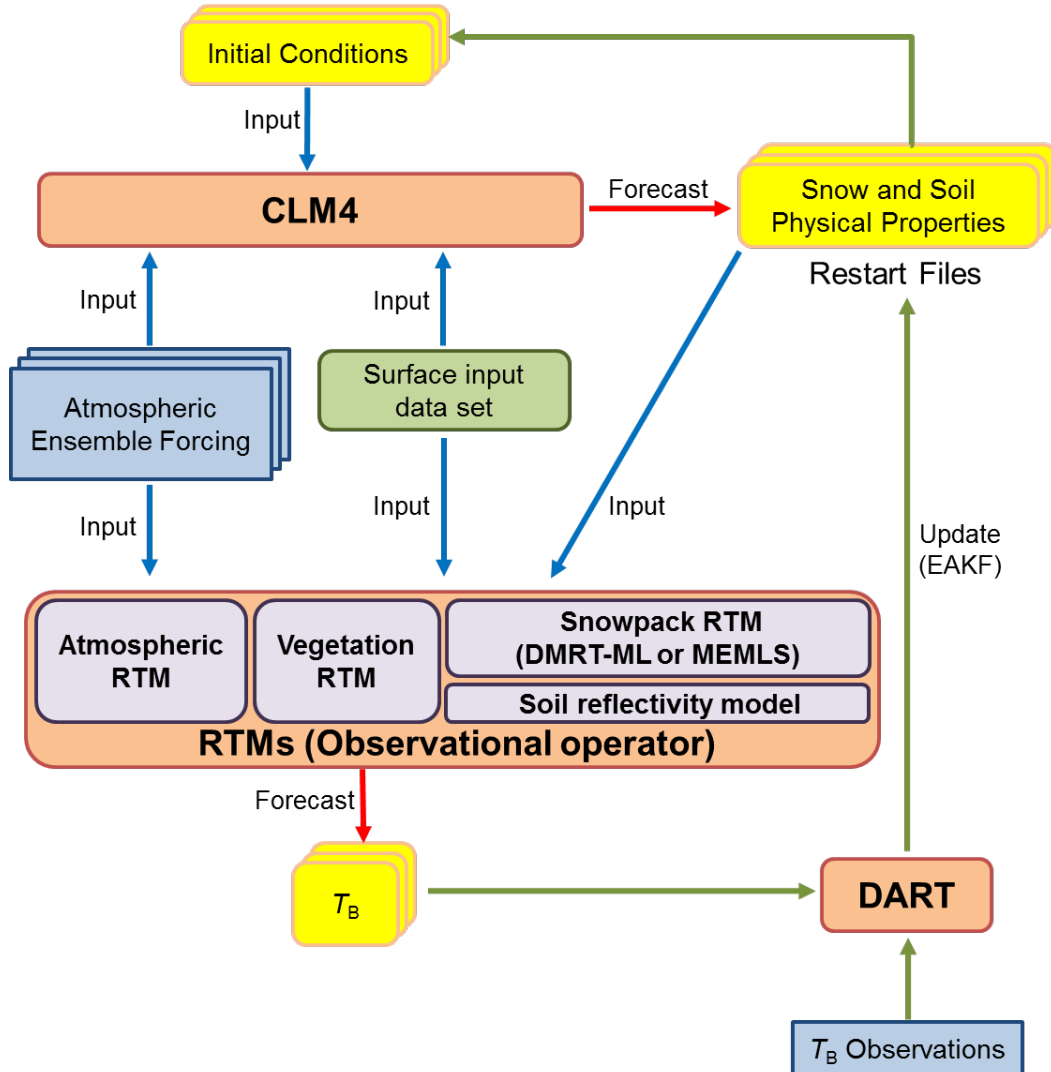
- ❖ Snow: important to the albedo and soil moisture feedback





# Data assimilation of snow microwave brightness temperature ( $T_B$ ) observations, i.e., radiance assimilation (RA)

## ◆ Coupled RA system (Kwon et al., 2016a, b)



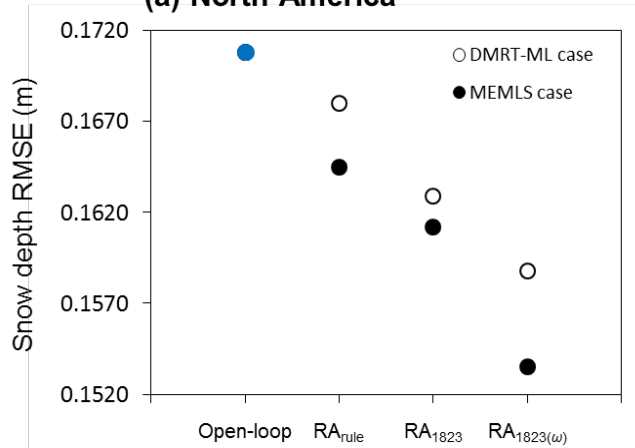
## ◆ Research questions

- Is the **RA** method **applicable** to **continental-scale** snow water storage estimations?
- Which **error characteristics** of estimated **snow** physical properties and  **$T_B$**  impede continental-scale applications of the RA method?
- Can the effect of these **error sources** be **mitigated** in the RA system?
- How to **improve** the **performance** of the **RA** system in characterizing snow under the **vegetation** canopy?

# Data assimilation of snow microwave brightness temperature ( $T_B$ ) observations, i.e., radiance assimilation (RA)

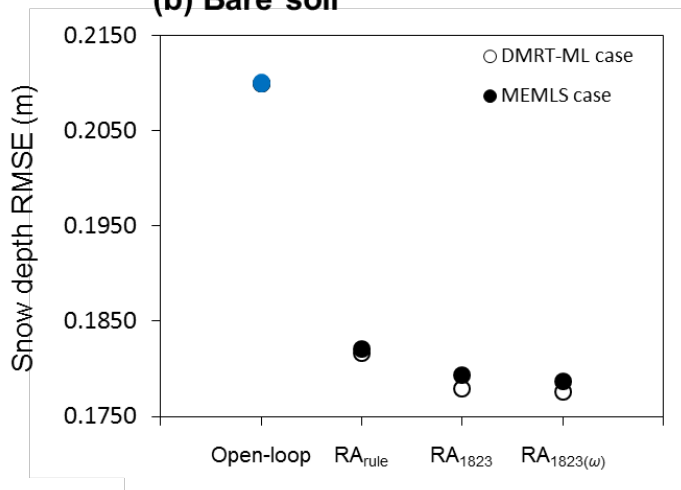
## ◆ Results: snow depth RMSE (Kwon et al., 2016a, b)

(a) North America

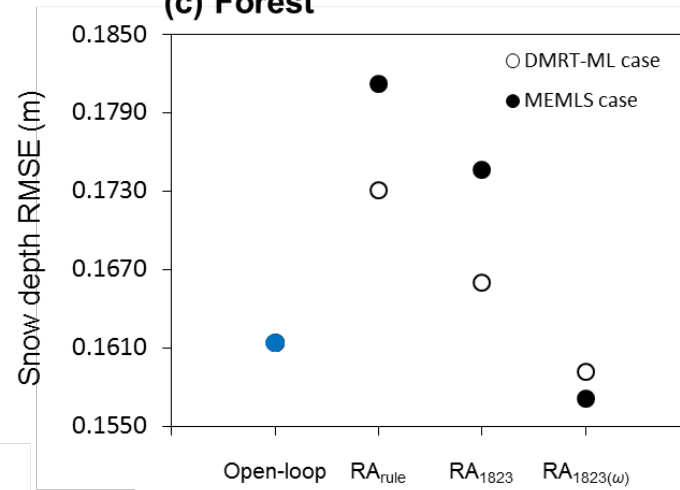


- The **performance** of the RA system in estimating **snow depth** over North America is **improved** (1) by **simultaneously updating** all model physical states and parameters involved in simulating  $T_B$  based on a **rule** (RA<sub>rule</sub>), (2) by using the **best-performing frequency** channels (i.e., 18.7 and 23.8 GHz) (RA<sub>1823</sub>), and (3) by considering the **vegetation single scattering albedo** (RA<sub>1823(ω)</sub>).
- Especially, the RA system **performed much better** than the open-loop run for areas **without vegetation cover** (Figure b).
- The snow depth estimates by RA were also **enhanced** for **forested areas** (Figure c) by better representing the **vegetation contribution** to  $T_B$  at the top of the atmosphere.

(b) Bare soil

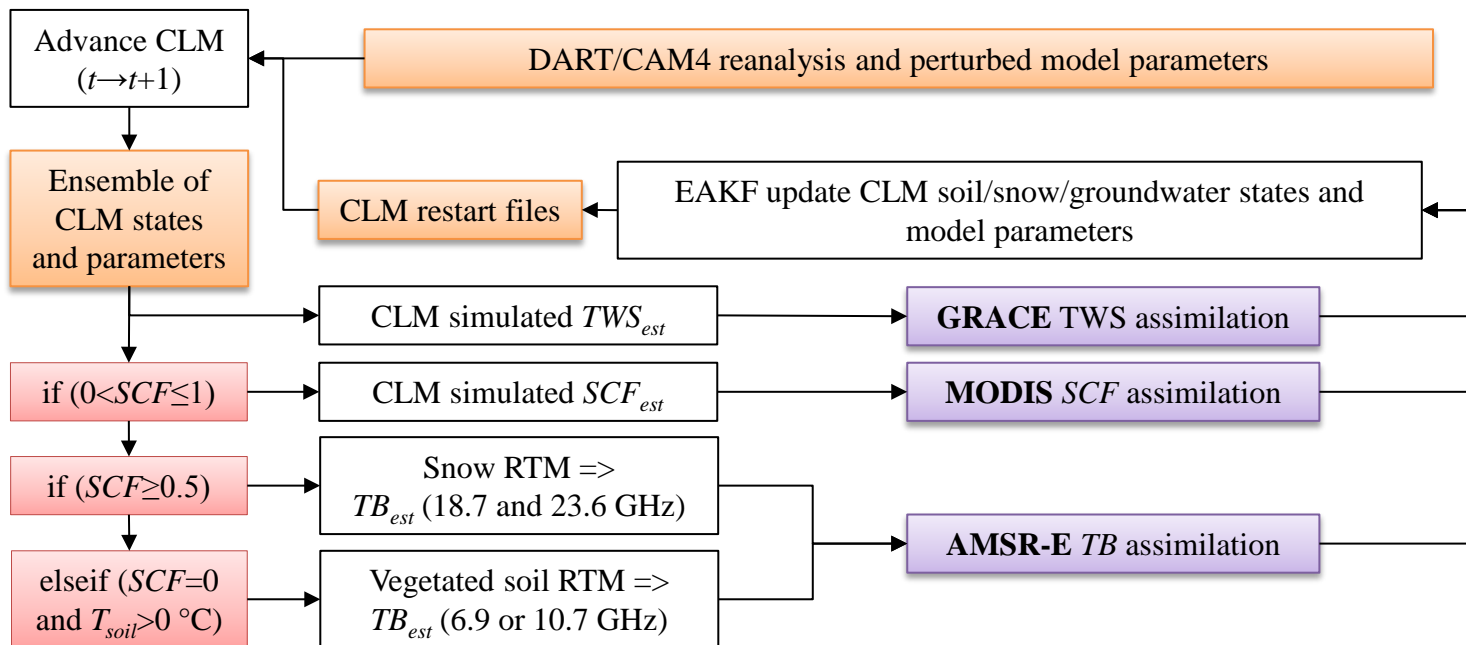


(c) Forest

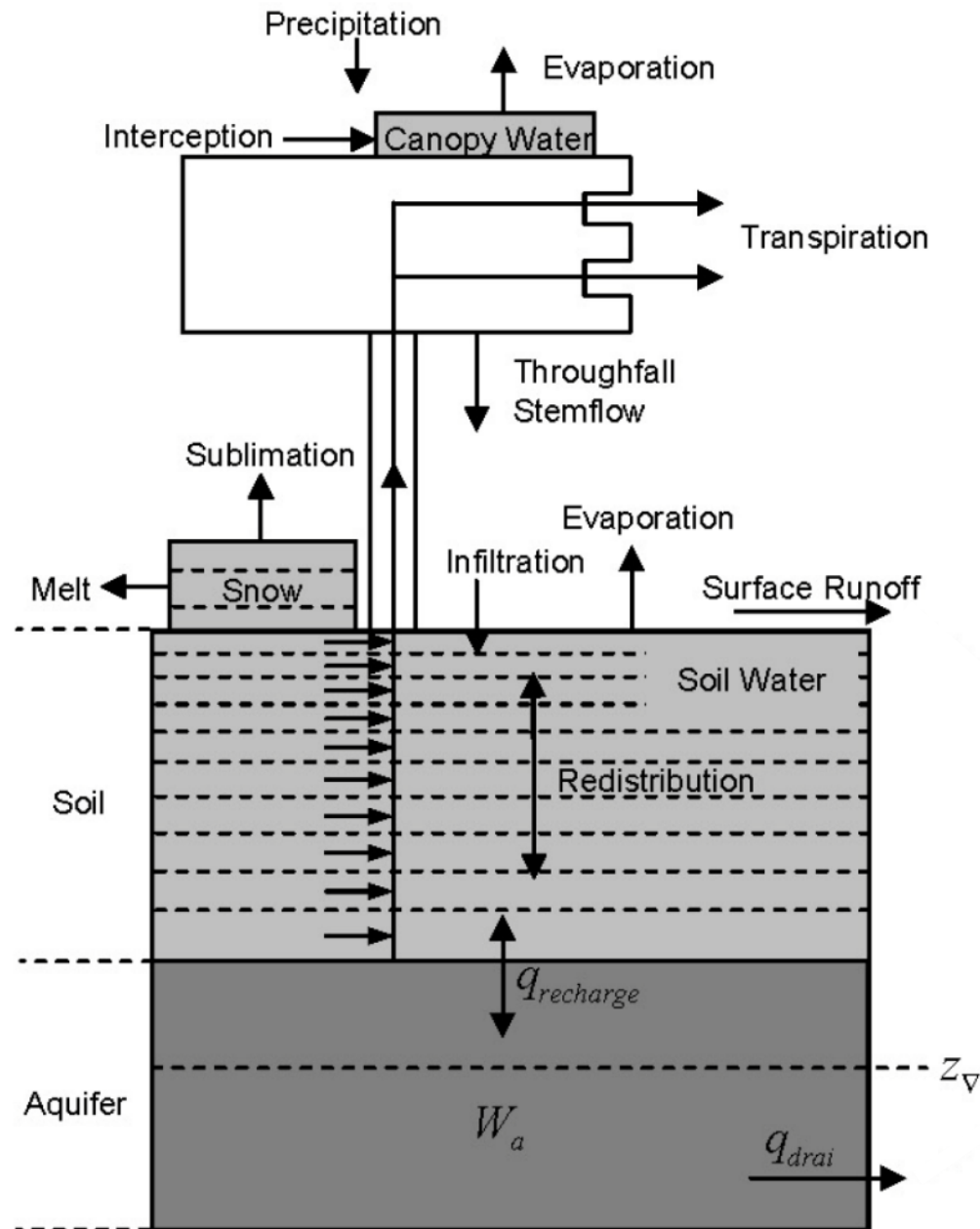


# CLM-DART-based multi-sensor land data assimilation

- The multi-sensor DA system is expected to
  - improve SCF estimate by assimilating MODIS SCF for unsaturated snow cover areas ( $0 < SCF \leq 1$ ) (Zhang et al. 2014, JGR);
  - improve SWE estimate by assimilating AMSR-E TB (18.7 and 23.6 GHz) for nearly saturated snow cover areas ( $SCF \geq 0.5$ ) (Kwon et al. 2016, JHM);
  - improve profile soil moisture estimate by assimilating AMSR-E TB (6.9 or 10.7 GHz) over snow free ( $SCF = 0$ ) and frozen-soil free ( $T_{soil} > 0$  °C) areas (Zhao et al. 2016, JHM);
  - improve both snow, soil moisture, and groundwater estimate by assimilating GRACE TWS.



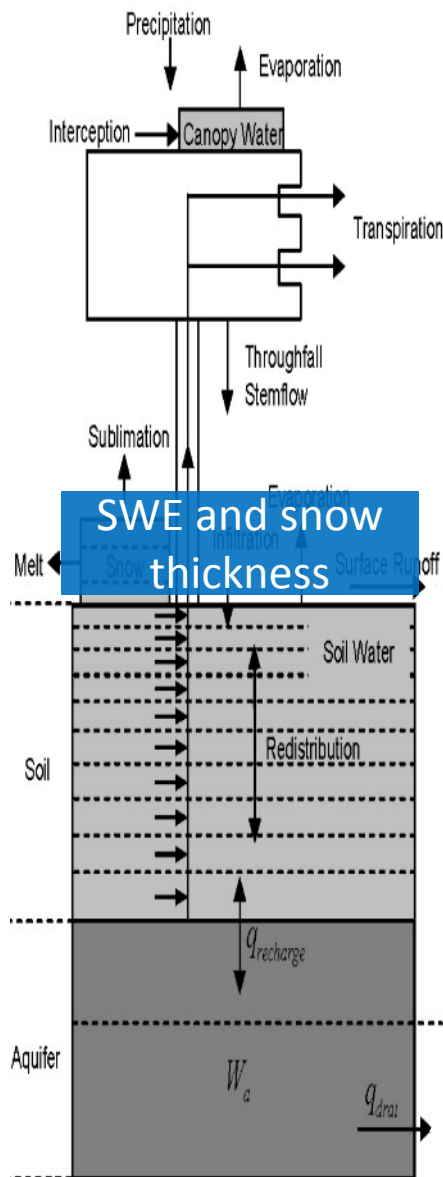
# The hydrologic processes in CLM4.0



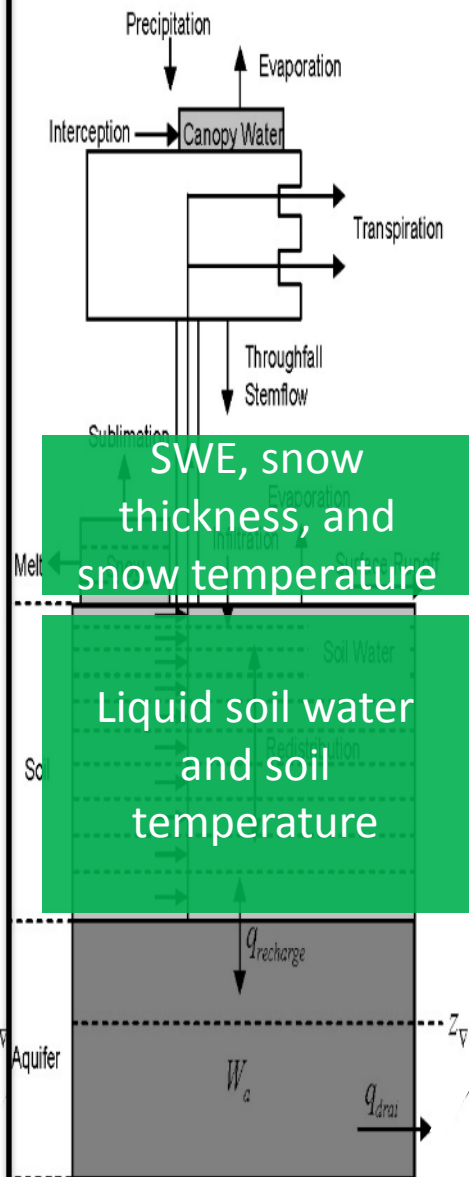
(Oleson et al. 2010, CLM4.0 Tech Note)



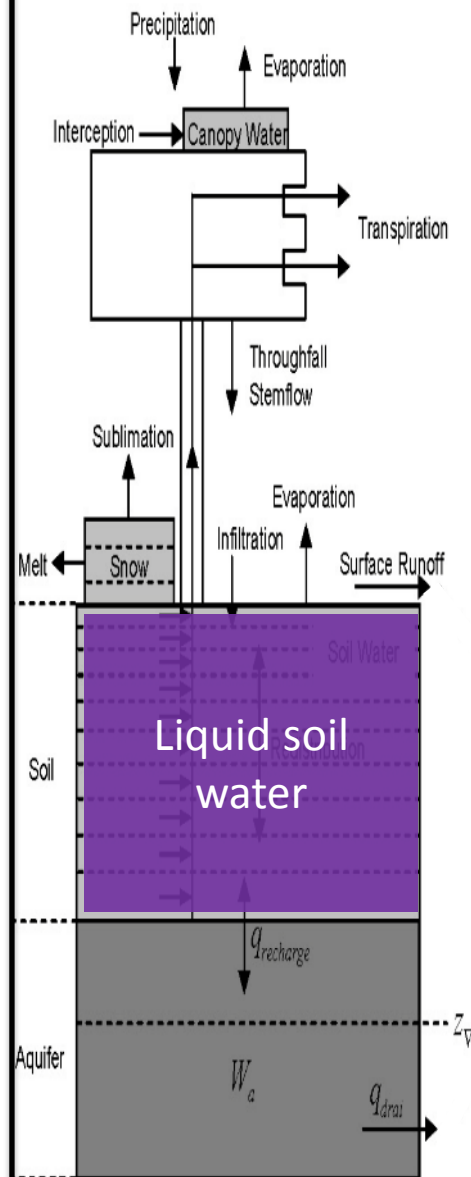
## MODIS SCF



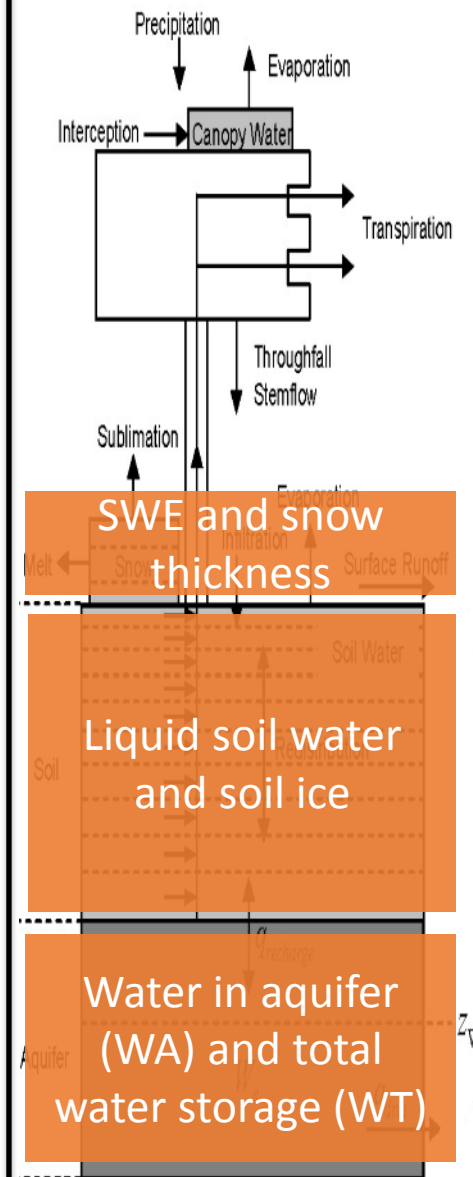
## AMSR-E TB (18.7/23.6 GHz)



## AMSR-E TB (6.9/10.7 GHz)



## GRACE TWS

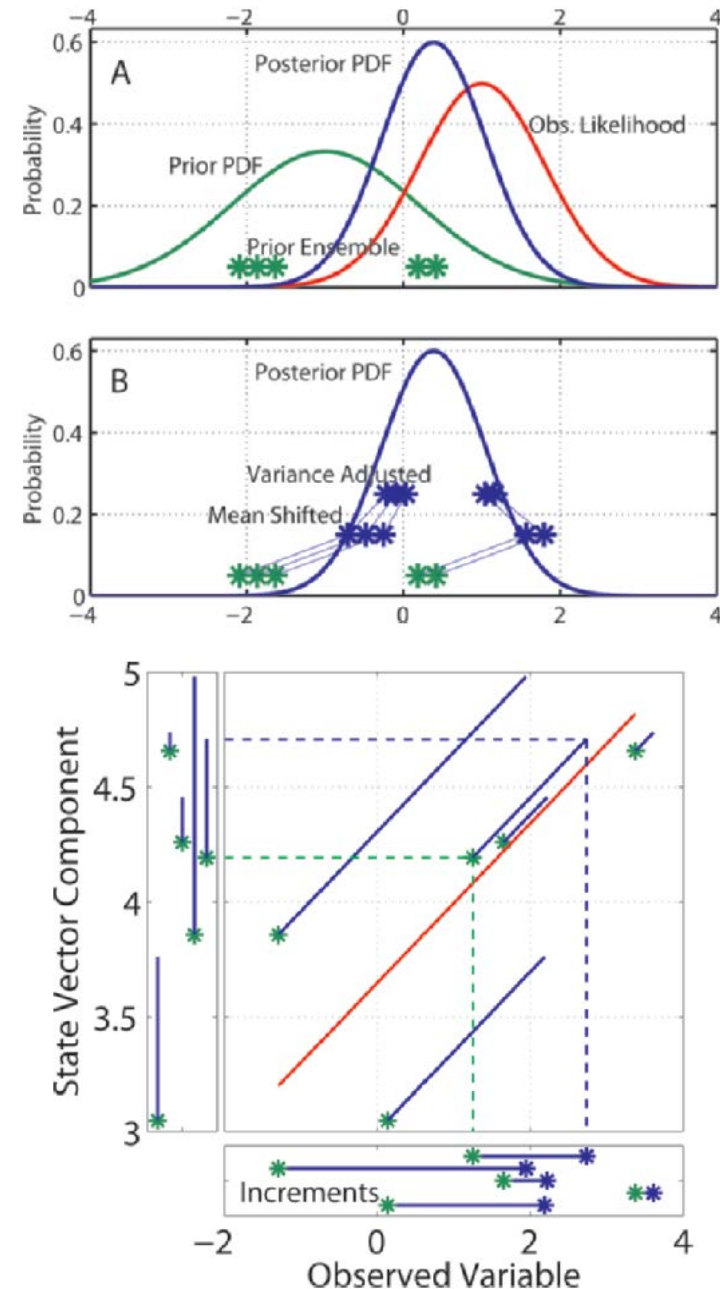


# EAKF in DART (Anderson et al. 2009 BAM)

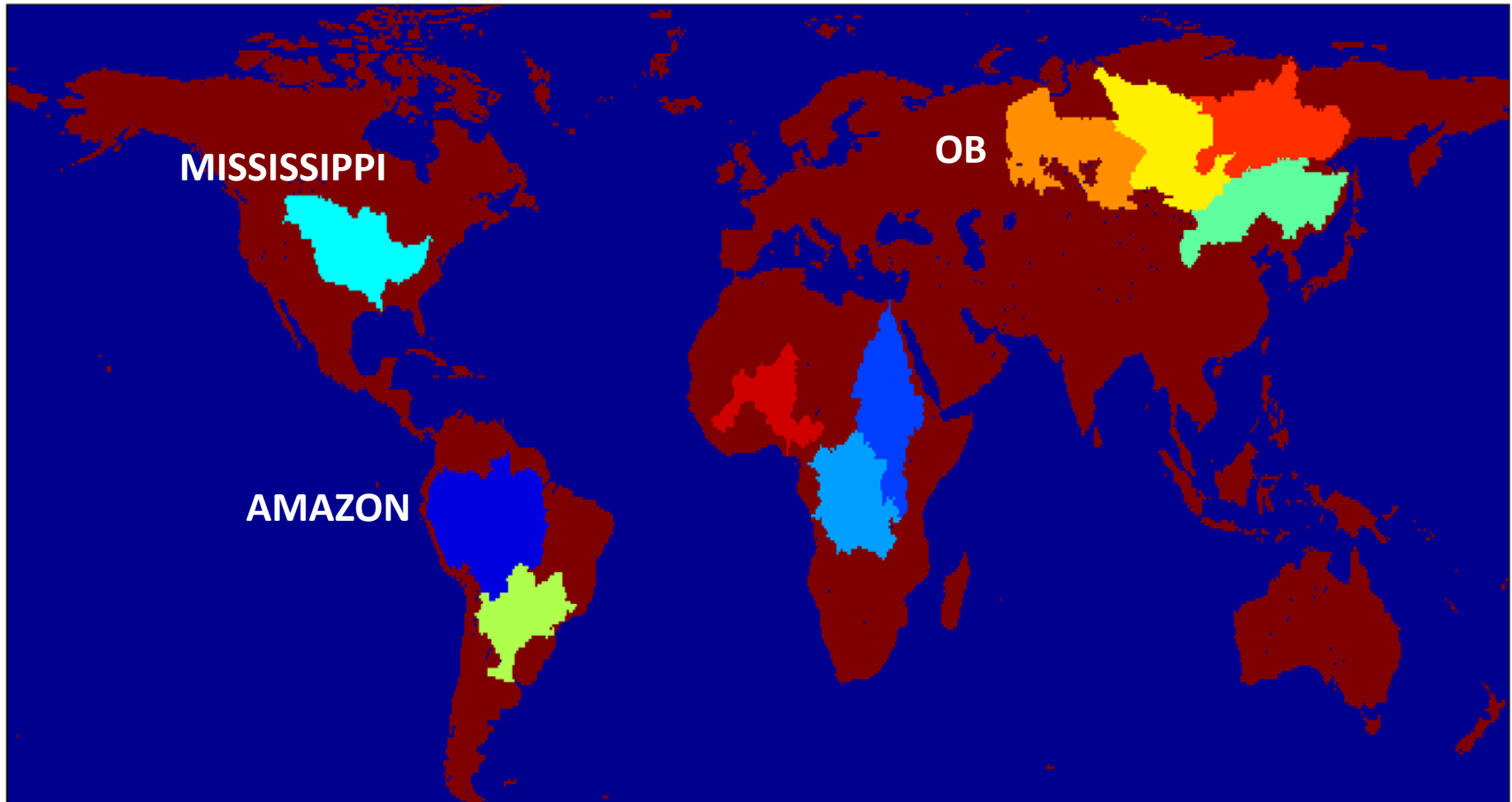
- How CLM states get updated (take GRACE assimilation as an example)?
  - First, an ensemble of prior observations is computed with forward operator
    - TWS=H2OCAN+H2OSOI+WA+H2OSO
  - Second, observation increments are first computed following Bayes theorem given the prior distribution (TWS ensemble mean and variance) and observation likelihood (GRACE TWS mean and error variance)
  - Third, increments for each component of the prior state vector (H2OCAN, H2OSOI, WA, and H2OSO) are individually computed from observation increments by linear regression (may have problem when forward operator is highly non-linear, e.g. for AMSR-E TB assimilation).

$$WA_{inc} = TWS_{inc} \cdot \frac{cov(WA_{prior}, TWS_{prior})}{var(TWS_{prior})},$$

$$cov(WA_{prior}, TWS_{prior}) = \frac{1}{N_{ens}-1} \sum_{i=1}^{N_{ens}} (WA_{prior,i} - \overline{WA_{prior}}) (TWS_{prior,i} - \overline{TWS_{prior}})$$

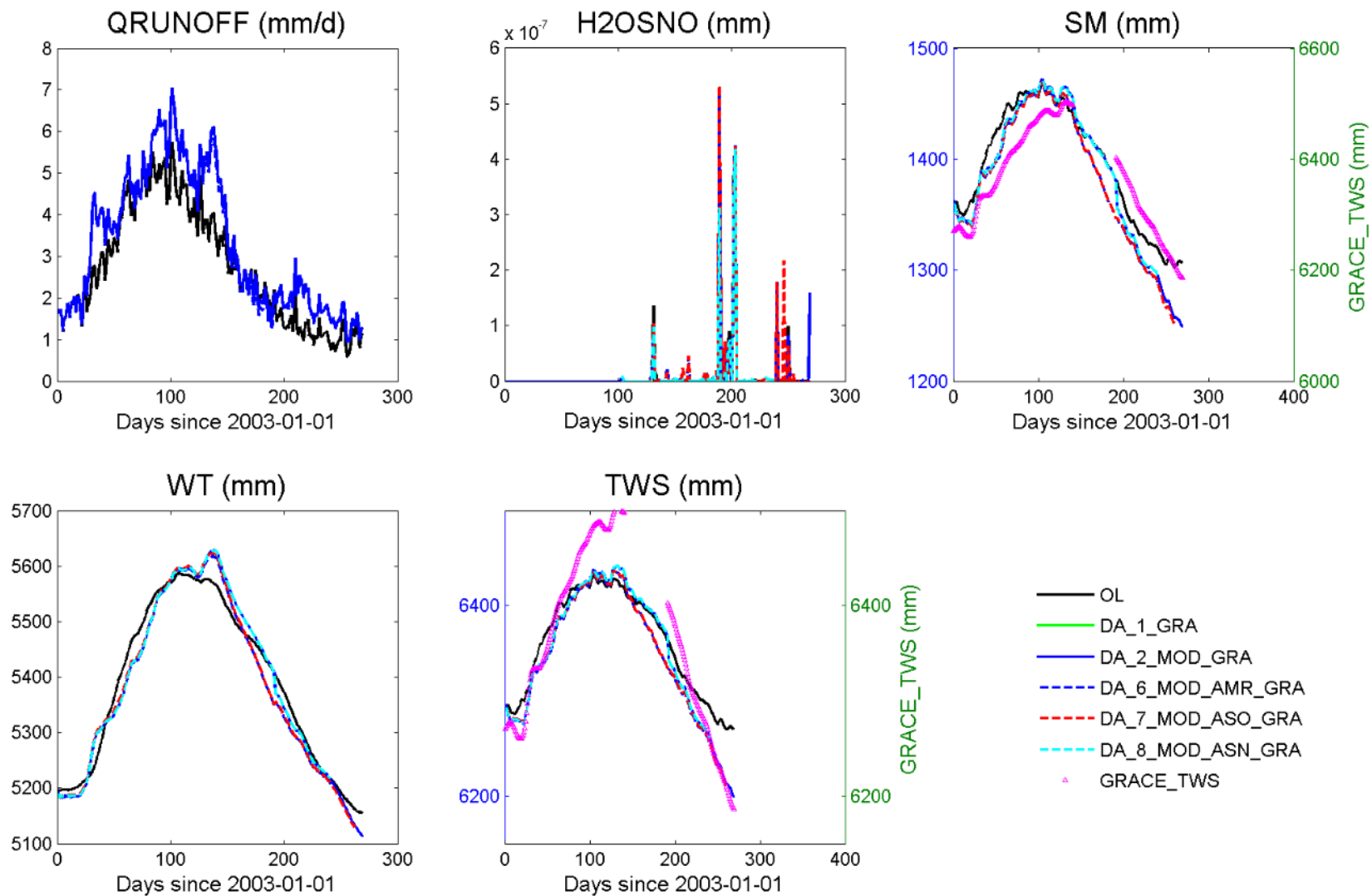


# Global River Basins (tropics, mid, and high latitudes)



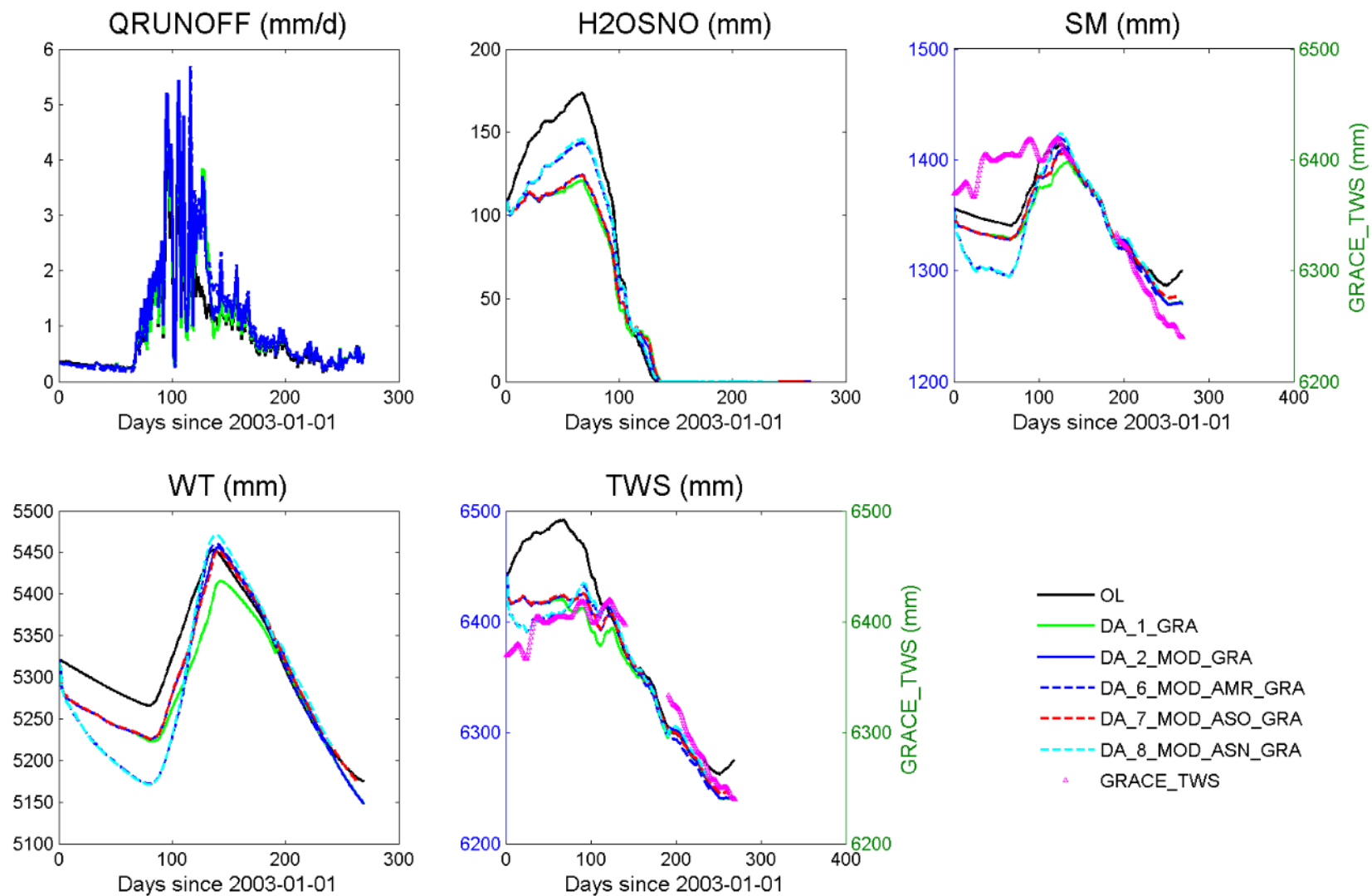
- Results from one-year integration (January–September 2003)

# AMAZON

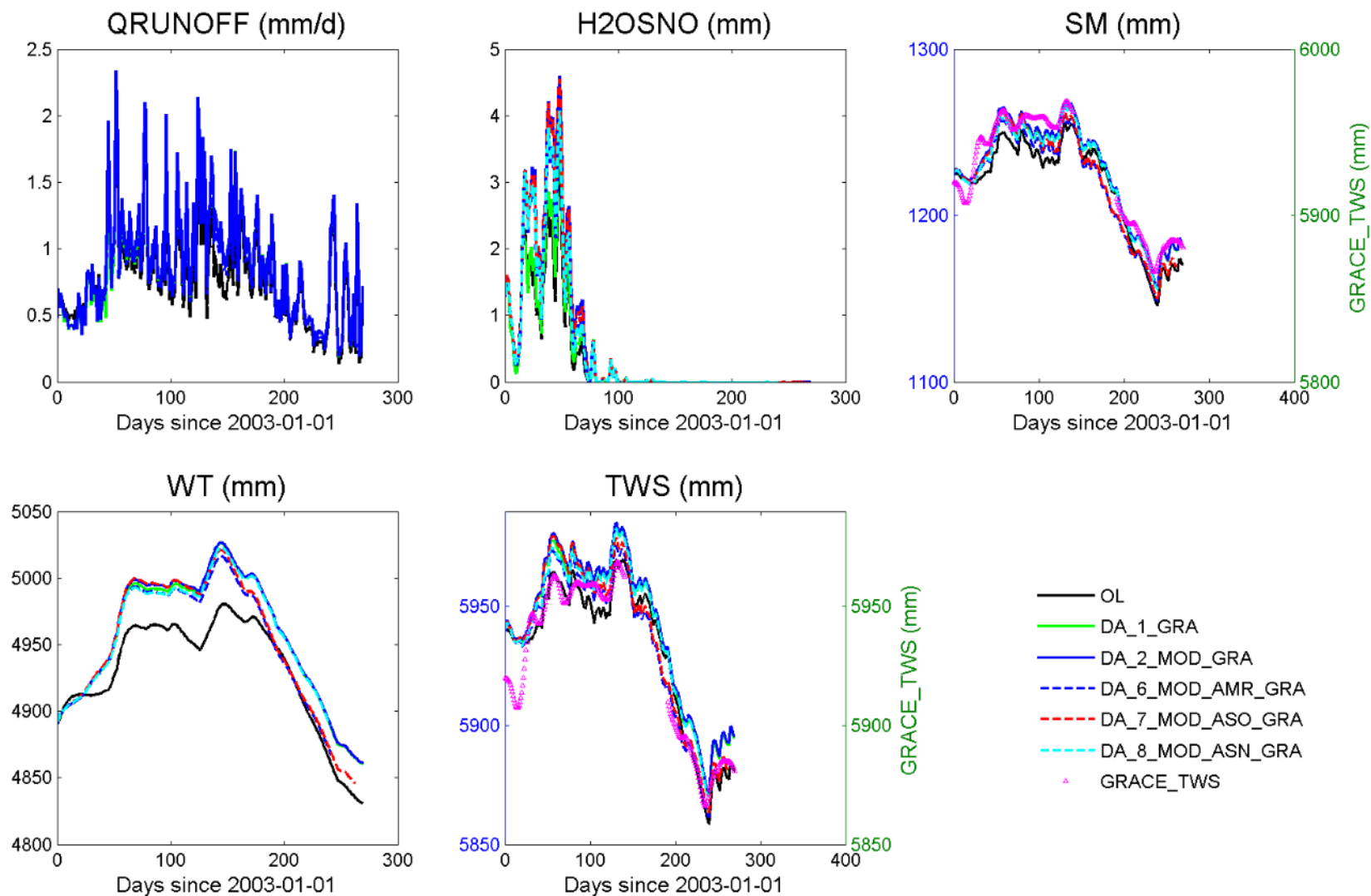




OB

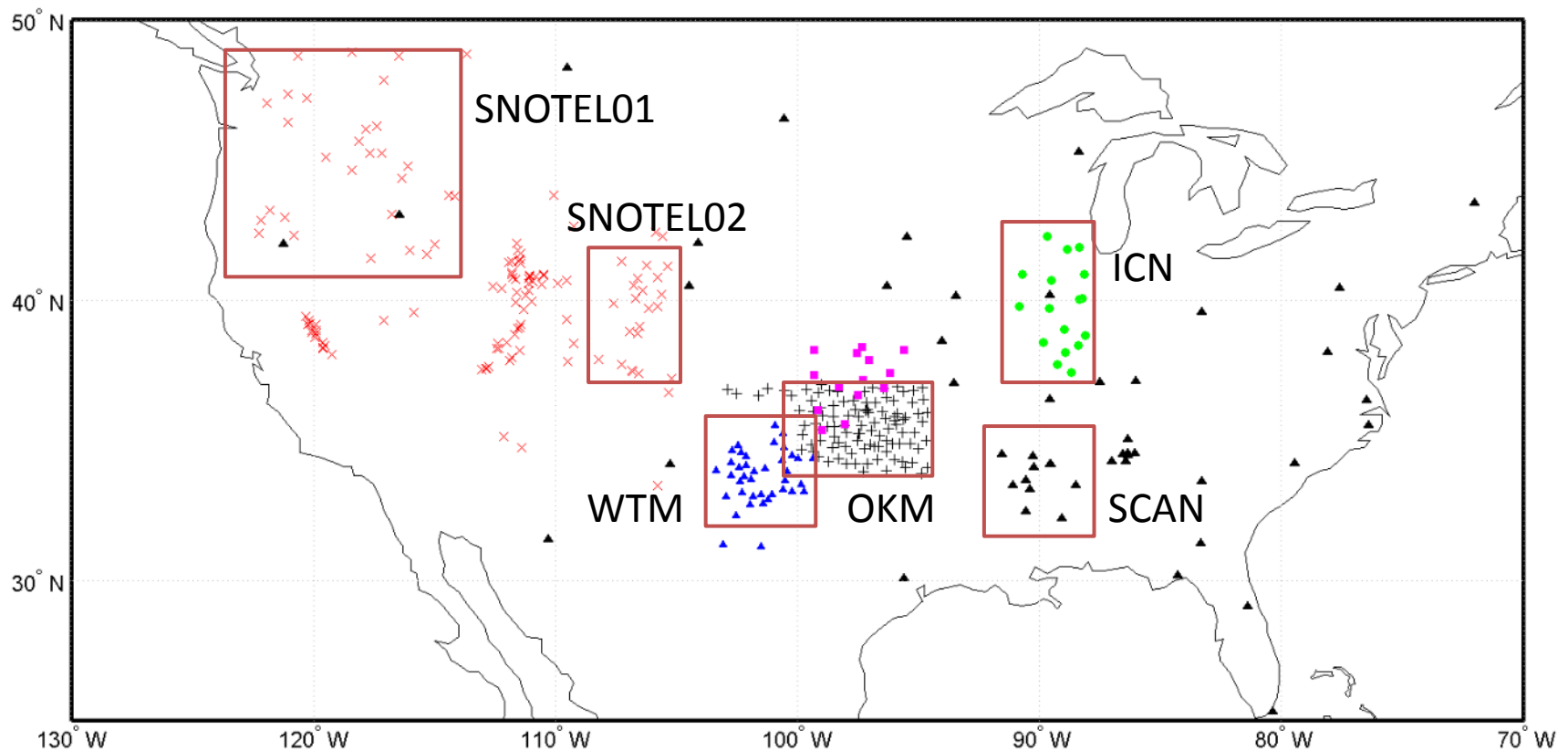


# MISSISSIPPI



# Soil moisture evaluation

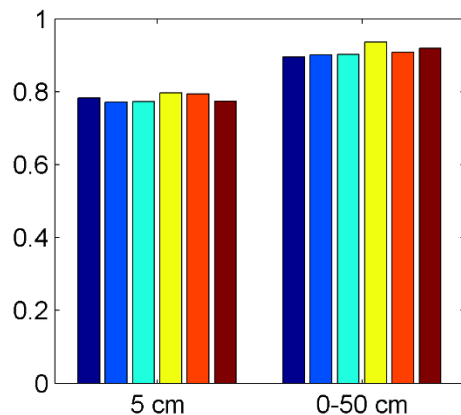
- Networks
  - Oklahoma Mesonet, [West Texas Mesonet](#), Soil Climate Analysis Network, [Illinois Climate Network](#), [SNOTEL](#)
- Evaluating depth:
  - Surf: 5 cm (CLM L3, 6.2 cm); Root: 0-50 cm (CLM L1-6 aggregated)
- Temporal coverage: 01/01/2003–09/25/2003



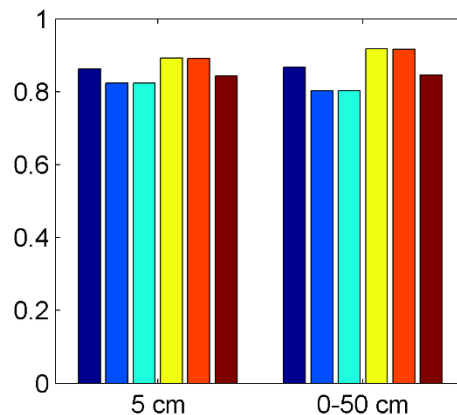
# Soil moisture evaluation: correlation

multi\_OL DA\_1\_GRA DA\_2\_MOD\_GRA DA\_6\_MOD\_AMR\_GRA DA\_7\_MOD\_ASO\_GRA DA\_8\_MOD\_ASN\_GRA

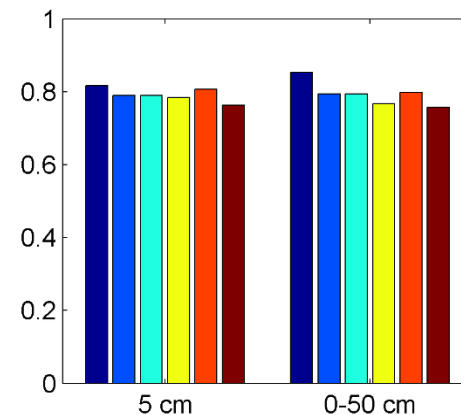
OKM



WTM

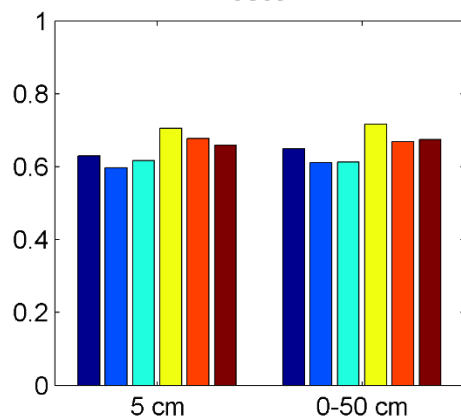


SCAN

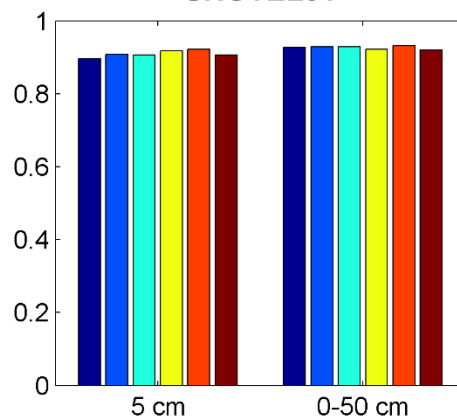


R

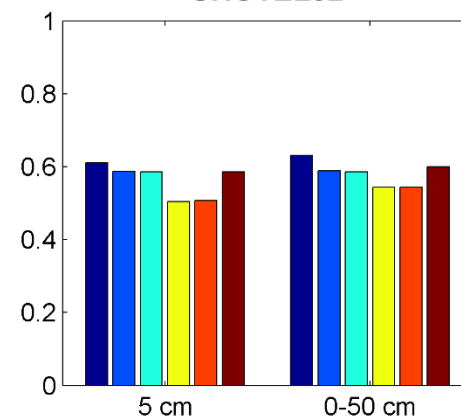
ICN



SNOTEL01



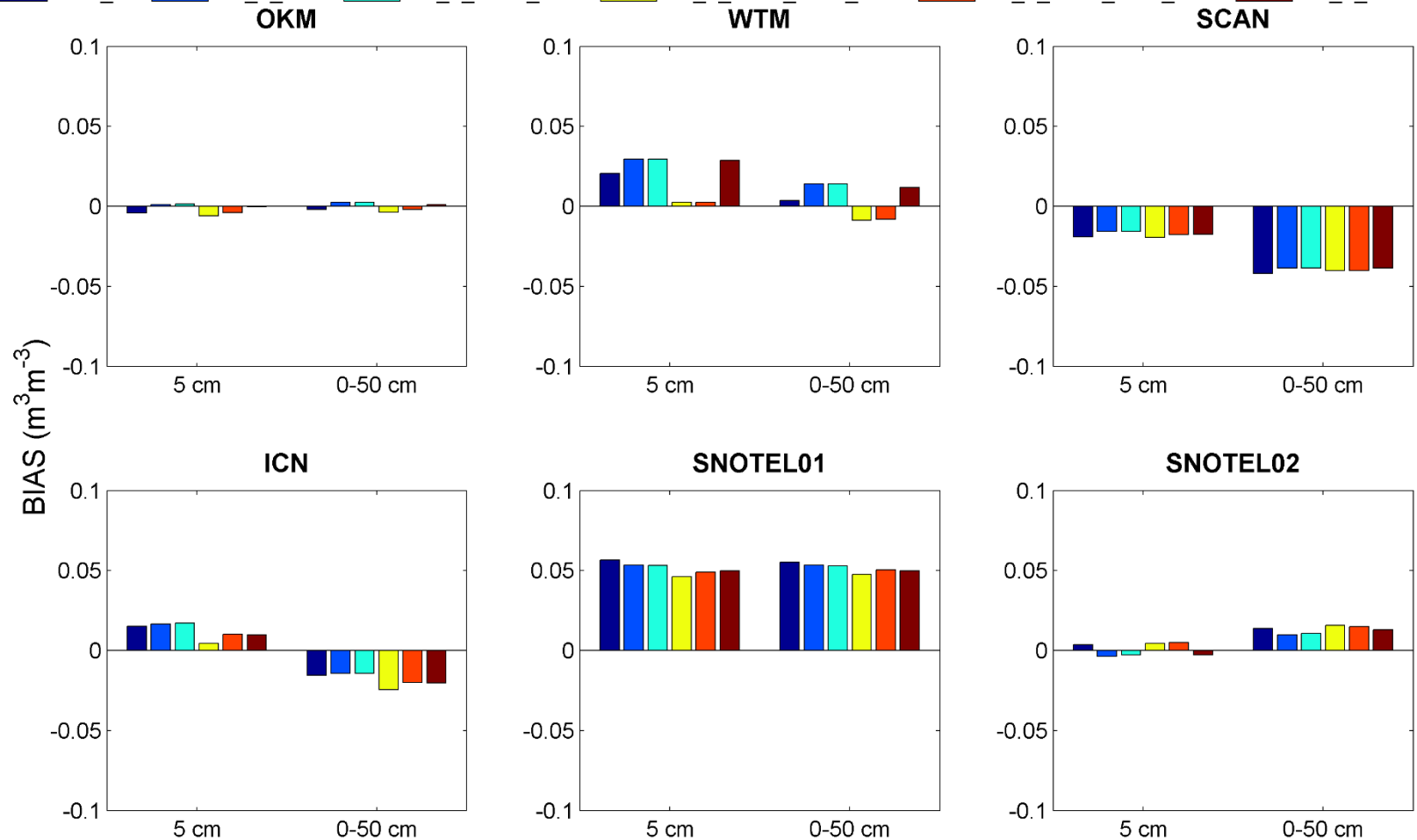
SNOTEL02





# Soil moisture evaluation: BIAS ( $\text{m}^3\text{m}^{-3}$ )

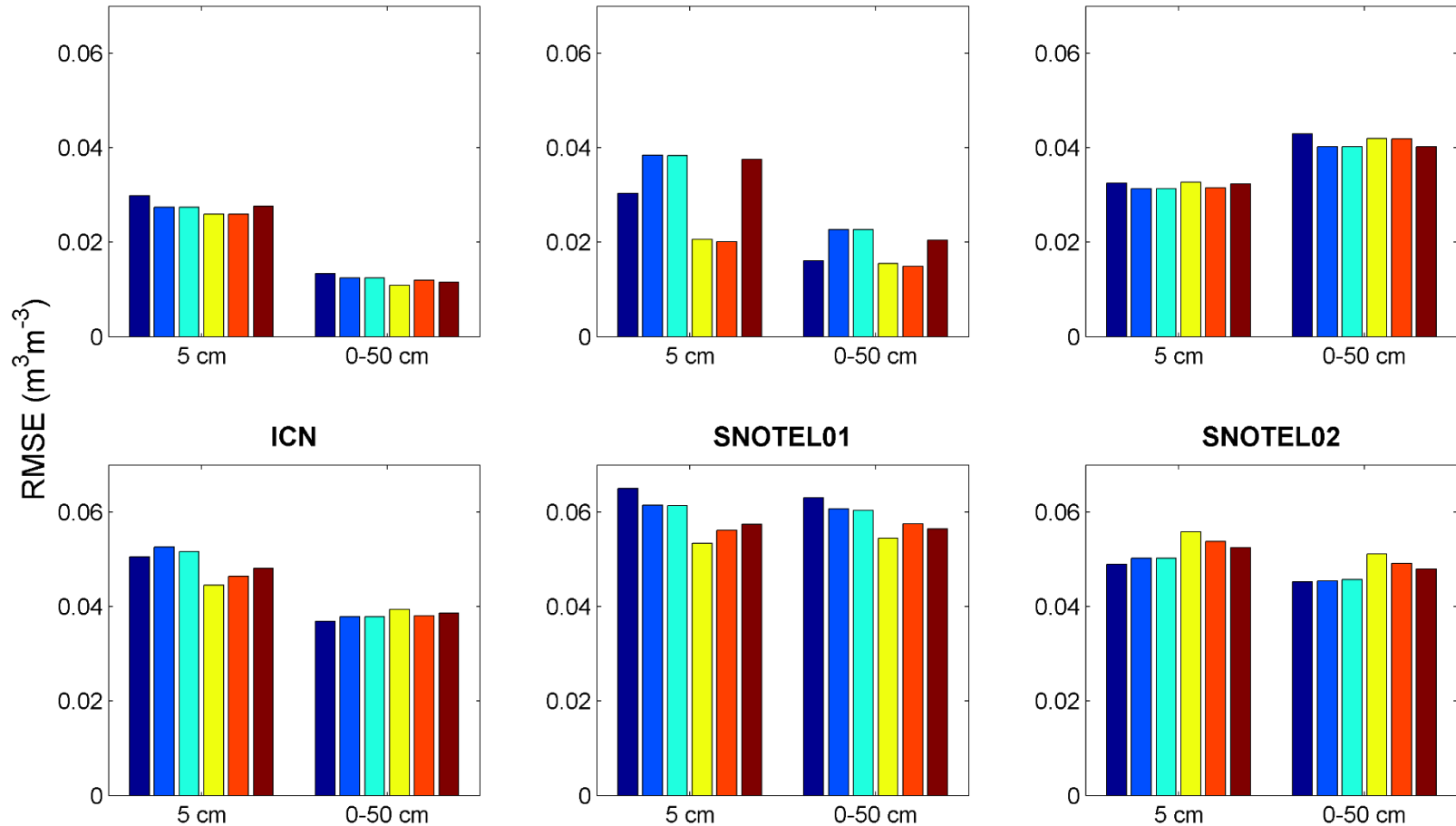
multi\_OL DA\_1\_GRA DA\_2\_MOD\_GRA DA\_6\_MOD\_AMR\_GRA DA\_7\_MOD\_ASO\_GRA DA\_8\_MOD\_ASN\_GRA



# Soil moisture evaluation: RMSE ( $\text{m}^3\text{m}^{-3}$ )

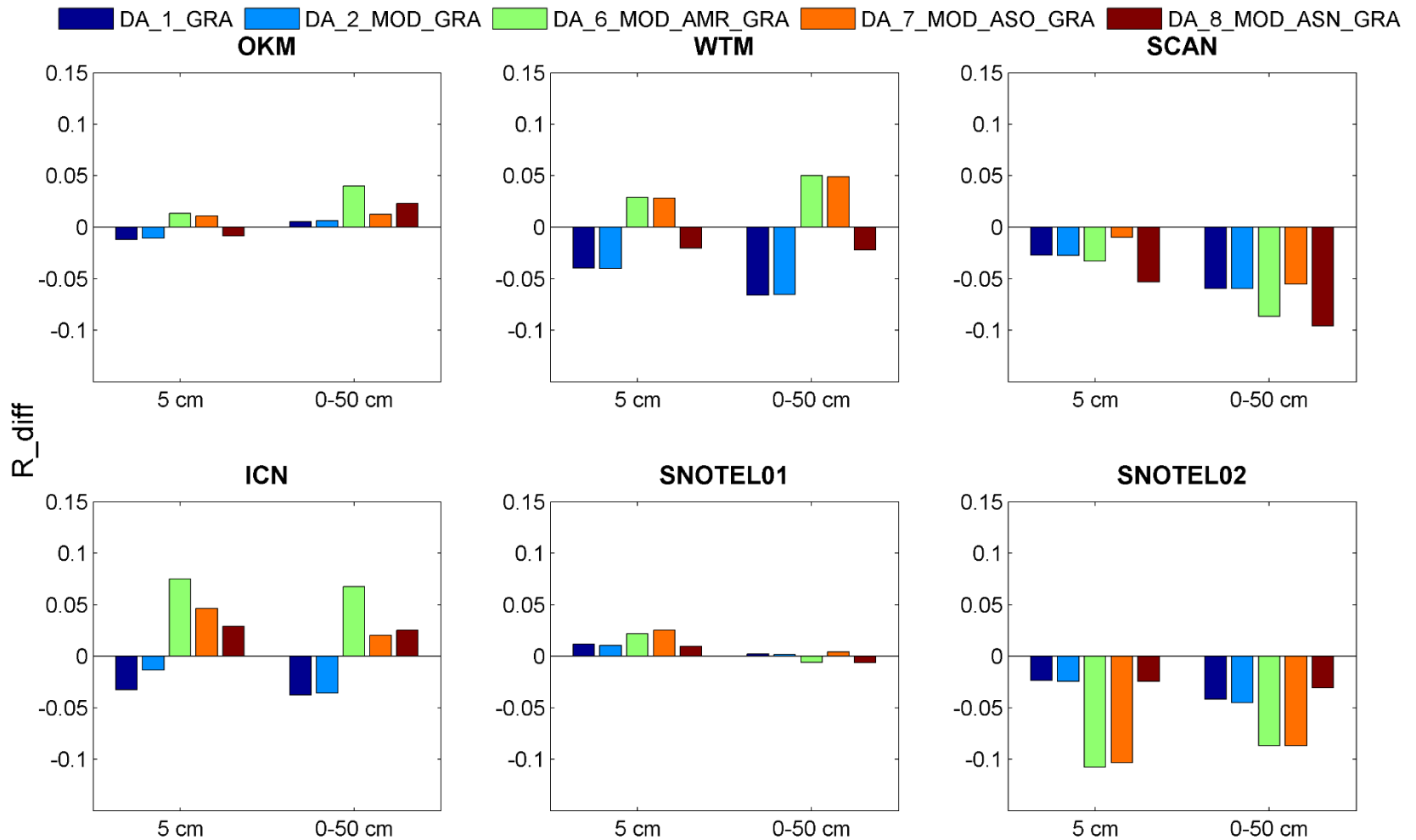
multi\_OL DA\_1\_GRA DA\_2\_MOD\_GRA DA\_6\_MOD\_AMR\_GRA DA\_7\_MOD\_ASO\_GRA DA\_8\_MOD\_ASN\_GRA

OKM WTM SCAN



# Soil moisture evaluation: relative improvement of DA from OL

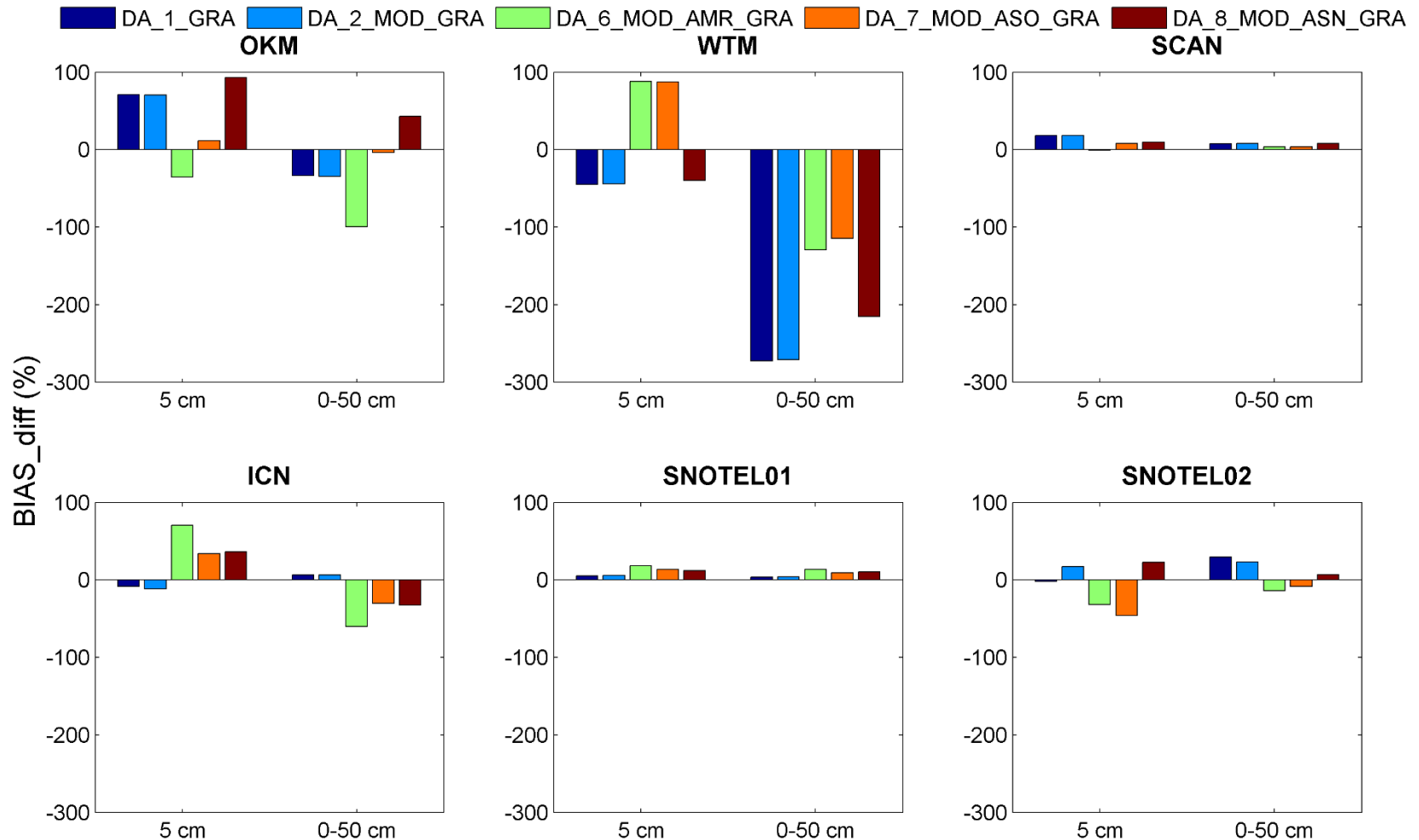
- $R_{diff} = R_{DA} - DA_{OL}$



Positive values – improvement; negative values - degradation

# Soil moisture evaluation: relative improvement of DA from OL

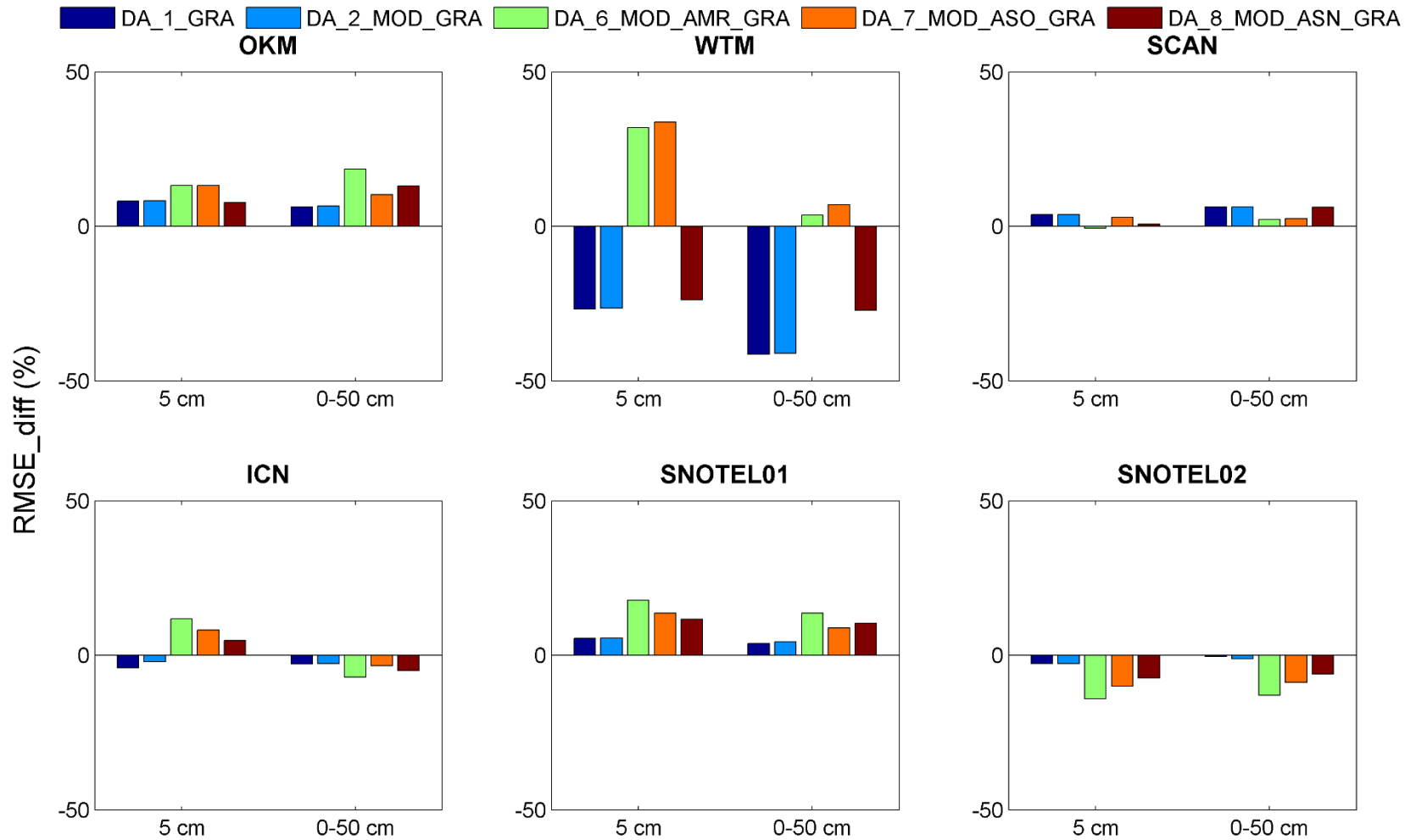
- $\text{BIAS\_diff} = [\text{abs}(\text{BIAS\_OL}) - \text{abs}(\text{BIAS\_DA})] / \text{abs}(\text{BIAS\_OL}) \times 100\%$



Positive values – improvement; negative values - degradation

# Soil moisture evaluation: relative improvement of DA from OL

- $RMSE\_diff = (RMSE\_OL - RMSE\_DA) / RMSE\_OL \times 100\%$



Positive values – improvement; negative values - degradation



# Summary (1)

- Key findings
  - Initial snow DA results (MODIS only, AMSR-E snow  $T_B$ , joint MODIS and GRACE) are encouraging.
  - Initial AMSR-E soil  $T_B$  DA is encouraging.
  - Performance from joint AMSR-E snow  $T_B$ , soil  $T_B$ , and GRACE DA is location-dependent.
  - *DA\_6\_MOD\_AMR\_GRA* and *DA\_7\_MOD\_ASO\_GRA* generally outperform other DA cases for most selected sub-regions (as seen from *RMSE\_diff*).
  - Assimilating AMSR-E  $T_B$  can introduce additional increments in soil moisture and/or snow, which in turn lead to different increments in groundwater through the assimilation of GRACE TWS.

# Summary (2)

- Reliable source of groundwater and runoff observations needed for a more comprehensive evaluation.
- Ongoing multi-sensor-DA implementations to produce long-term (2003–2010) land surface state outputs.

# Future Work

- Future directions
  - Use this multi-sensor land DA framework
    - to test different groundwater schemes
    - To guide model developments
  - Link land DA with multi-physics and parameter estimation
  - Explore information content in GRACE
  - Climate and hydrological predictions
  - Theoretical DA research
    - DA with coupled land–atmosphere system
    - DA with fully coupled earth system
    - DA with decision support system

# Summary (3)

Ultimately, we will provide historical and near real-time high-resolution ( $<10$ -km and hourly) gridded products of soil moisture, snow mass, water table depth, vegetation phenology, evapotranspiration, and runoff, a suite of critical variables for monitoring droughts and floods.

To archive the time series of these variables for the past decade for detailed spatiotemporal pattern analysis.

Regional-scale applications for water resource management by collaborating with local and state agencies.