Global Multisensor Multivariate Land Data Assimilation and Its Value in Hydroclimate Prediction

Peirong Lin, **Zong-Liang Yang***, Long Zhao
(liang@jsg.utexas.edu)

UT-Austin: Wen-Ying Wu, Yonghwan Kwon, Yongfei Zhang, Jiangfeng Wei, Xiaolu Ling, Hua Su
NCAR: Timothy Hoar, Jeffrey Anderson
NASA: Alley Toure, Matthew Rodell

CESM Land Model and Biogeochemistry Working Group Meeting
Feb 6, 2018

Grand Objectives

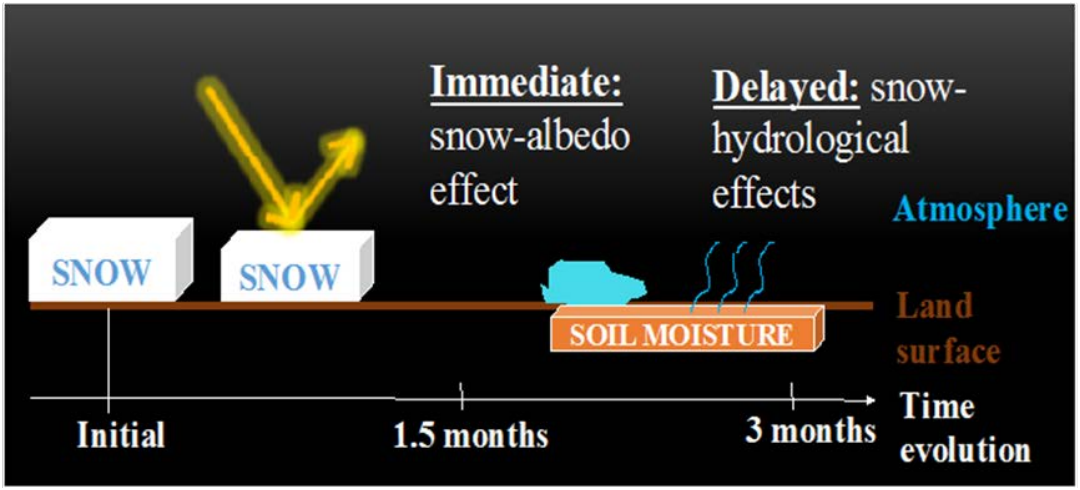
- **Develop** a multi-mission, multi-platform, multi-source, and multi-scale land data assimilation system combining latest developments in both observations and models

- **Improve** intraseasonal to seasonal climate and hydrological predictions

Land vs. Seasonal Climate Prediction

- **Land memory: important sources of predictability**
  - **Snow:** Douville (2010); Jeong et al. (2013); Orsolini et al. (2013)
  - **Soil moisture:** Koster et al. (2004; 2010; 2011); Hirsch et al. (2013)
  - **Vegetation:** Koster and Walker (2015); William and Torn (2015)
  - **Groundwater:** Jiang et al. (2009)

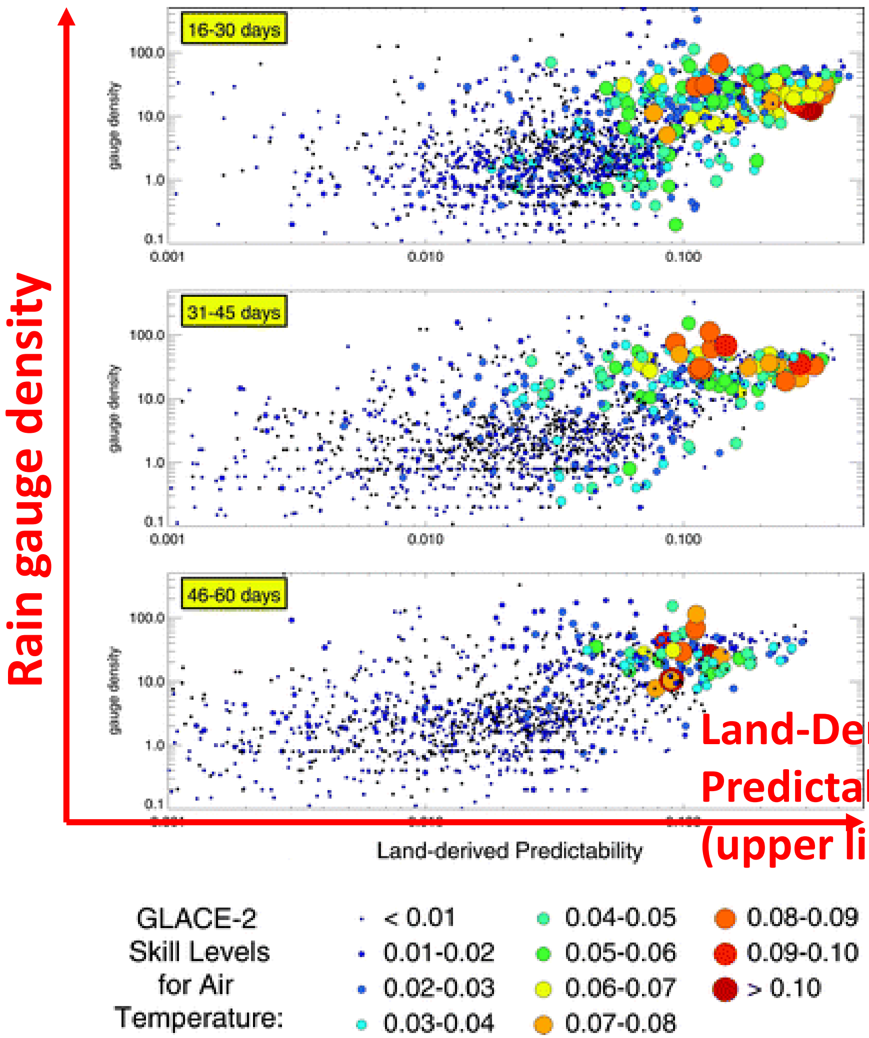
Example: snow in the climate system



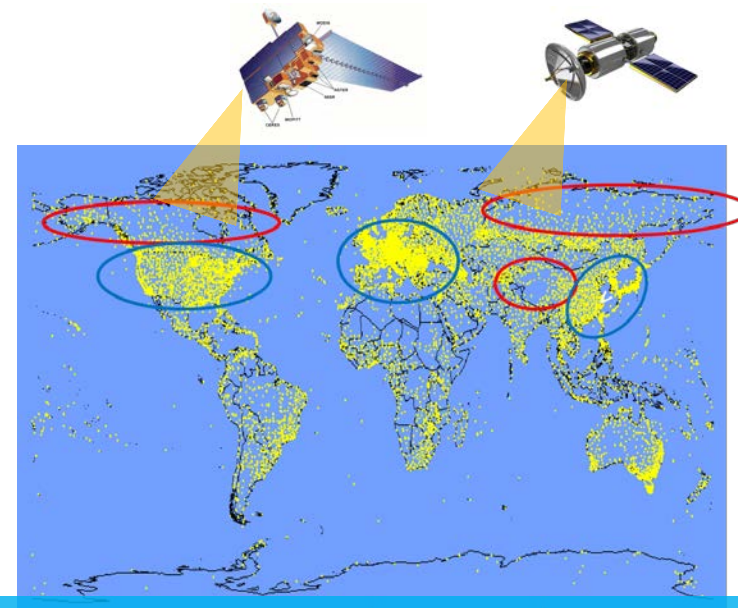
However, a lack of high-quality global land state datasets has been limiting the skill for climate prediction.

Land-Derived Seasonal Climate Skill

Koster et al. (*2011, JHM; GLACE-2*)



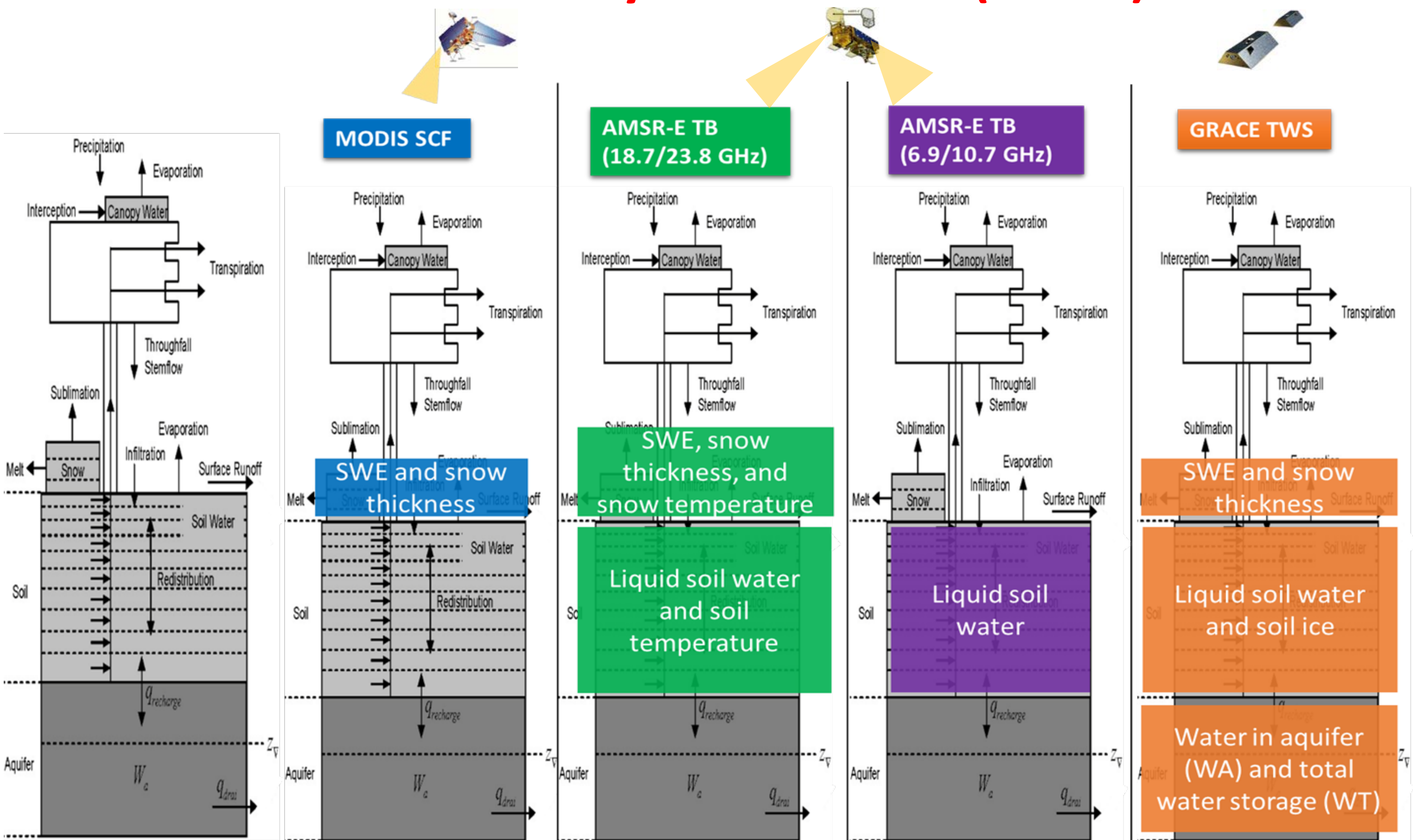
Land-Derived Predictability (upper limit)



Caveat

- Global land DA methodologies remain to be developed and refined;
- No land DA involved in state-of-the-art operational forecasting systems such as the NMME

Data Assimilation Research Testbed (DART) + Community Land Model (CLM4)



Zhang et al. (2014; 2016); Kwon et al. (2015; 2016); Zhao et al. (2016; 2018)

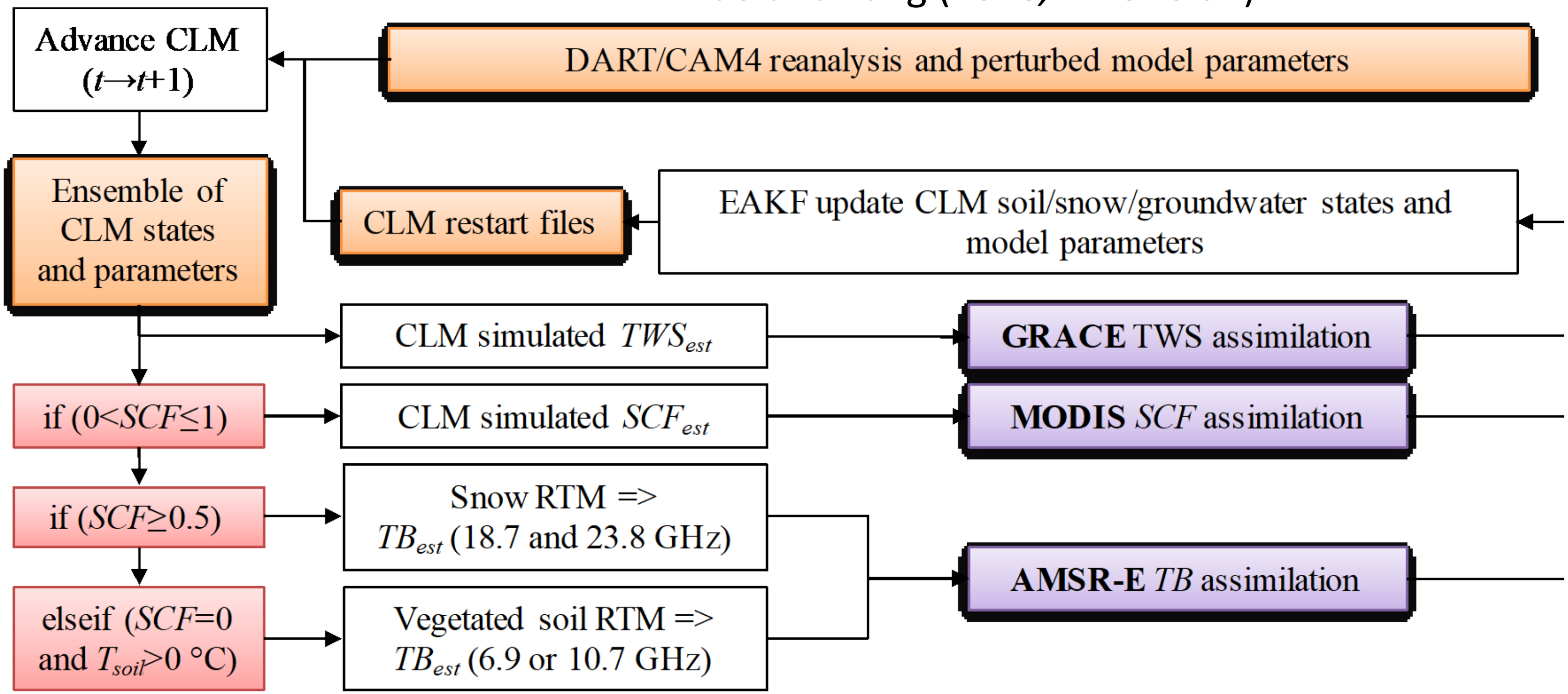
Methodology Development

Our **global multi-sensor multi-variate land DA system:**

- improves SCF and SWE estimates by assimilating MODIS SCF for unsaturated snow cover areas (0<SCF≤1)
- (Zhang et al. 2014, JGR; Zhang and Yang, 2016, JGR);
- improves SWE estimates by assimilating AMSR-E TB (18.7 and 23.8 GHz) for nearly saturated snow cover areas (SCF≥0.5)
- (Kwon et al., 2015; Kwon et al. 2016, JHM);
- improves soil moisture estimates 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);
- improves snow, soil moisture, and groundwater estimates by assimilating GRACE TWS.
- (Zhang and Yang, 2016, JGR; Zhao and Yang, 2018, RSE);

Multi-Sensor Land DA Prototype

Zhao and Yang (2018, *in revision*)



Research Questions:

- What are the relative contributions of different sensors?
- Can joint assimilation of multi-sensor observations improve the DA performance?

Eight Data Assimilation Experiments

Cases	MOD	GRA	ASO	ASN
OL	Open-loop, no DA			
DA_1_GRA		×		
DA_2_MOD_GRA	×	×		
DA_3_MOD_ASO	×		×	
DA_4_MOD_ASN	×			×
DA_5_MOD_AMR	×		×	×
DA_6_MOD_AMR_GRA	×	×	×	×
DA_7_MOD_ASO_GRA	×	×	×	
DA_8_MOD_ASN_GRA	×	×		×

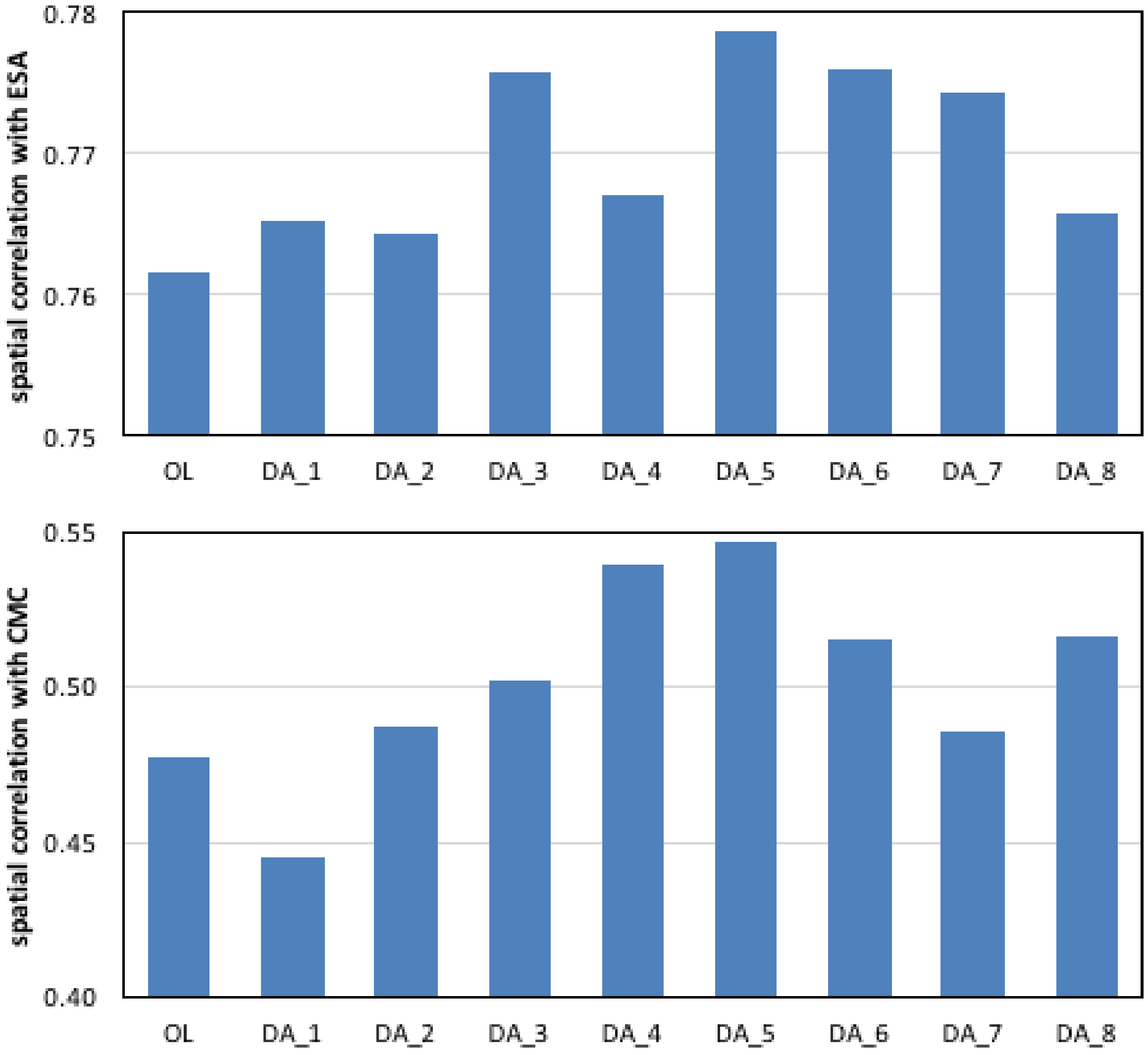
Zhao and Yang (2018; *Remote Sensing of Environment, in revision*)

Eight DA Experiments: Spatial Correlation

Spatial correlation:

Soil moisture (with ESA)

Snow depth (with CMC)

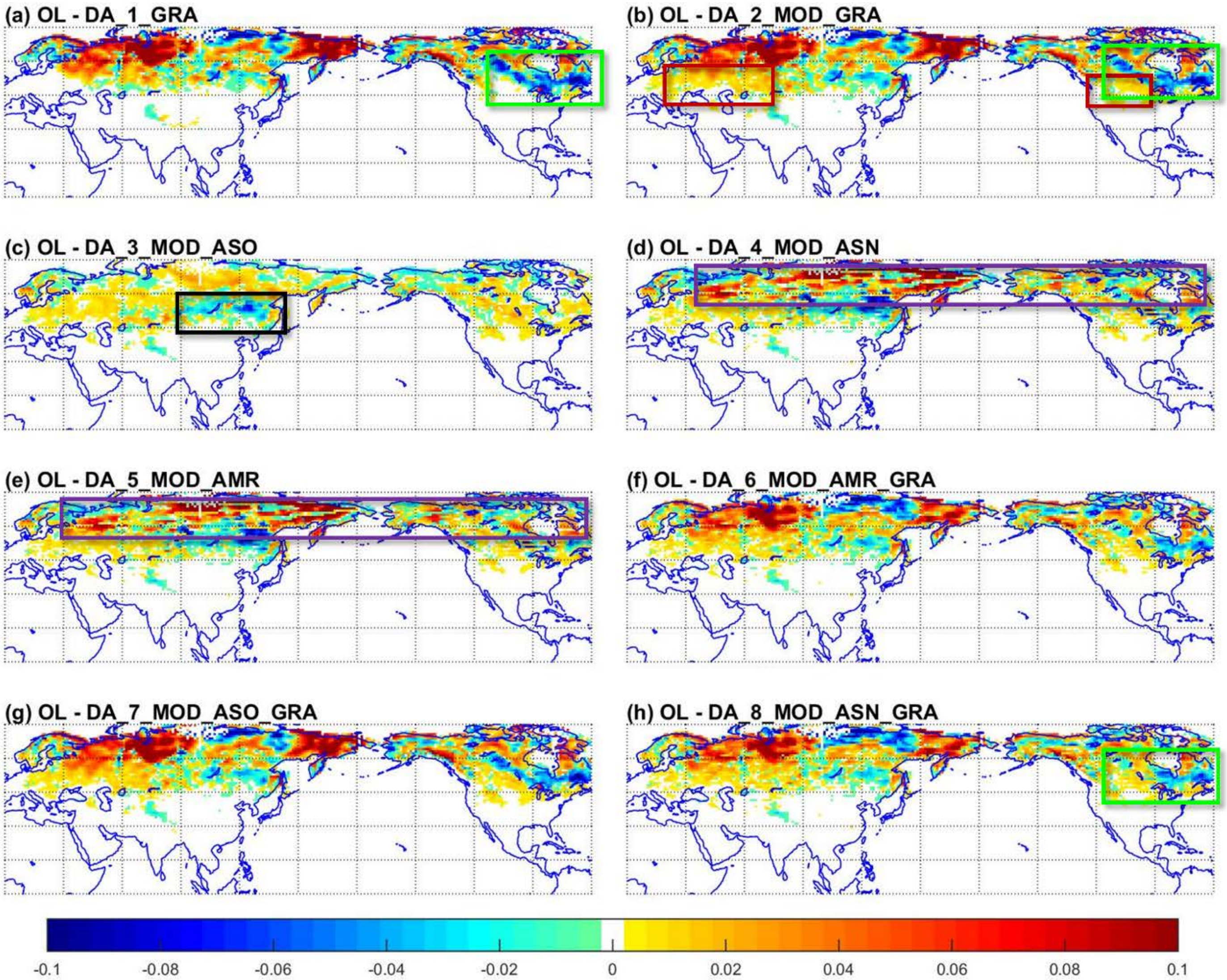


Zhao and Yang (2018; *Remote Sensing of Environment, in revision*)

Eight DA Experiments: Snow Depth

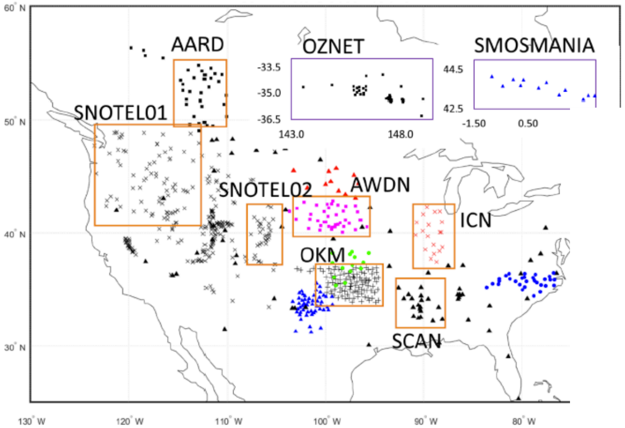
RMSE_diff = OL – DA

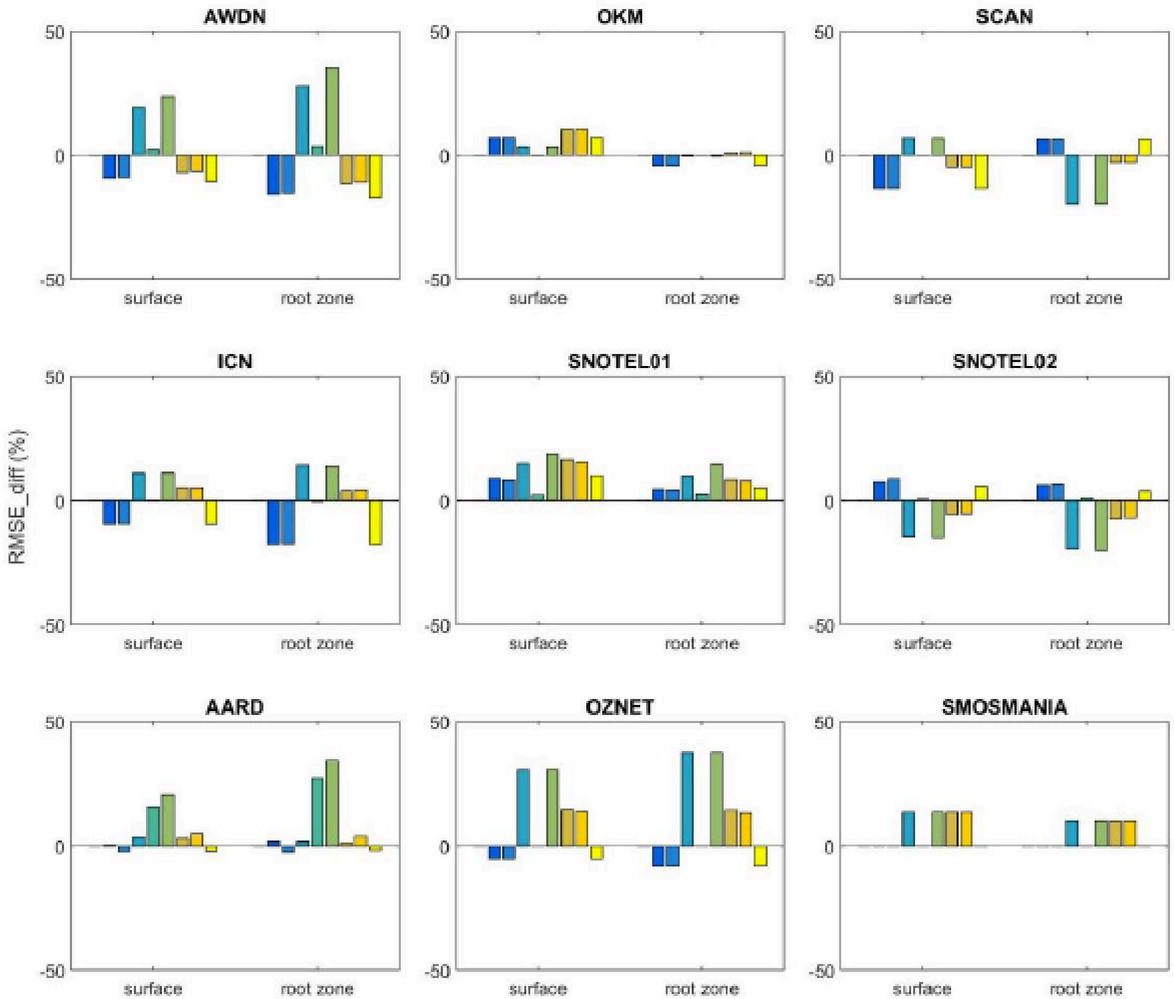
Red colors: improvements



Zhao and Yang (2018; *Remote Sensing of Environment, in revision*)

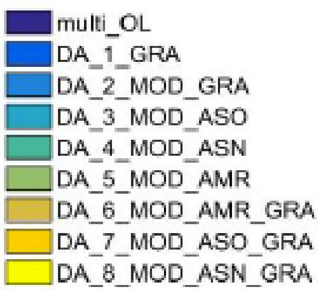
Eight DA Experiments: Soil Moisture





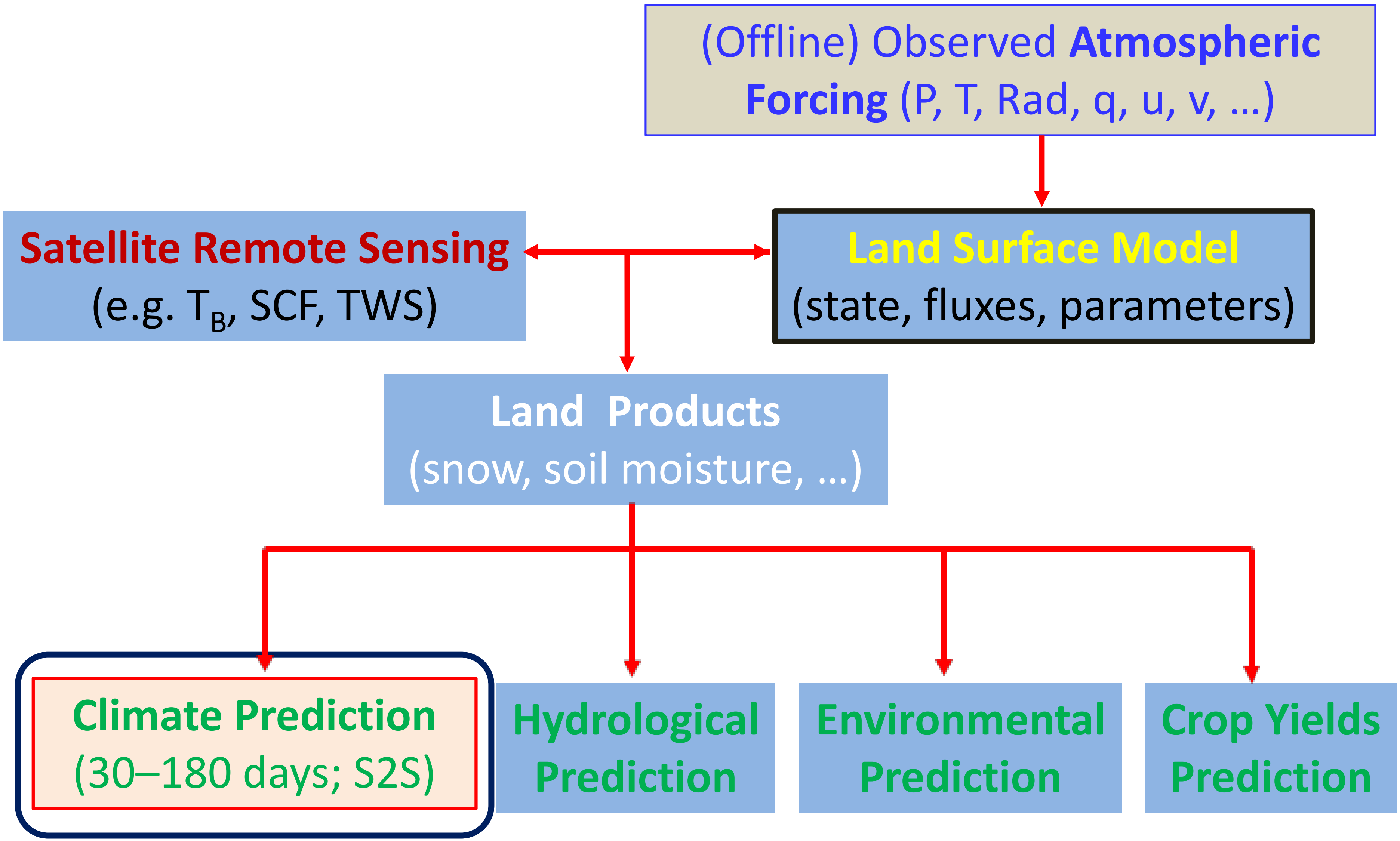
RMSE$_{_diff}$ =
OL – DA

Positive values:
improvements

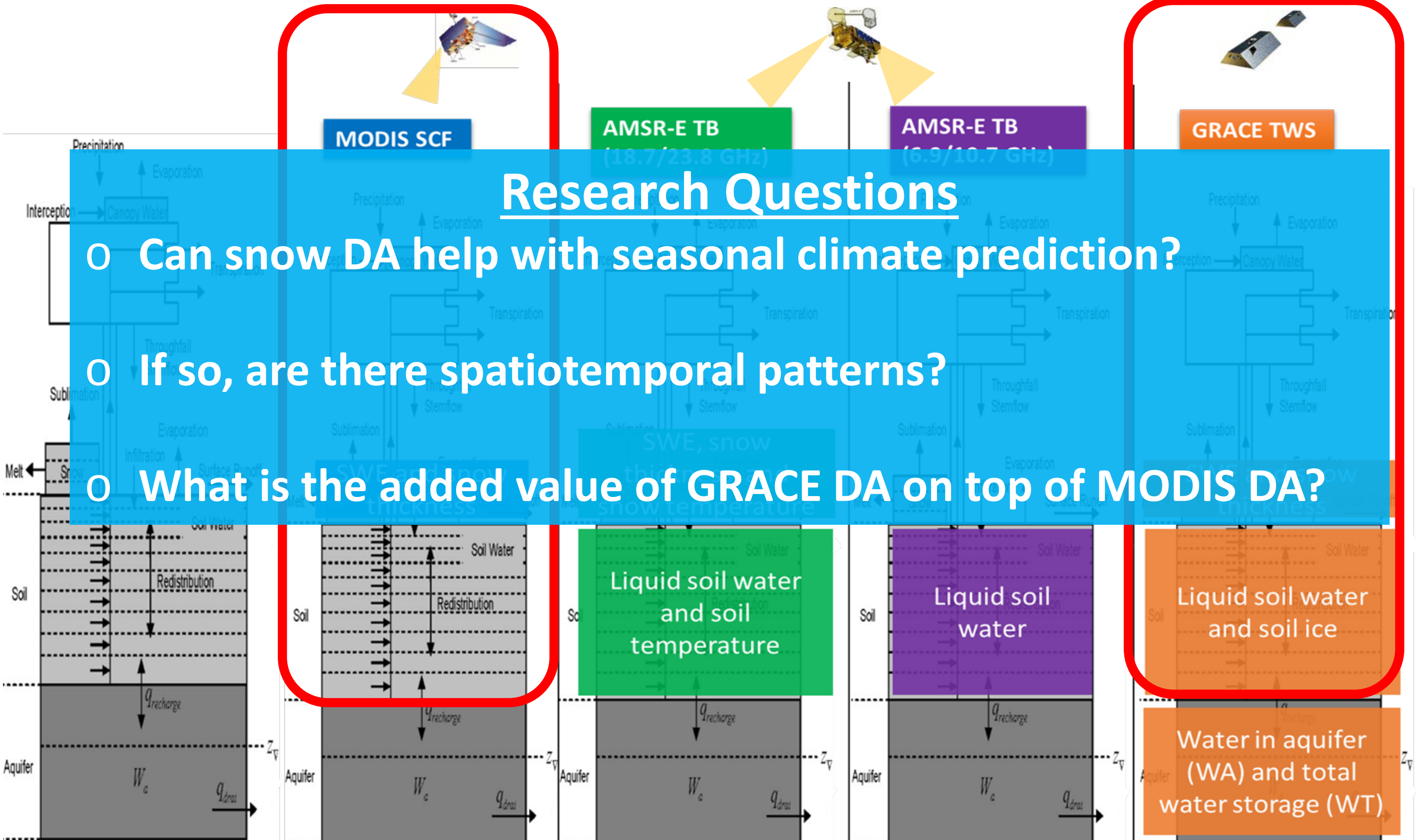


Zhao and Yang (2018; *Remote Sensing of Environment, in revision*)

Land DA in Seasonal Climate Prediction



Data Assimilation Research Testbed (DART) + Community Land Model (CLM4)



Research Questions

- Can snow DA help with seasonal climate prediction?
- If so, are there spatiotemporal patterns?
- What is the added value of GRACE DA on top of MODIS DA?

Zhang et al. (2014; 2016); Kwon et al. (2015; 2016); Zhao et al. (2016; 2018)

Experimental Design

- **<u>504 ensemble-based "hindcast" simulations</u>**
  - **Using the Community Earth System Model (CESM 1.2.1);**
  - **"AMIP" type runs: coupled CLM4-CAM5 experiments;**
- 2003 to 2009 (7 years): Initialized on Jan 1, Feb 1, Mar 1
  - *3 suites x 7 years x 3 start dates x 8 ensemble members*

	SST & Sea Ice	Atmosphere (CAM5)	Land Initialization
OL	Prescribed using Hadley Centre data	Initialized using ERA-Interim data, 8-ensemble	CLM4 simulation **without DA**
MOD			CLM4 simulation that assimilated **MODIS SCF**
GRAMOD			CLM4 simulation that jointly assimilated **MODIS SCF** & **GRACE TWS**

Lin et al. (2016; GRL)

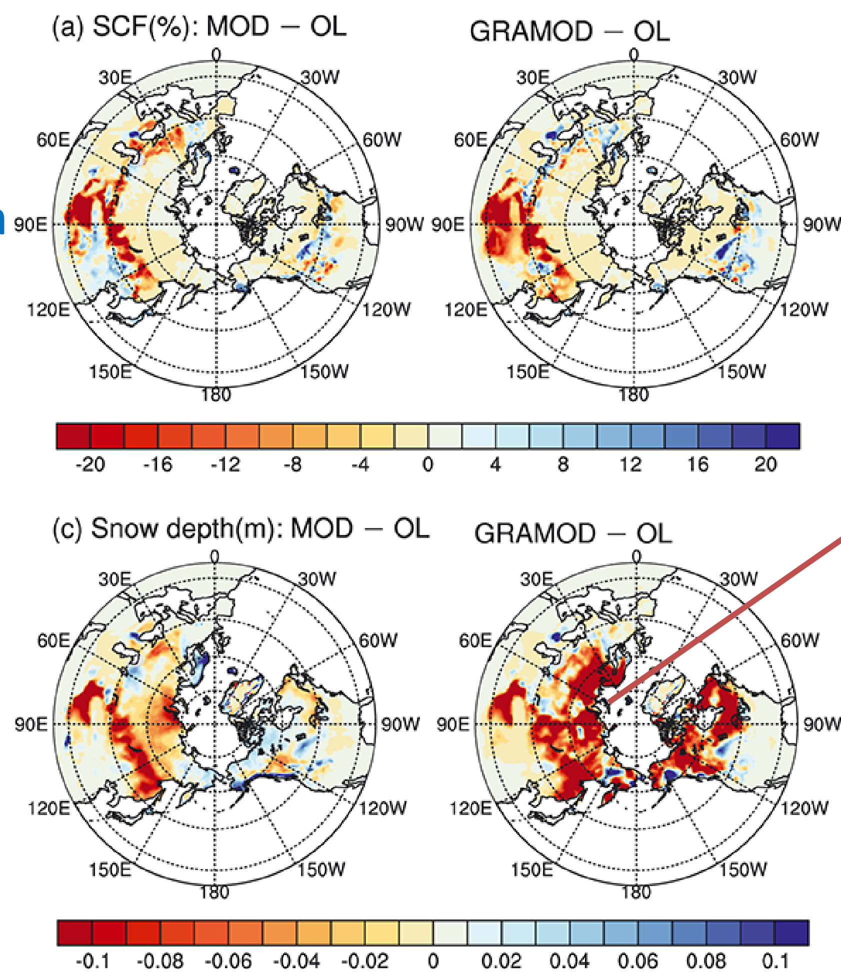
DA-Induced Changes: Initial Snow Conditions

MOD – OL

GRAMOD – OL

Snow Cover Fraction

Snow depth



- OL mostly overestimates snow
- DA alleviates this problem by reducing snow over most land areas

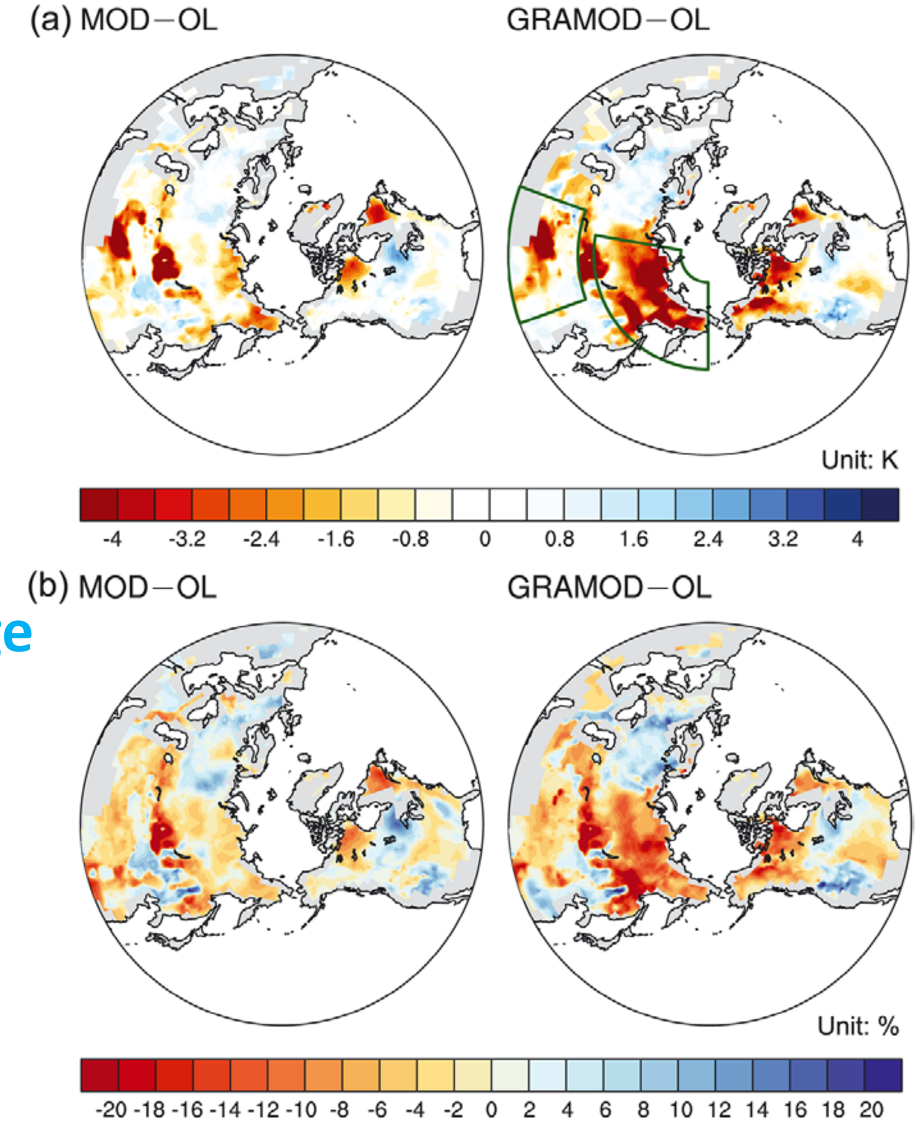
GRACE: additional snow mass information

Lin et al. (2016; GRL)

2-m Temperature Prediction

cRMSE

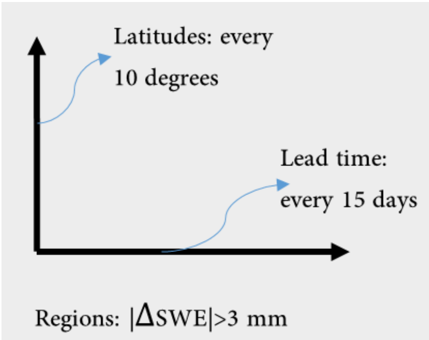
Percentage change

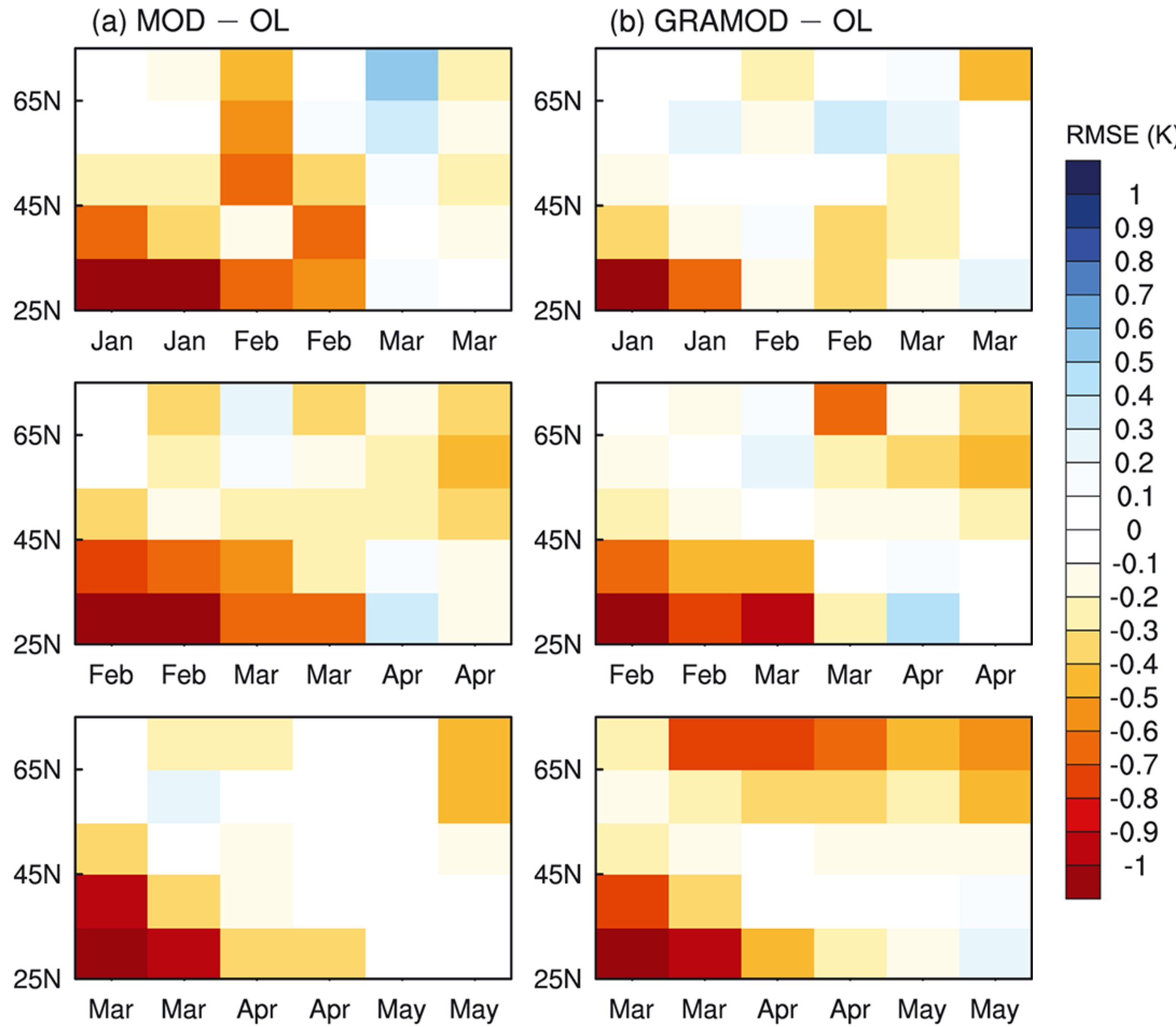


Lin et al. (2016; GRL)

5 – 25% local improvements:
- Tibetan Plateau
- High-latitude (e.g. Siberia)

Interesting Latitudinal Pattern





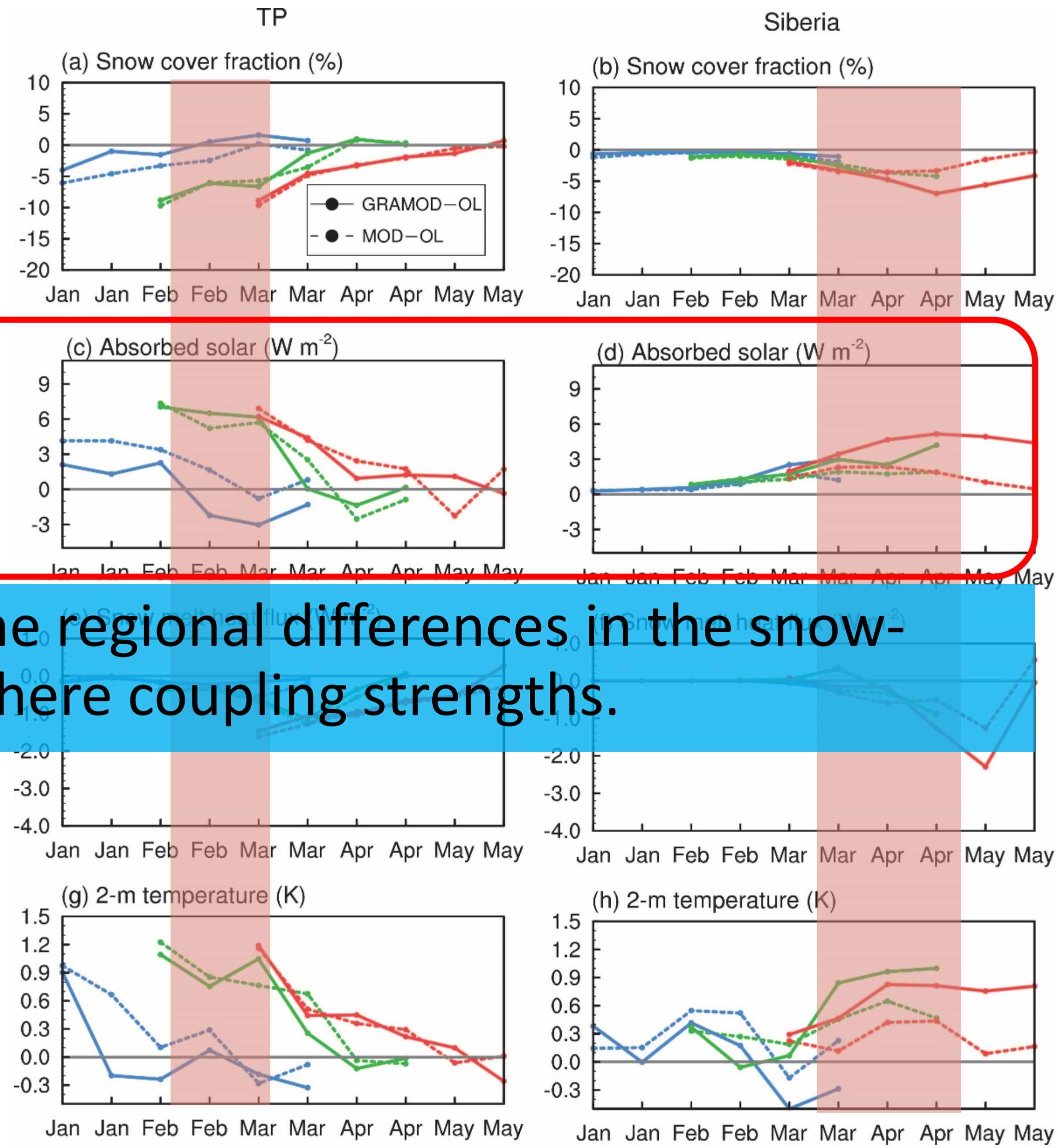
Lower latitude: immediate improvements;

Higher latitude: improvements appear later in warmer months

Lin et al. (2016; GRL)

Why Such Latitudinal Patterns?

- Snow cover fraction (%)
- Absorbed solar (w m^{-2})
- Snowmelt heat flux (w m^{-2})
- T_{2m} (K)

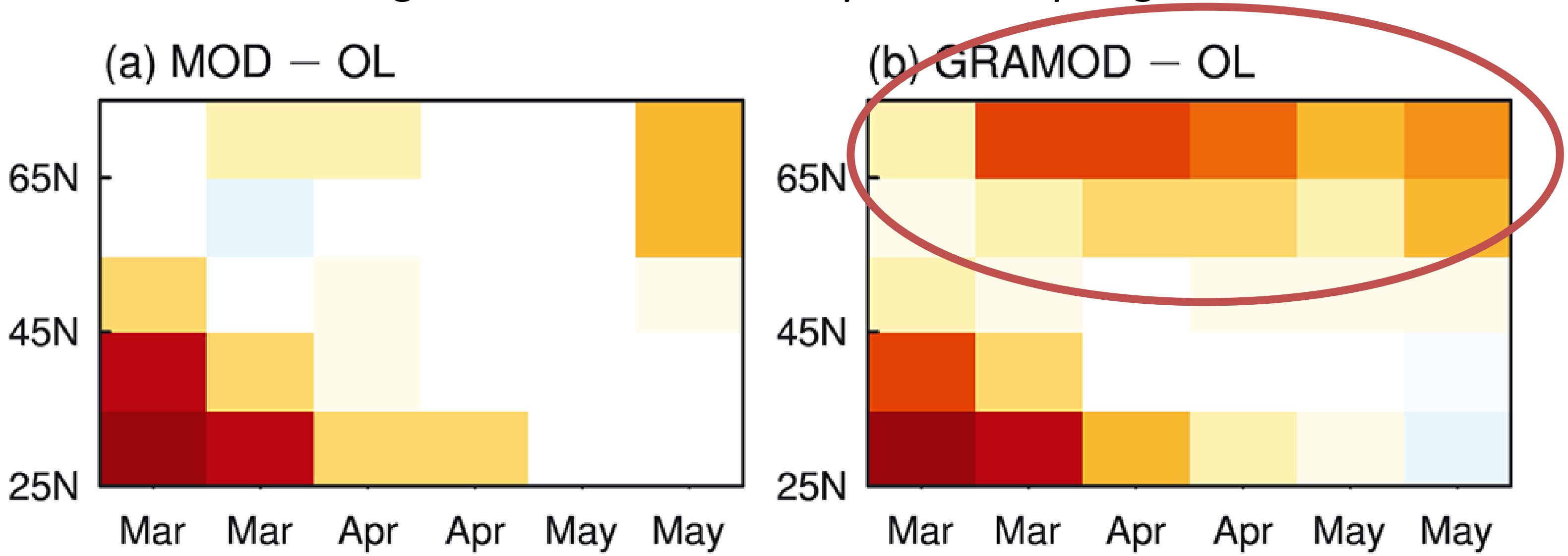


This is related to the regional differences in the snow-atmosphere coupling strengths.

Lin et al. (2016; GRL)

Rebound in Predictability

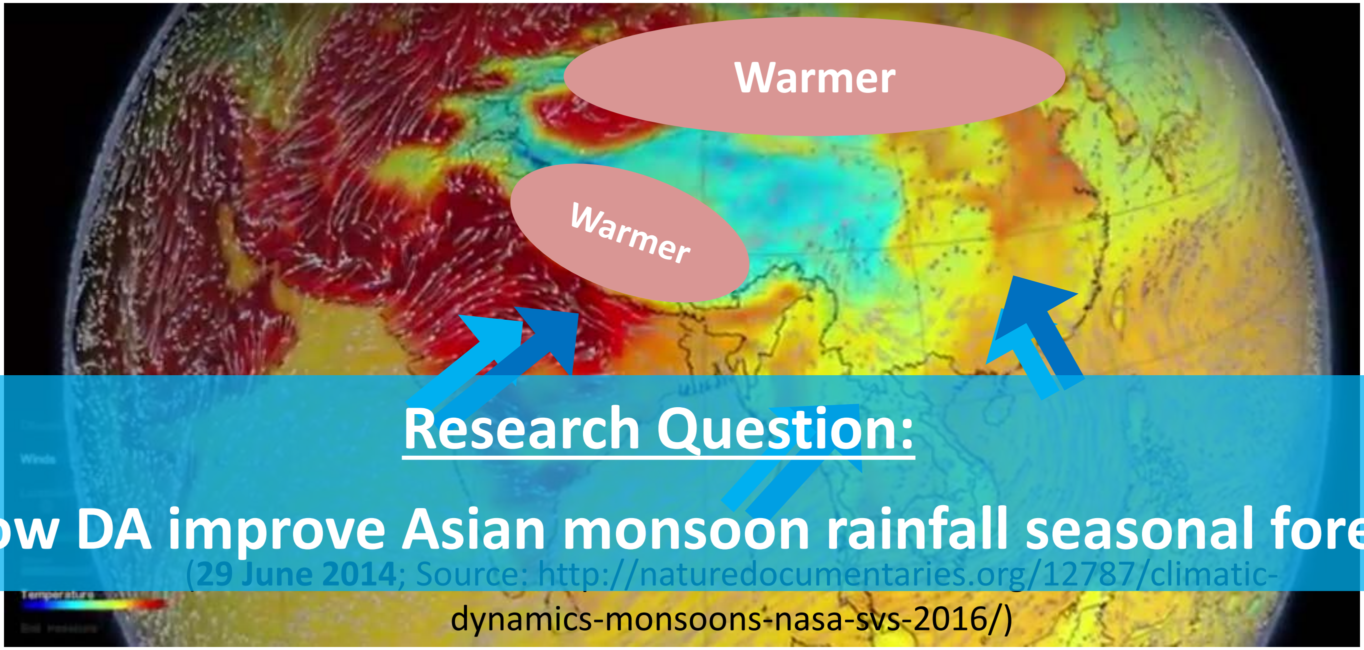
- Higher-latitude such as the Siberia
  - *Improved temperature prediction appears later in warmer months*
  - *Due to strengthened snow-atmosphere coupling*



Lin et al. (2016; GRL)

Seasonal Monsoon Rainfall Prediction

- **Key drivers of Asian monsoon:** the *land-sea thermal contrast* between the Eurasian landmass and the oceans
  - TP and Siberian snow are two important players



Research Question:

Can snow DA improve Asian monsoon rainfall seasonal forecast?

(**29 June 2014**; Source: http://naturedocumentaries.org/12787/climatic-dynamics-monsoons-nasa-svs-2016/)

- CLM4-CAM5 experiments initialized on 1 March of 2003 to 2009
- Model runs extended to the end of August

Seasonal Asian Monsoon Prediction

Robust improvement in <u>India monsoon region</u>:

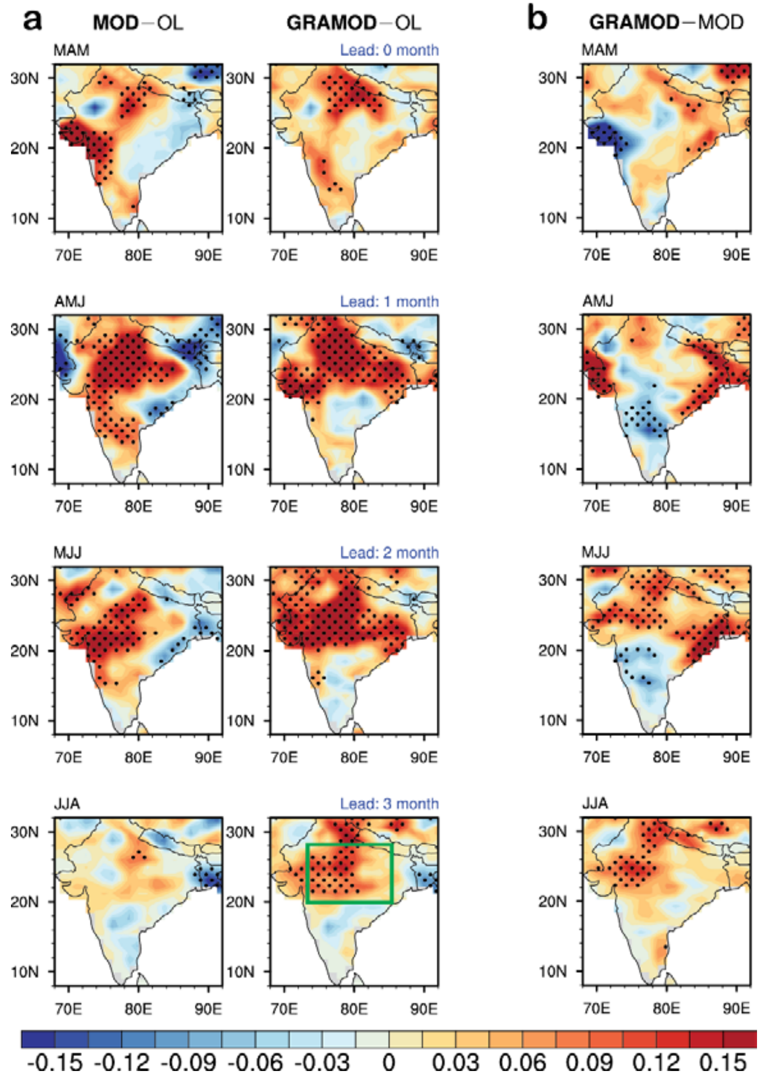
- Compared with five precip. datasets;
- Using both r^2 and *RMSE* skill metrics (21 samples);
- Dots: 95% confidence level with bootstrap for 1,000 times;

MAM

AMJ

MJJ

JJA

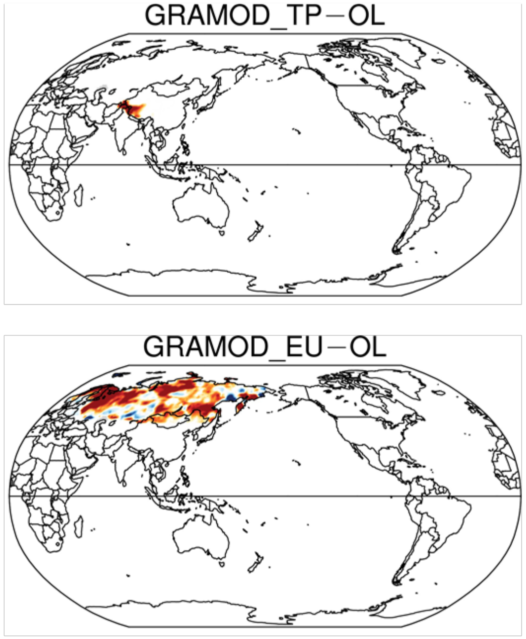


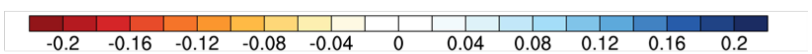
Lin et al. (2018; to be submitted)

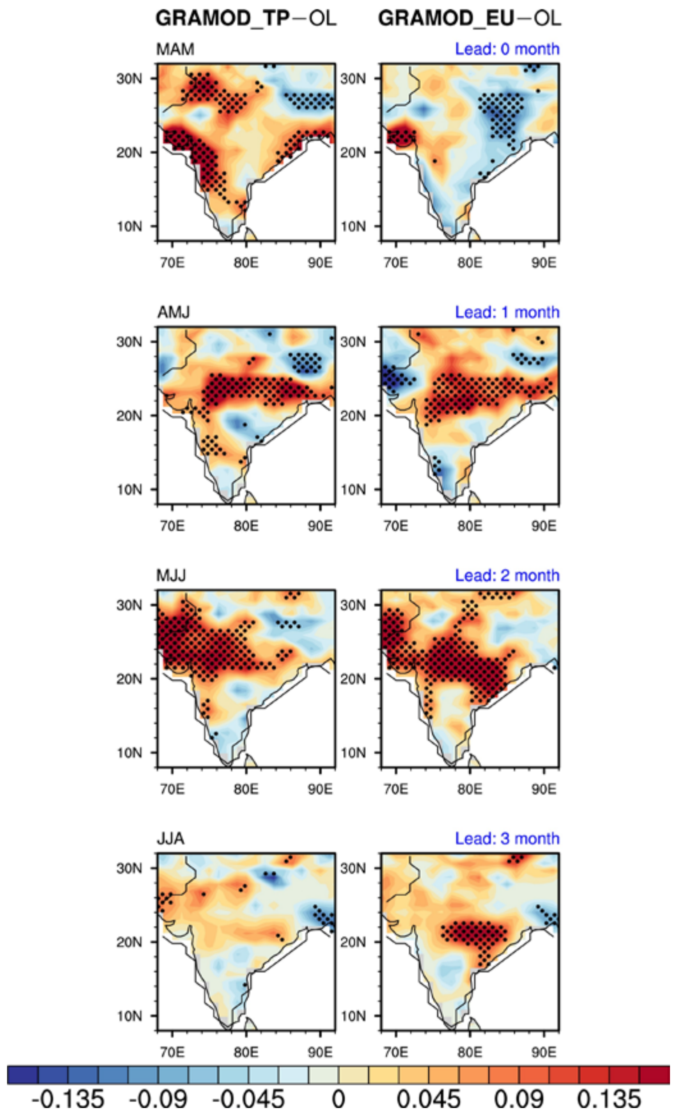
Regional Land DA vs. Seasonal Prediction

TP_only

EU_only





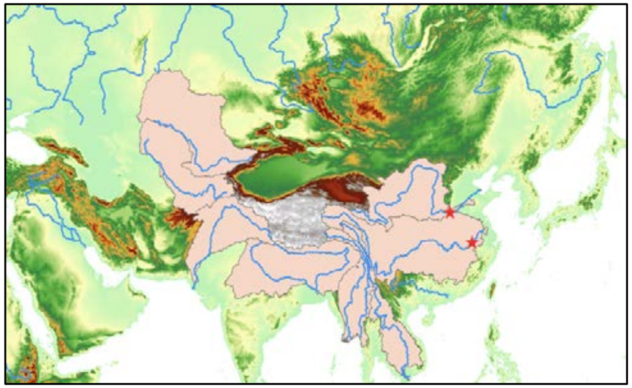


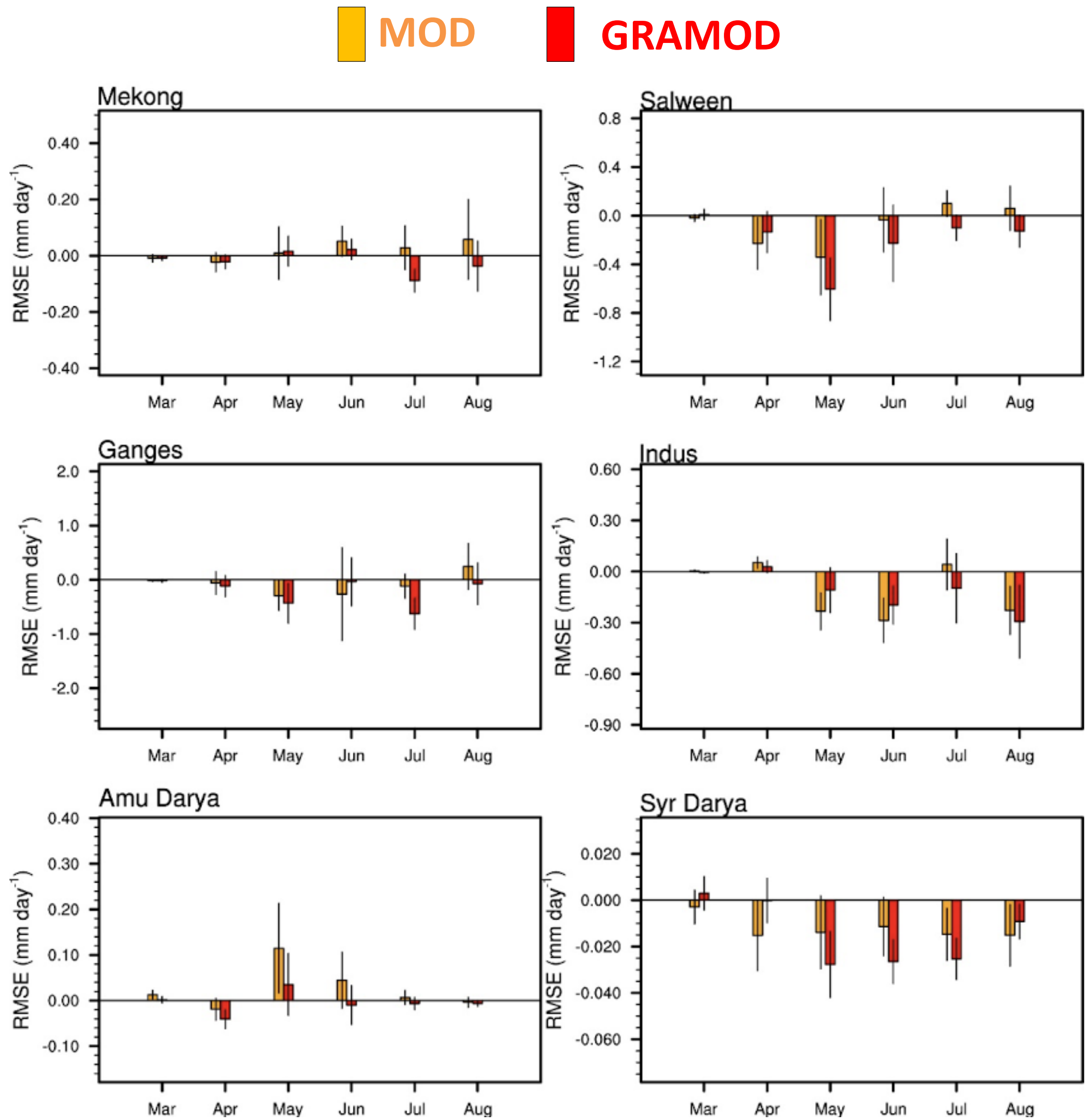
High-latitude Eurasian snow + GRACE DA:

Key to long-lead (3-month) Indian monsoon prediction

Lin et al. (2018; to be submitted)

River Basins Originating from the Tibetan Plateau

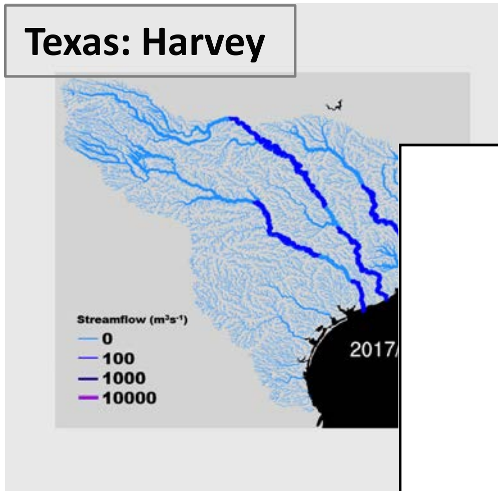




RMSE_diff = DA – OL

- Basin-averaged runoff against ERA-Land runoff;
- Negative RMSE_diff: improved runoff forecast

River Discharge Modeling with Vector-Based Routing



1/8° Noah-MP +
15 sec HydroSHEDS

25 km GLDAS + Hydro1K

W. Wu, Z.-L. Yang, P. Lin (2017, *AGU*): A 37-year historical global simulation to study floods and droughts

Summary

- **Developed a global land DA system** capable of assimilating MODIS, GRACE, and AMSR-E observations
  - Providing a robust soil moisture and snow estimation at the global scale;
- **Different sensors offer complementary information**
  - MODIS SCF leads to marginal improvements in the snow estimation at mid- and high-latitude, where GRACE offers unique contribution;
  - However, more sensors do not necessarily lead to optimal updates (uncertainties with observations)
- **Land DA holds promise for improving seasonal hydroclimate prediction:** temperature, rainfall, runoff
  - DA methodological improvements can further enhance the existing skills

Future Plans

- **Potential collaborative efforts with NCAR and NASA:**

1) Land DA with CLM5, Noah-MP, or the future unified NCAR Land Model;
2) Extended CAM/DART forcing from 2010 to 2017;
3) Assimilation of other satellite datasets such as SMAP, SWOT;
4) DA as a tool to assess the groundwater, snow, and vegetation representations in the model

- **Other applications with land DA:**

1) DA with fully coupled earth system;
2) DA for river flow modeling;
3) DA with decision support system for early alert & warning

Relevant Publications

1. Kwon, Y., 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.
2. Kwon, Y., Z.-L. Yang, L. Zhao, T. J. Hoar, A. M. Toure, and M. Rodell, 2016: Estimating snow water storage in North America using CLM4, DART, and snow radiance data assimilatiton, *J. Hydrometeorology*, **17**, 2853-2874.
3. Kwon, Y., Z.-L. Yang, T. J. Hoar, and A. M. Toure, 2017: Improving the Radiance Assimilation Performance in Estimating Snow Water Storage across Snow and Land Cover Types in North America. *J. Hydrometeorology,* doi:10.1175/JHM-D-16-0102.1.
4. Lin, P., J. Wei, Z.-L. Yang, Y.-F. Zhang, and K. Zhang, 2016: **Snow data assimilation-constrained land initialization improves seasonal temperature prediction**. *Geophys. Res. Lett.,* **43**, 11423–x11432.
5. 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 Assimilaton Research Testbed and the Community Land Model version 4, *J. Geophys. Res. – Atmospheres*, **119**, 7,091–7,103.
6. 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.
7. Zhang, Y.-F., Z.-L. Yang, 2018: Eight-year snow water equivalent over the Northern Hemisphere from joint MODIS and GRACE land data assimilation, *J. Geophys. Res. – Atmospheres*, in revision.
8. 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, *J. Hydrometeorology*, **17 (9)**, 2431–2454, doi: 10.1175/JHM-D-15-0218.1.
9. Zhao, L., Z.-L. Yang, 2018: Multi-Sensor Land Data Assimilation: Toward a Robust Global Soil Moisture and Snow Estimation, *Remote Sensing Environment, in revision.*
10. ……

Thank you for your attention!

Q & A

Peirong Lin: prlin@utexas.edu

* Zong-Liang Yang: liang@jsg.utexas.edu

THE UNIVERSITY OF TEXAS AT AUSTIN
CIESS
CENTER FOR INTEGRATED EARTH SYSTEM SCIENCE

TEXAS Geosciences
The University of Texas at Austin
Jackson School of Geosciences

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

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

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)

- But high-quality global land state datasets have been lacking

- **Our collaborative efforts have been made in**
  - Developing a multivariate global land data assimilation framework
  - Quantifying uncertainties
  - Producing high-quality datasets
  - Improving predictions (e.g., intraseasonal to seasonal climate prediction)