Multi-satellite Land Data Assimilation

Zong-Liang Yang

University of Texas at Austin

Create knowledge.
Foster change.

UT AUSTIN PORTUGAL PROGRAM

UTAustin Portugal

Who am I?

Name: **Zong-Liang YANG**
Professor, Jackson Chair in Earth System Science
Director, Center for Integrated Earth System Science

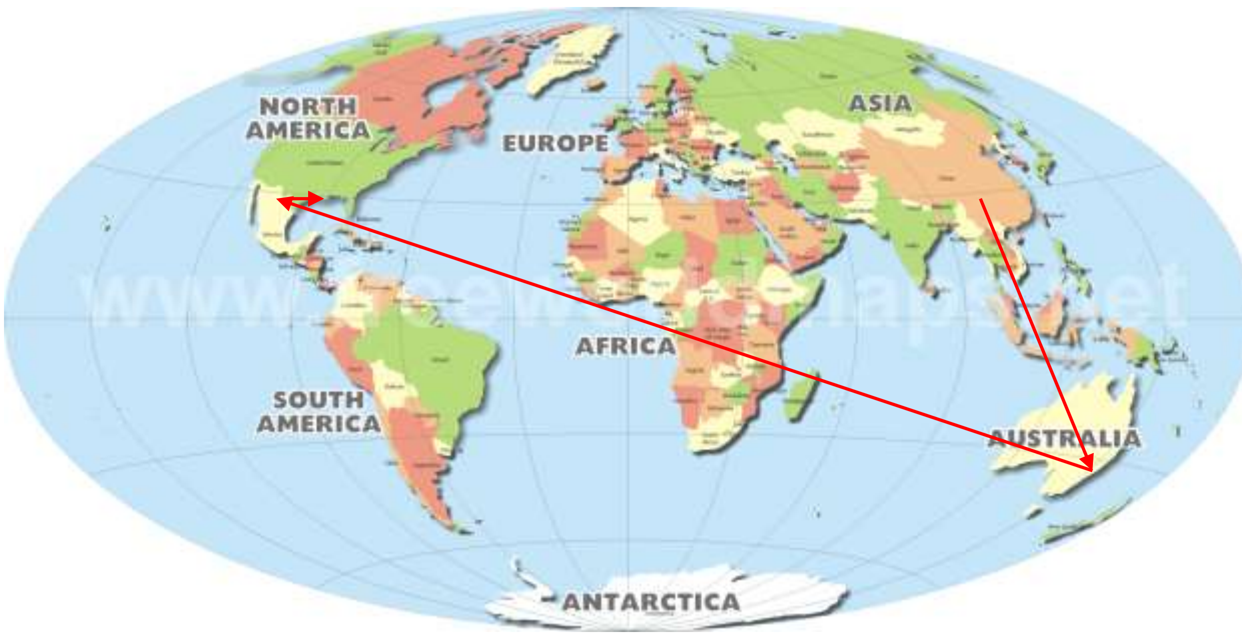
Education: BSc and MSc in Meteorology
PhD in Atmospheric Science

Research: Land Surface Hydrology, Model Development & Evaluation
Land–Atmosphere Interaction, Climate Modeling,
Climate Impacts on Water Resources and Environment

Teaching: Living with a Planet;
Earth, Wind and Fire
Physical Climatology;
Climate: Past, Present and Future
Hydroclimatology; Asian Monsoon
Land–Atmosphere Interaction Dynamics

Email: **liang**@jsg.utexas.edu

My Career Paths



China	Nanyang:	16 years
	Nanjing:	5 years
	Shanghai:	1 year
Australia	Melbourne:	3 years
	Sydney:	4 years
USA	Tucson:	8 years
	Austin:	**18 years**

Attending the AIR Center Meeting at Azores, June 2016

Hosting Portugal Delegation to UT Austin, November 2016

Assimilating Multi-Satellite Snow Data in Ungauged Eurasia Improves the Asian Monsoon Seasonal Forecasts

Zong-Liang Yang
(liang@jsg.utexas.edu)

UT-Austin: Peirong Lin, Long Zhao, Wen-Ying Wu, Yonghwan Kwon, Yongfei Zhang, Jiangfeng Wei, Xiaolu Ling, Hua Su, Robert Dickinson

NCAR: Timothy Hoar, Jeffrey Anderson

Canada/France: Alley Toure, Ghislain Picard

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

NCAR NATIONAL CENTER FOR ATMOSPHERIC RESEARCH

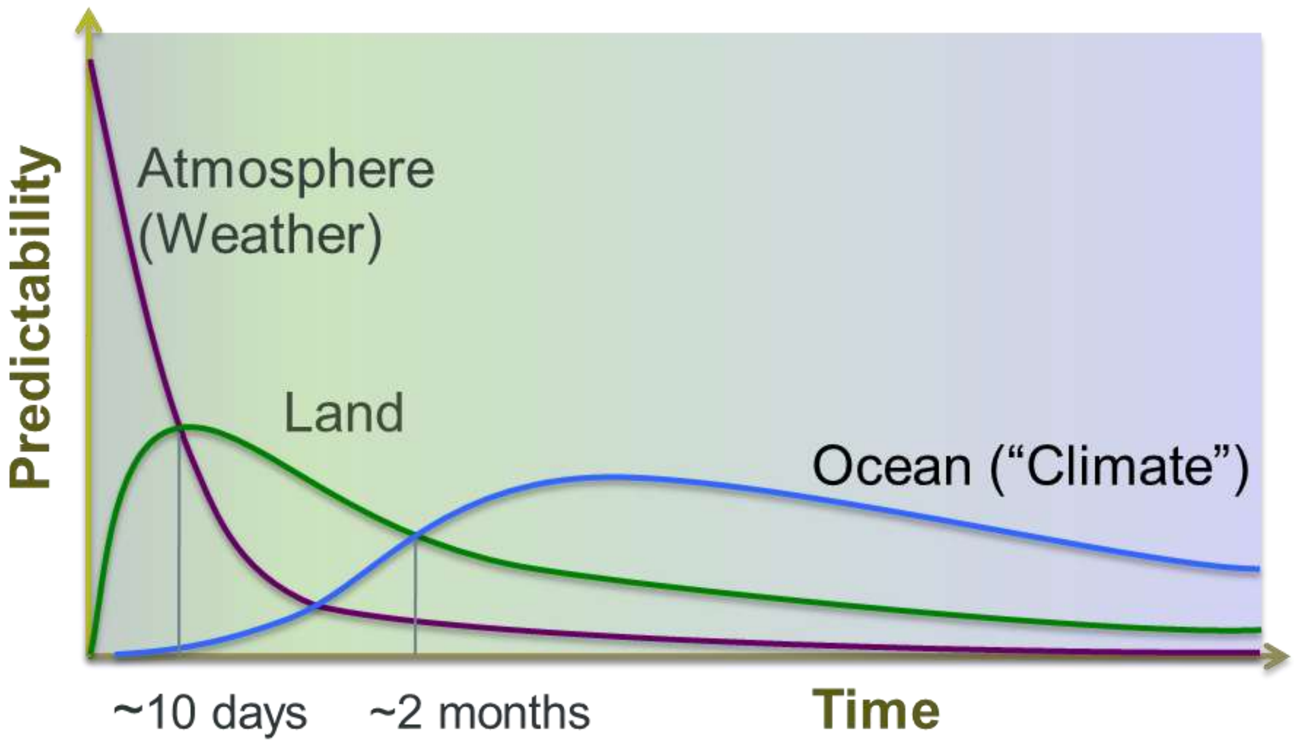
TEXAS Geosciences The University of Texas at Austin Jackson School of Geosciences

WHAT STARTS HERE CHANGES THE WORLD THE UNIVERSITY OF TEXAS AT AUSTIN

UT Austin Portugal Interdisciplinary Earth Observation: Land, Ocean, and Atmosphere, Porto, 11 November, 2019

Different Roles of Atmosphere, Land, and Ocean in Predictability

"Subseasonal" (2–4 weeks) and seasonal (3–6 months) forecasts are a hot topic in operational forecast centers.

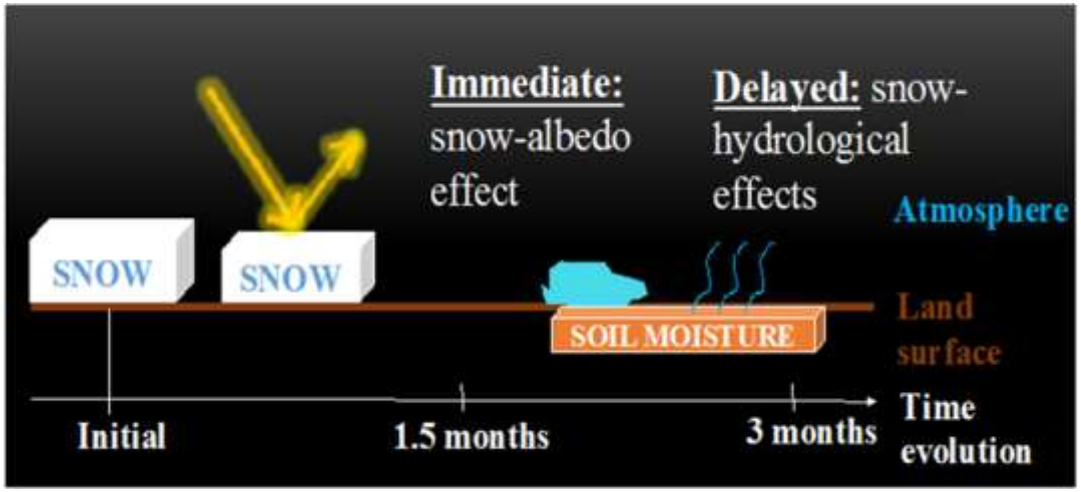


Courtesy of Dirmeyer
(personal comm.)

Land vs. Seasonal Climate Prediction

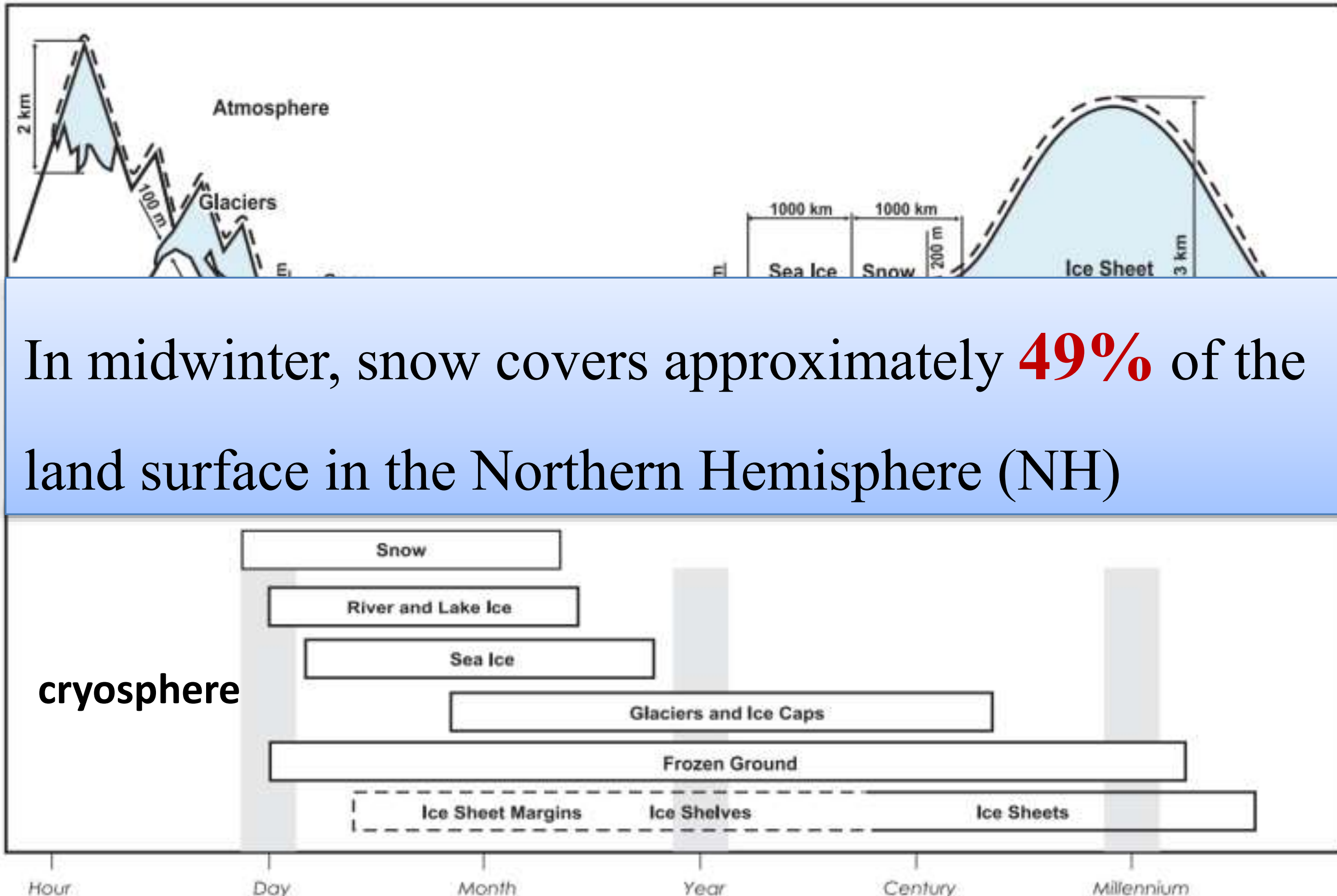
- **Land memory: important sources of predictability**
  - **Snow:** Douville (2010); Jeong et al. (2013); Orsolini et al. (2013)
  - **Soil moisture:** Koster et al. (2004; 2010; 2011); Hirsch et al. (2013)
  - **Vegetation:** Koster and Walker (2015); William and Torn (2015)
  - **Groundwater:** Jiang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

Example: snow in the climate system



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

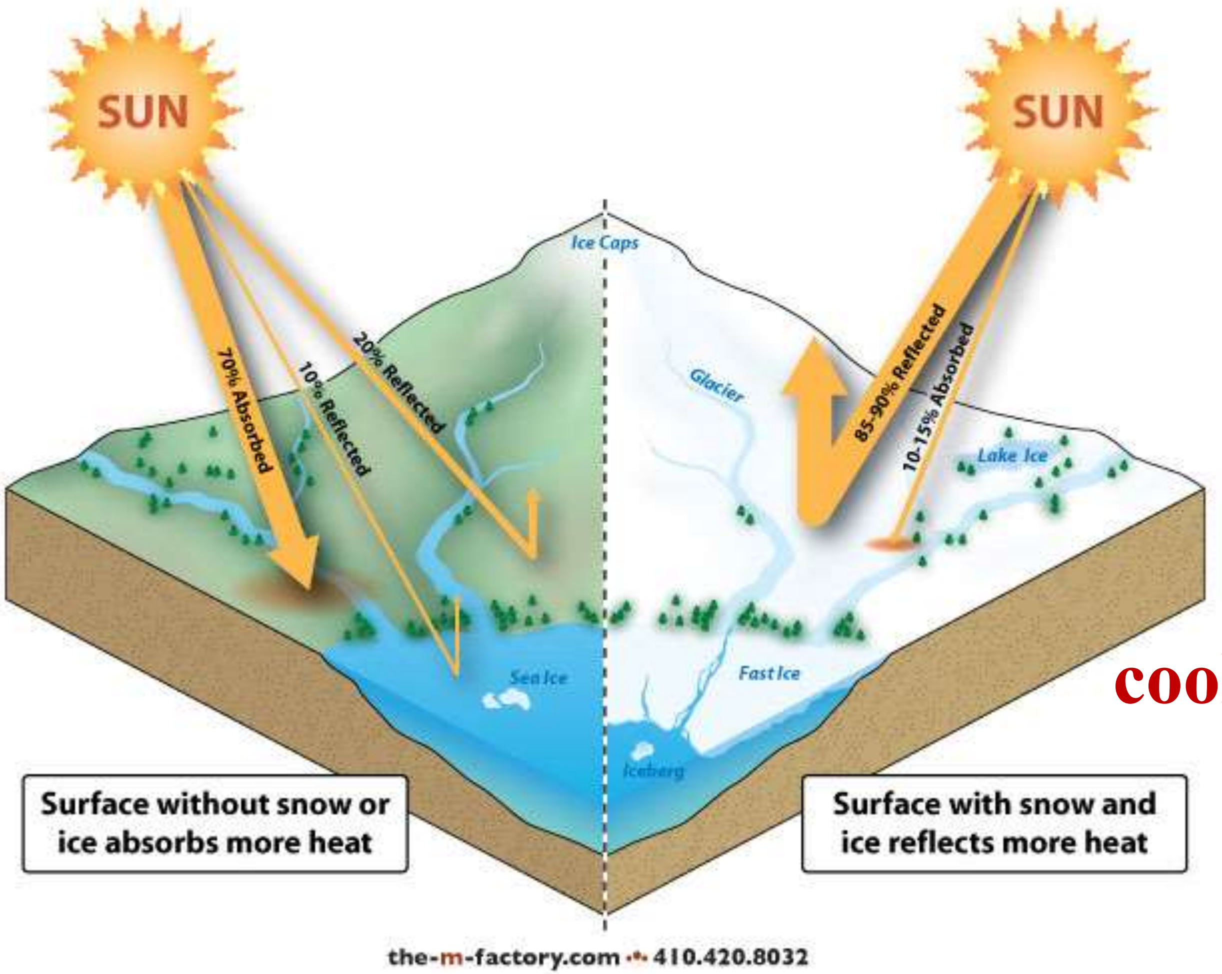
Importance of snow *Cryosphere*



In midwinter, snow covers approximately **49%** of the land surface in the Northern Hemisphere (NH)

IPCC, 2018

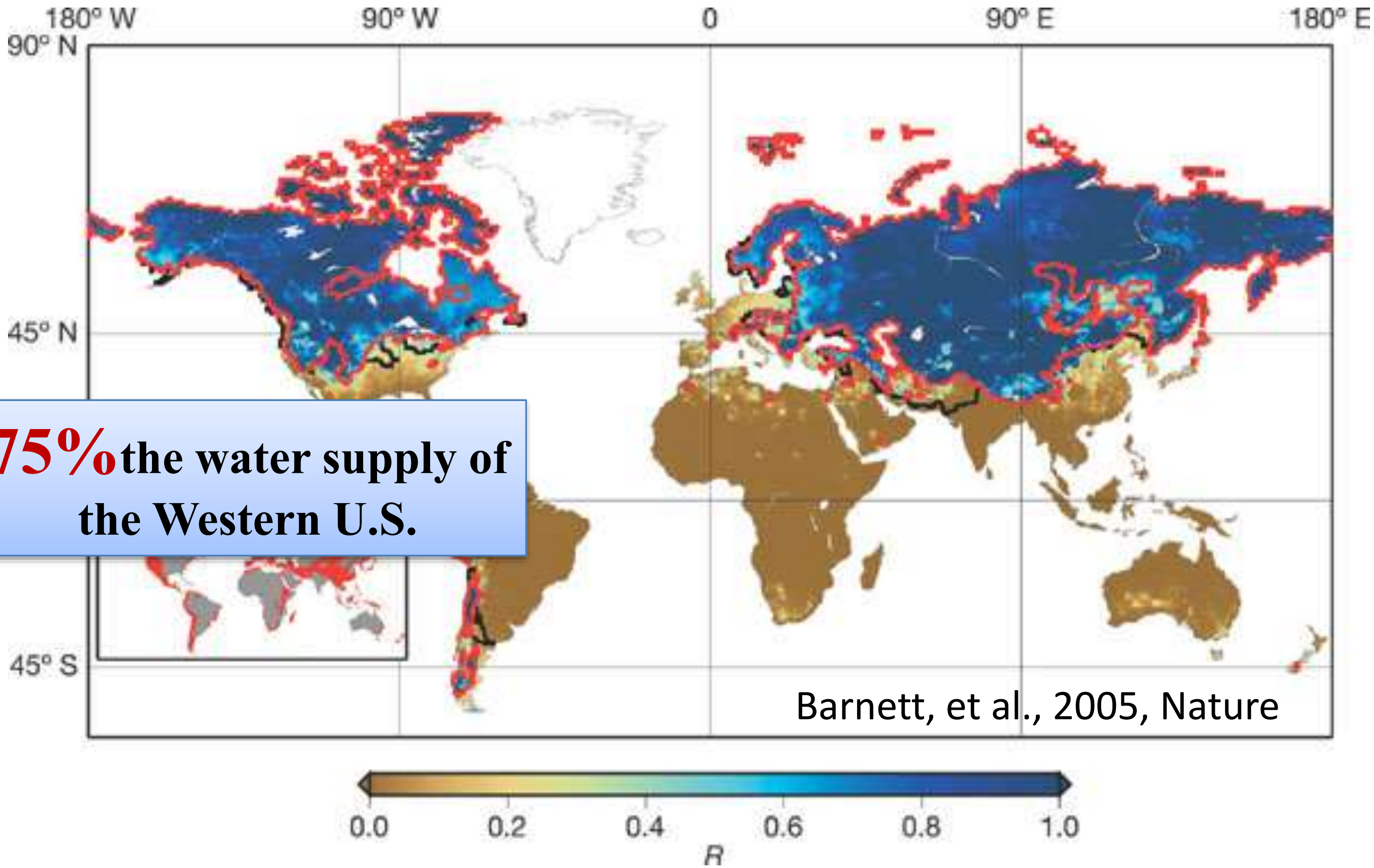
Importance of snow *High albedo*



cool the planet

https://www.tes.com/lessons/N_4TXBTntT9ARw/albedo-high-quality

Importance of snow *Fresh water*



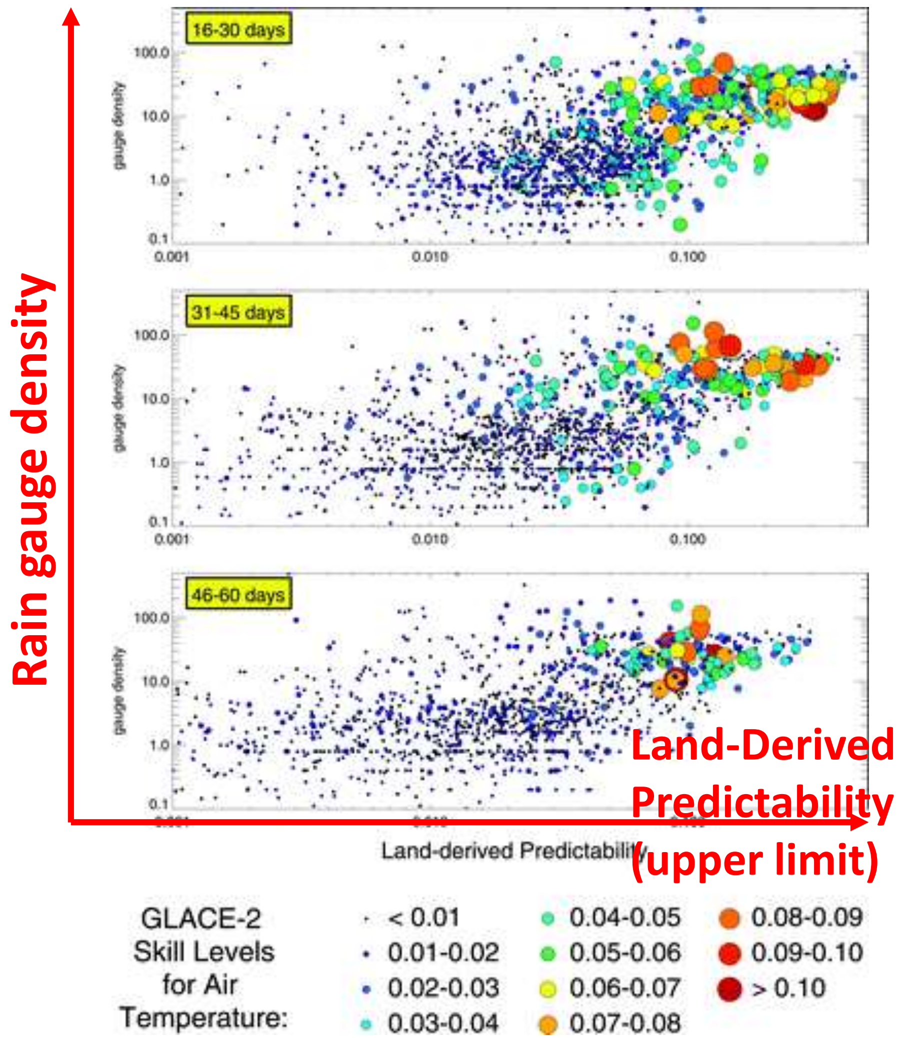
75% **the water supply of the Western U.S.**

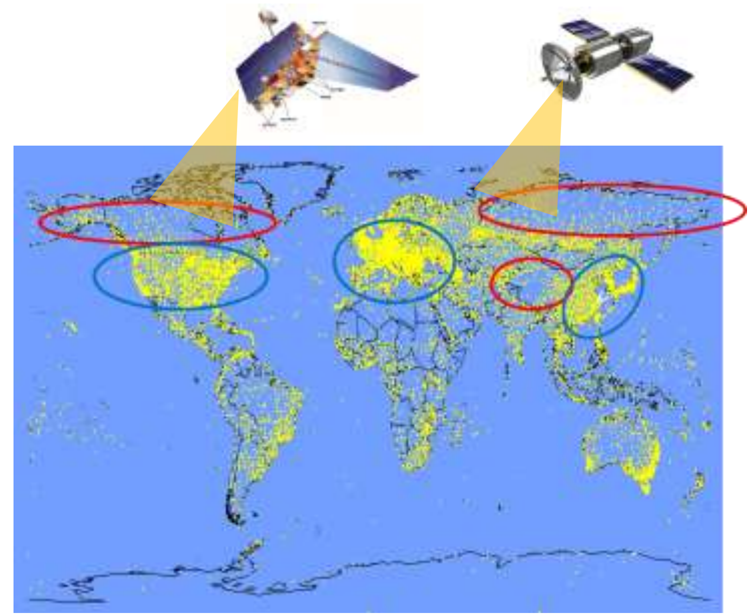
Barnett, et al., 2005, Nature

(annual snowfall)/(annual runoff)

Land Skill Depends on Rain Gauge Density

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





Caveat

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

Land Data Assimilation

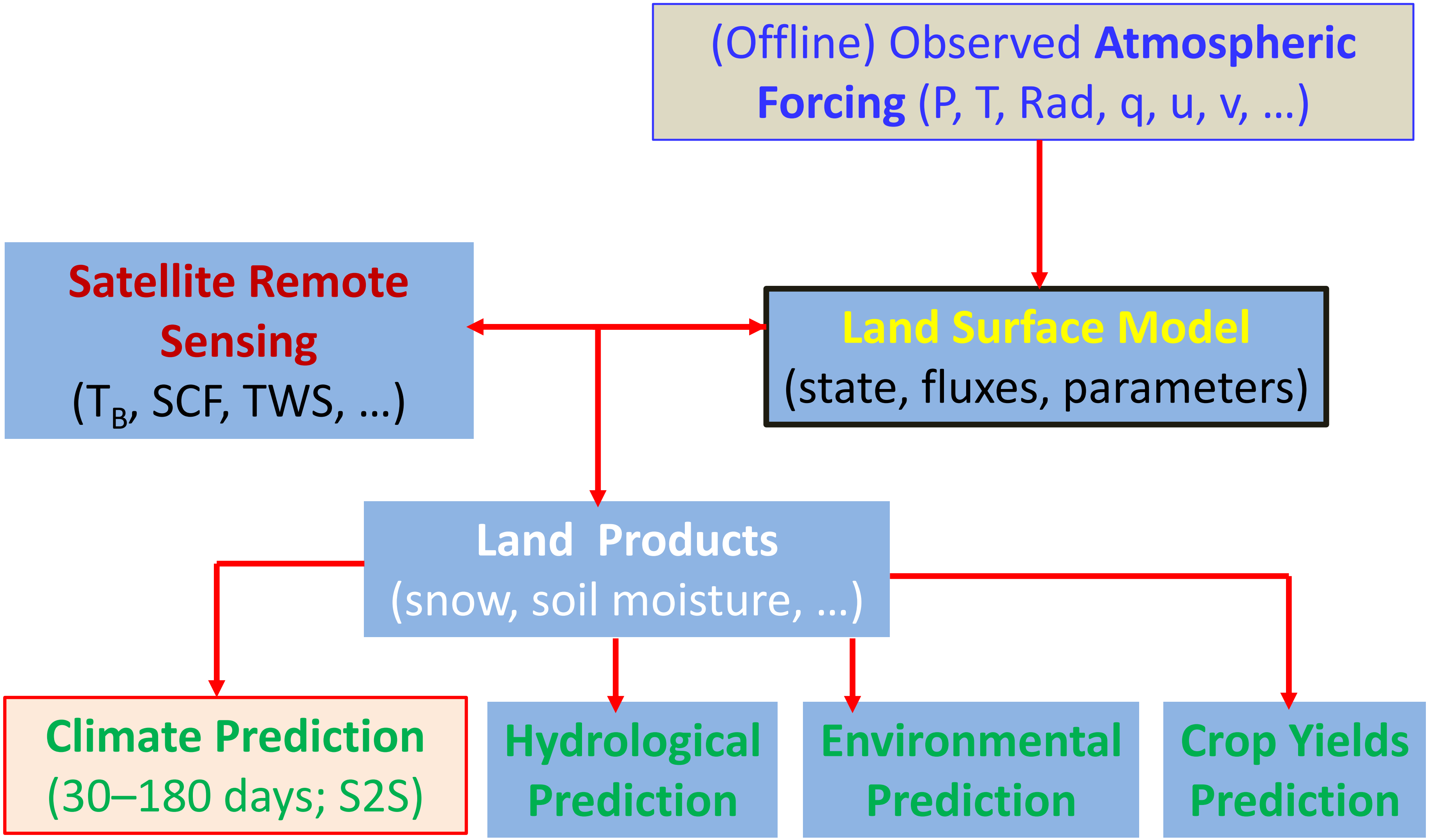
- Began in early 1990s; much later than atmospheric and oceanic data assimilation
- CAHMDA workshops have been important to push the research forward.

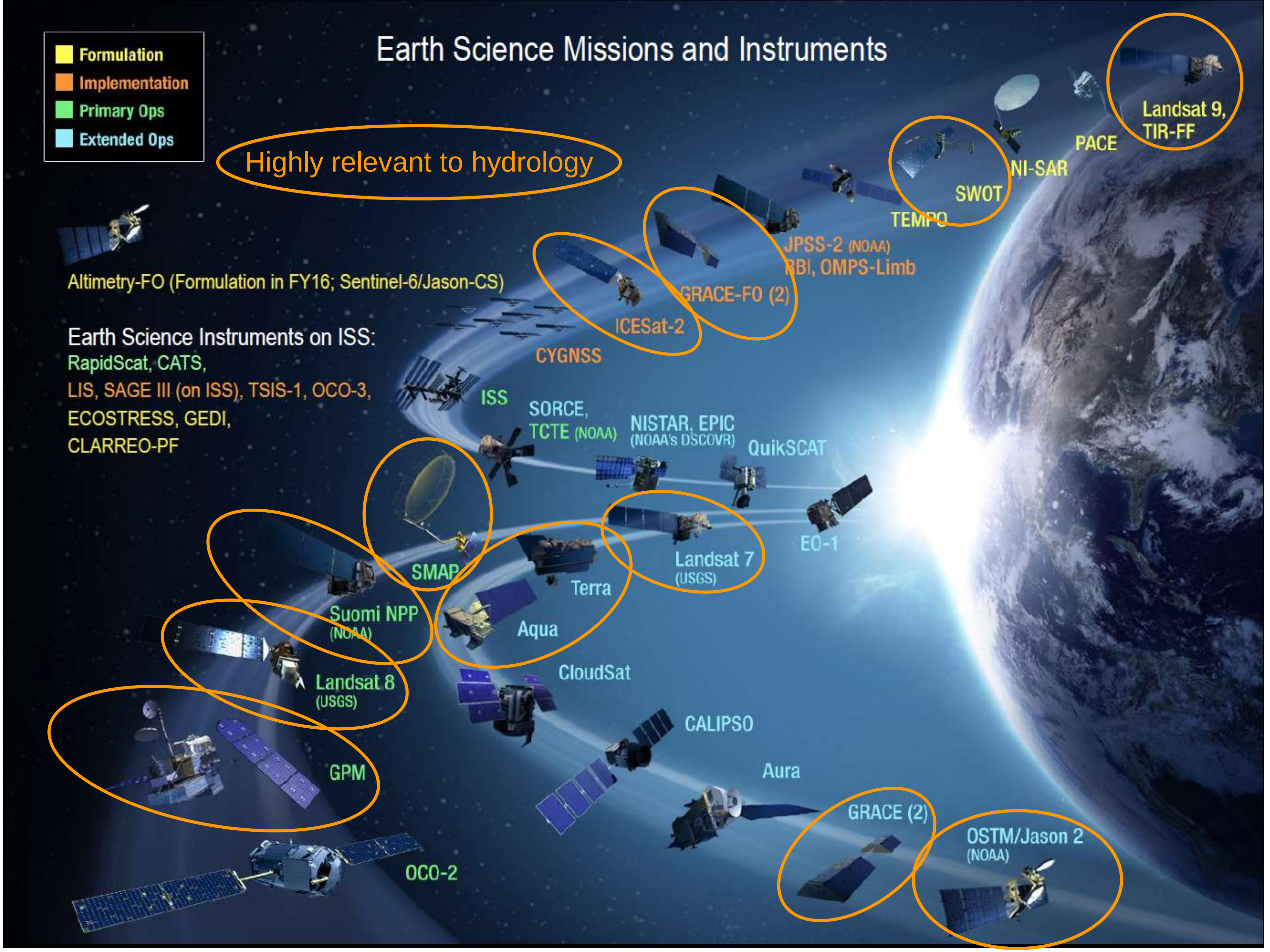
6th International Workshop on Catchment Hydrological Modeling and Data Assimilation (CAHMDA VI)

3rd International Workshop on Data Assimilation for Operational Hydrology and Water Management of the Hydrologic Ensemble Prediction Experiment (HEPEX-DAFOH III)

Austin, TX, USA 8-12 Sept, 2014

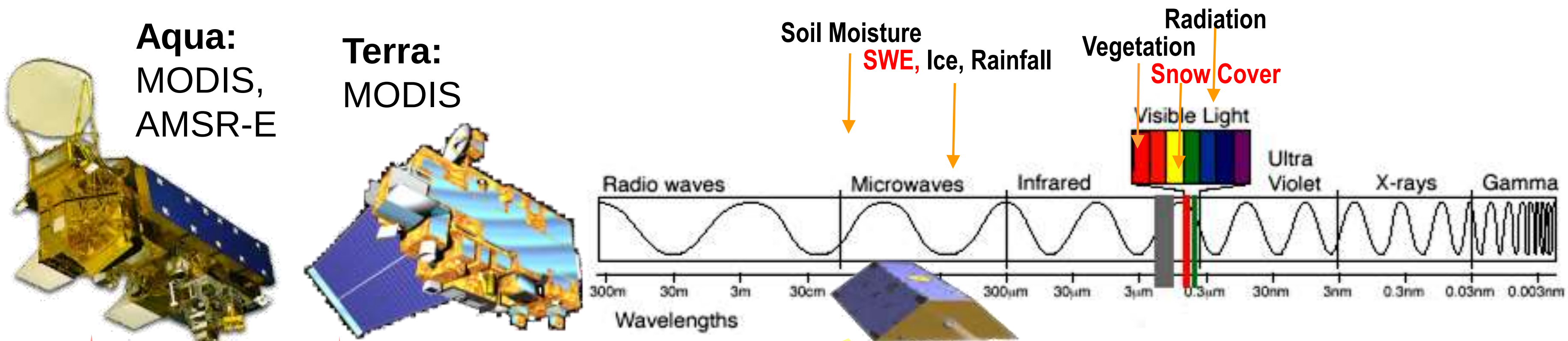
Land Data Assimilation in a Nutshell





Earth Science Missions and Instruments
Formulation
Implementation
Primary Ops
Extended Ops
Highly relevant to hydrology
Landsat 9, TIR-FF
PACE
NI-SAR
SWOT
TEMPO
JPSS-2 (NOAA) RBI, OMPS-Limb
GRACE-FO (2)
ICESat-2
CYGNSS
Altimetry-FO (Formulation in FY16; Sentinel-6/Jason-CS)
Earth Science Instruments on ISS:
RapidScat, CATS,
LIS, SAGE III (on ISS), TSIS-1, OCO-3,
ECOSTRESS, GEDI,
CLARREO-PF
ISS
SORCE,
TCTE (NOAA)
NISTAR, EPIC
(NOAA's DSCOVR)
QuikSCAT
EO-1
Landsat 7
(USGS)
SMAP
Terra
Suomi NPP
(NOAA)
Aqua
CloudSat
Landsat 8
(USGS)
CALIPSO
GPM
Aura
GRACE (2)
OSTM/Jason 2
(NOAA)
OCO-2

Complementary Information from Different Satellites



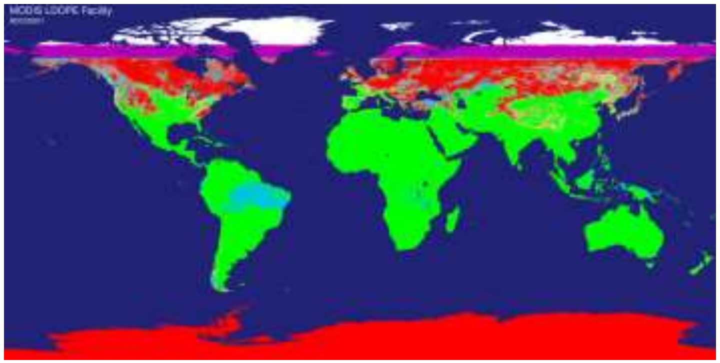
MODIS provides high resolution snow cover data but not SWE; AMSR-E provides SWE data but with significant errors where snow is deep or wet

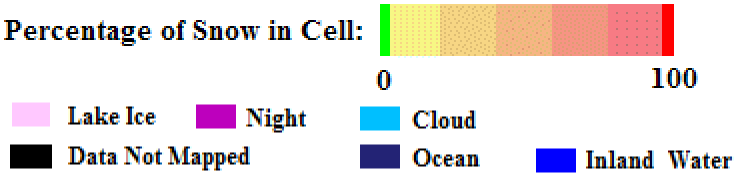
GRACE provides changes in total water storage, which are dominated by SWE at high latitudes and altitudes, but at very coarse resolution

Rodell, 2011

Available satellite observations of snow

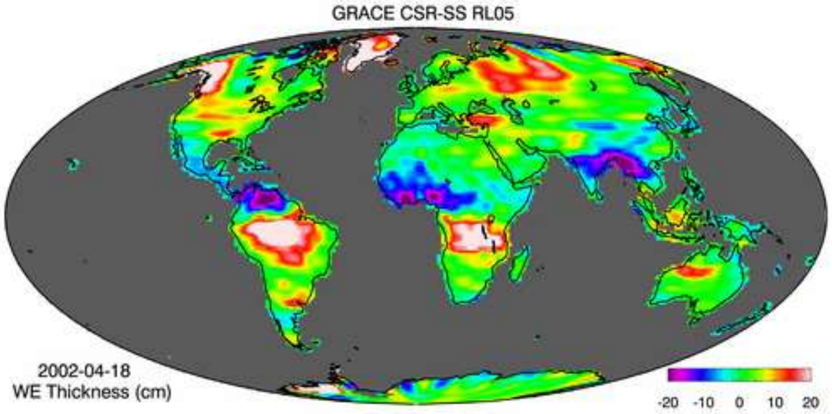
Daily MODIS snow cover observation





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

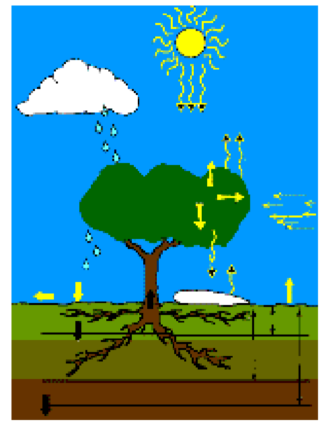
Monthly GRACE terrestrial water storage observation

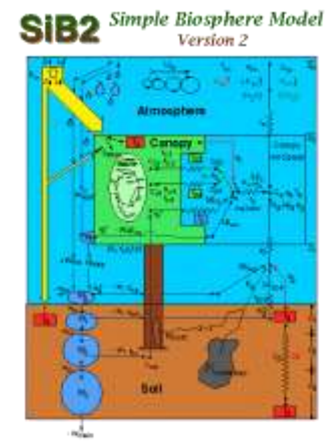


ftp://podaac-ftp.jpl.nasa.gov/allData/tellus/L3/land_mass/RL05/animation/

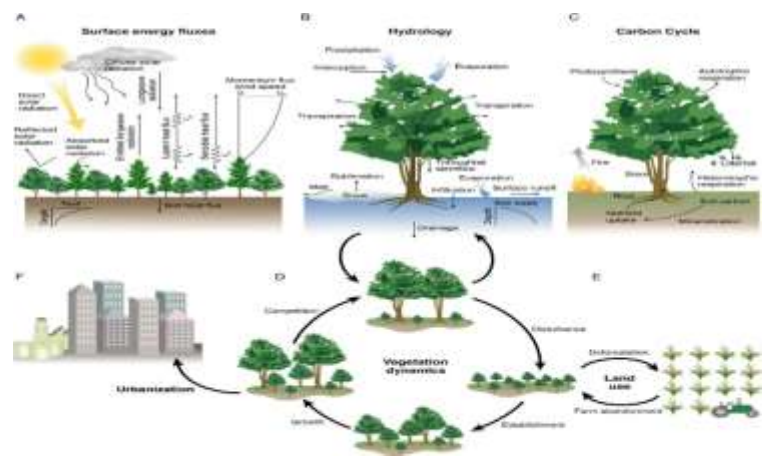
3+ decades of efforts in developing LSMs

- BATS, Bucket,
  CABLE, CLM, CoLM,
  ECHAM,
  FUN,
  IAP94, ISBA,
  JULES,
  LSM,
  Noah, Noah-MP,
  SiB, SSiB,
  PLACE,
  VIC,
  …





- Models are becoming more and more complex

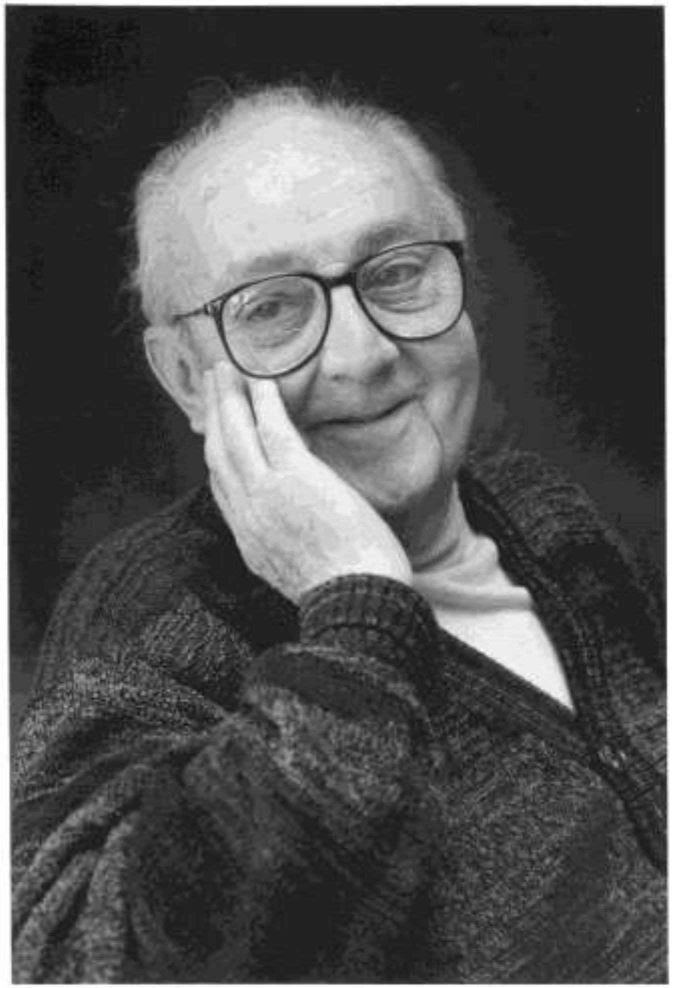


- PILPS and other land MIPs
- Benchmarking

A famous quote on modeling

Essentially, all models are wrong, but some are useful.

George E. P. Box (arch 2013),
statistician, quali alysis, design of
experiments, and e of the great
statistical minds



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

- **Produce** mutually consistent long-term earth system data records

- **Improve** subseasonal to seasonal (S2S) climate and hydrological predictions

Methodology in this talk

- Why CLM?
- Why DART?

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

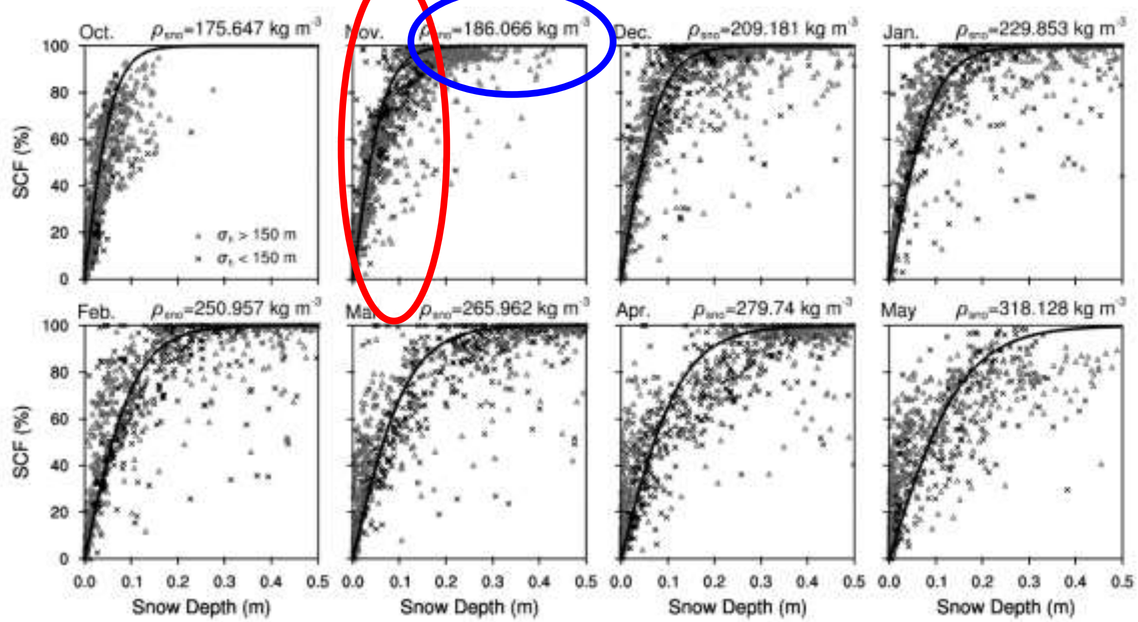
- CLM4 (released in 2010) improves over CLM3.5
  - Updated hydrology and ground evaporation
  - New density-based snow cover fraction (Niu and Yang, 2007), snow burial fraction, snow compaction
  - Improved permafrost scheme: organic soils, 50-m depth (5 bedrock layers)
  - Conserving global energy by separating river discharge into liquid and ice water streams

Co-Chairs: David Lawrence (NCAR), Zong-Liang Yang (Univ of Texas at Austin, 2008-2013)

Parameterization of Snow Cover Fraction (SCF) in CLM4

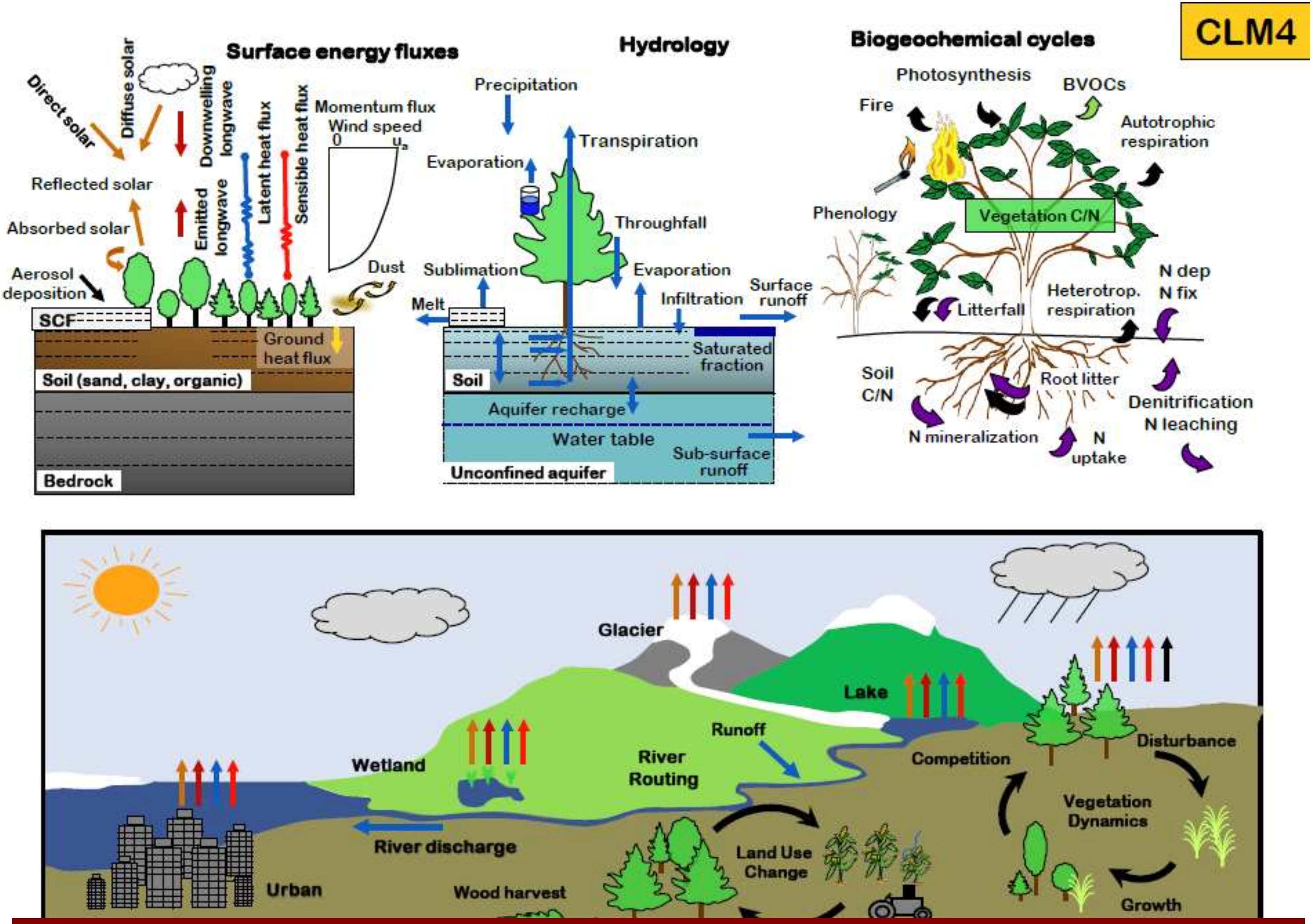
*Niu and Yang (*2007): function of snow depth, land cover, snow density, and watershed property

MODIS



GRACE

$$f_{sno} = \tanh\left(\frac{h_{sno}}{2.5 z_{0g}(\rho_{sno}/\rho_{new})^{m}}\right)$$



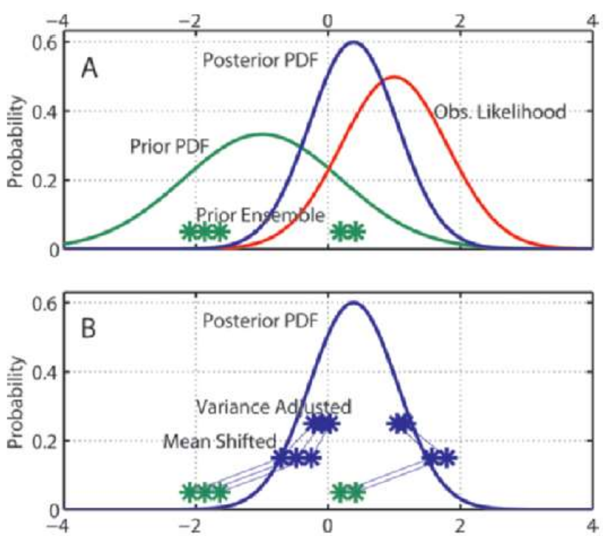
Co-Chairs: David Lawrence (NCAR), Zong-Liang Yang (Univ of Texas at Austin, 2008-2013)

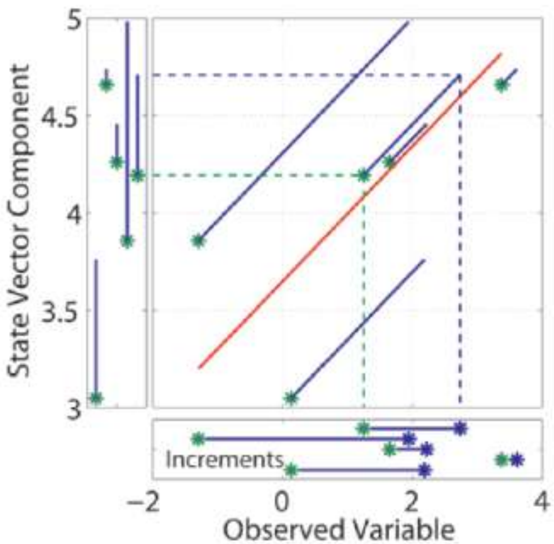
Finding Truth is like playing DART

Data Assimilation Research Testbed (DART)

NCAR IMAGe: Data Assimilation Research Section

- http://www.image.ucar.edu/DAReS/DART
- developed and maintained by Jeff Anderson's group at NCAR
- linked to atmospheric models (WRF, CAM) and oceanic models
- linked to CLM4 (UT and NCAR collaboration)
- EAKF (Anderson et al. 2009 BAMS) is used in this study.

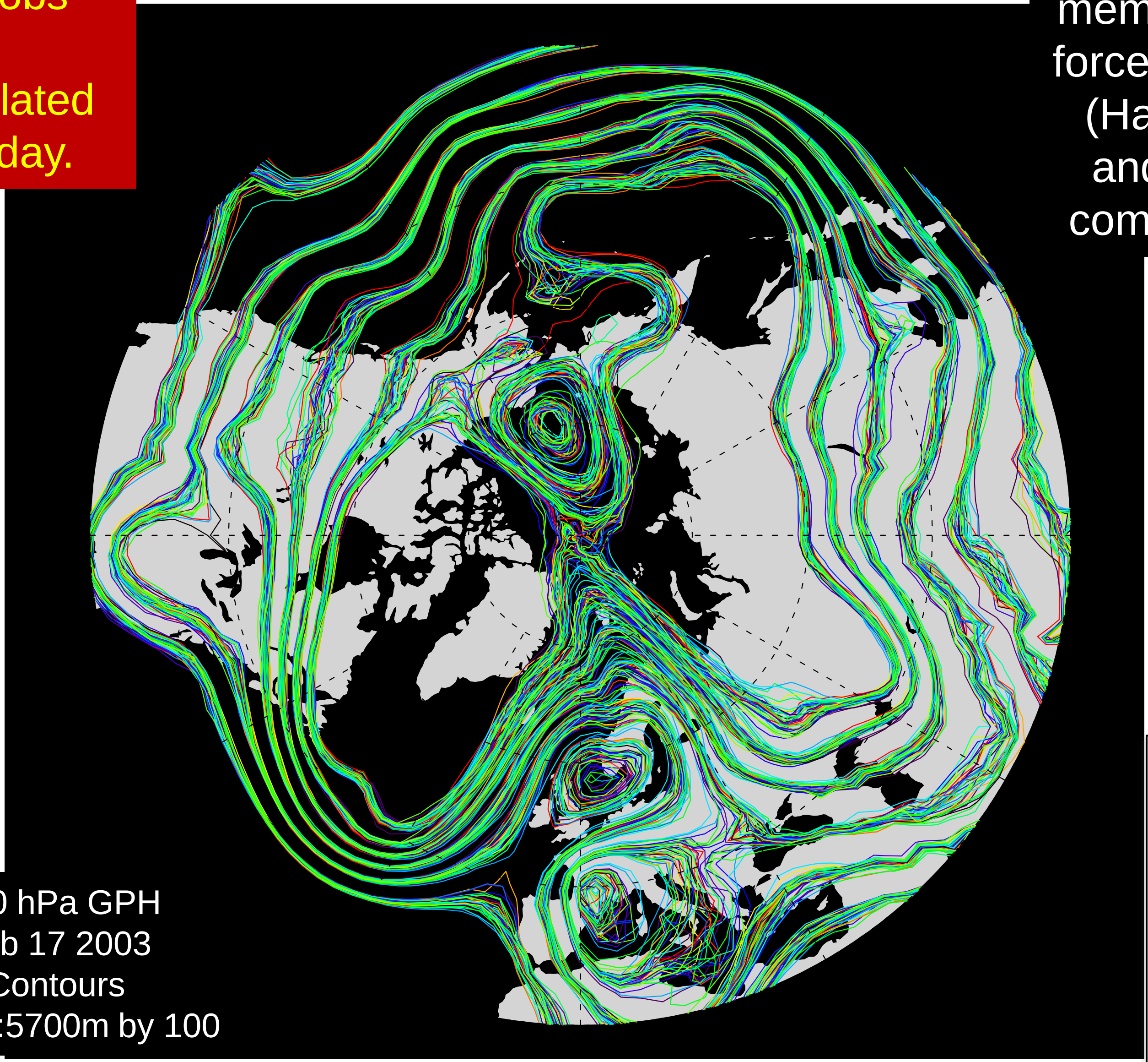




Atmospheric Reanalysis

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

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

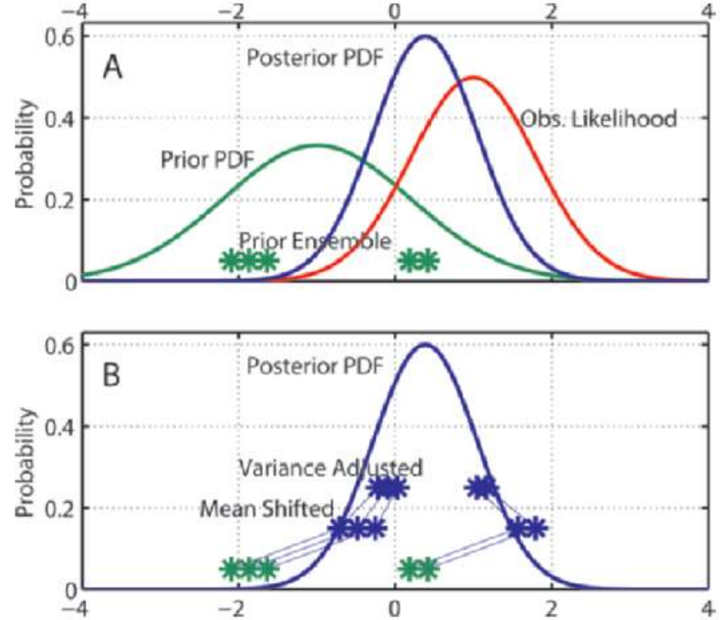


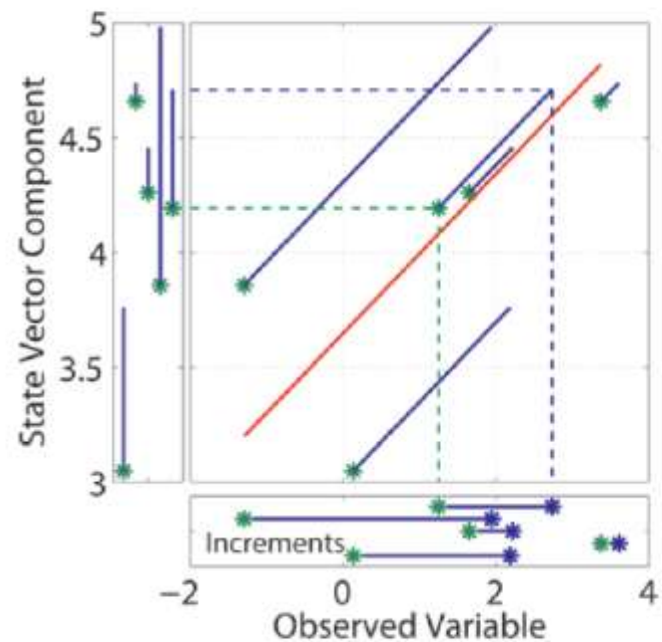
500 hPa GPH
Feb 17 2003
Contours
5200m:5700m by 100

1998-2010
4x daily
is free and available.
Contact
dart@ucar.edu

EAKF in DART (Anderson et al. 2009 BAMS)

- 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).

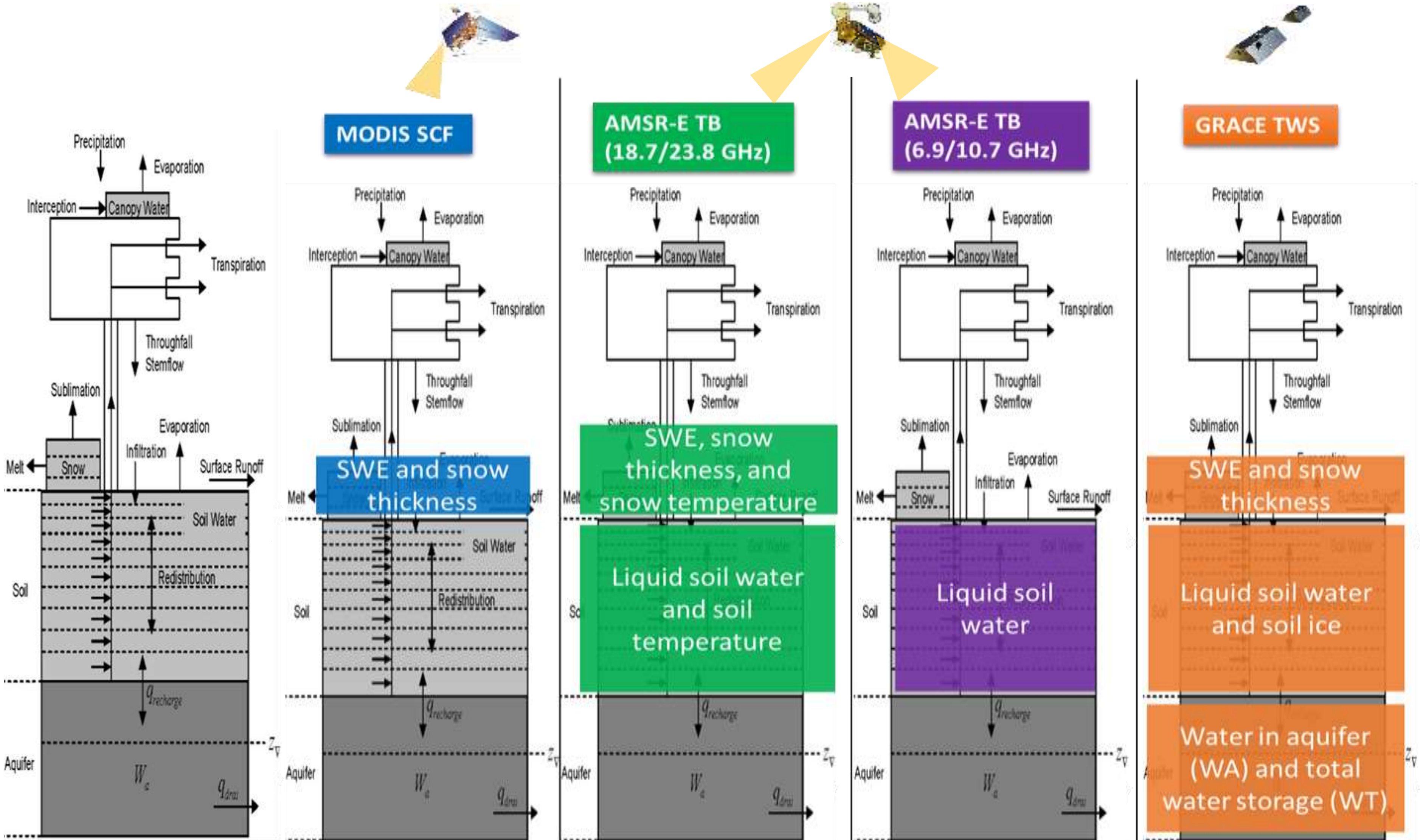




$$WA_{inc} = \mathrm{TWS}_{inc} \cdot \frac{cov(WA_{prior}, TWS_{prior})}{var(TWS_{prior})},$$

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

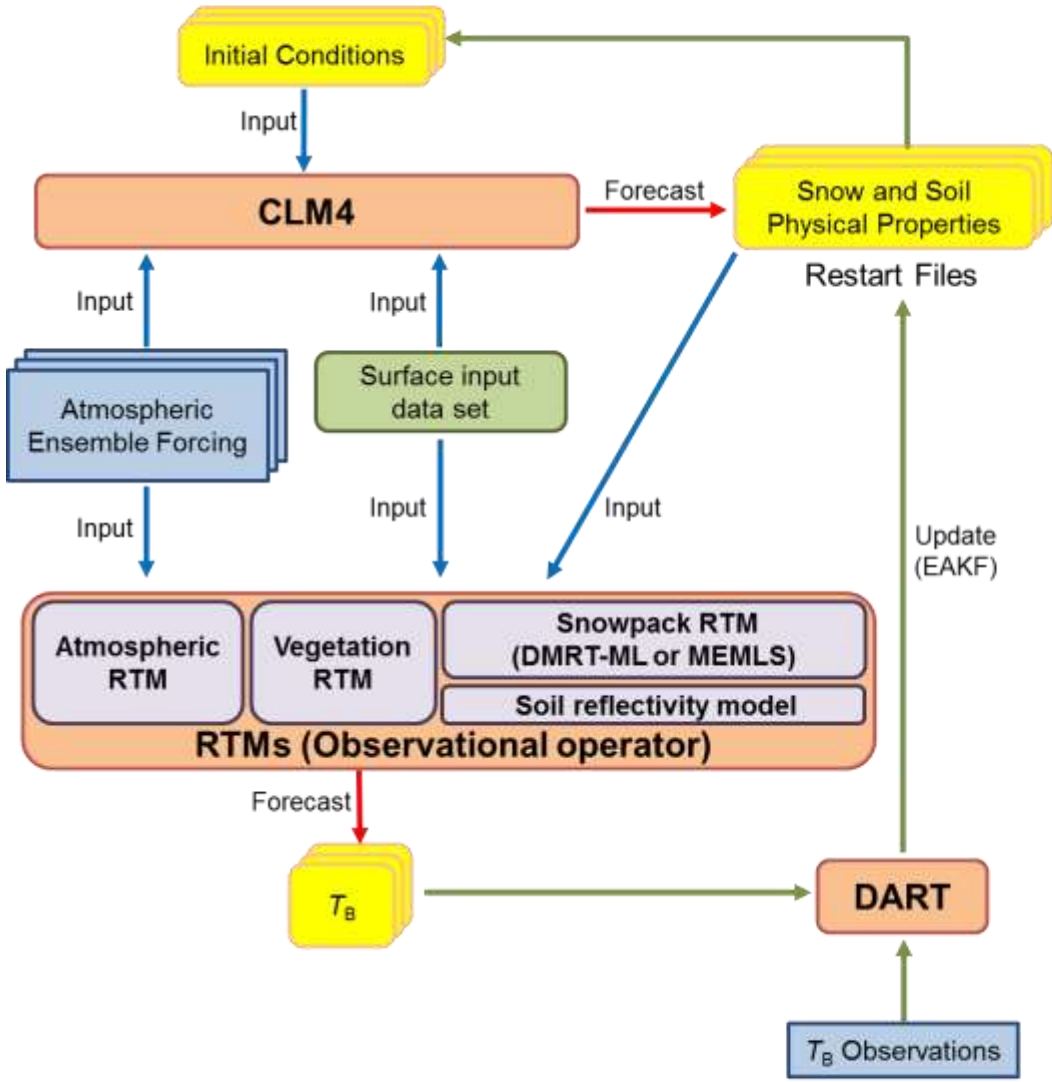
Data Assimilation Research Testbed (DART) + Community Land Model (CLM4)



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

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

- Coupled CLM4–RTM–DART system (Kwon et al., 2015, 2016, 2017)



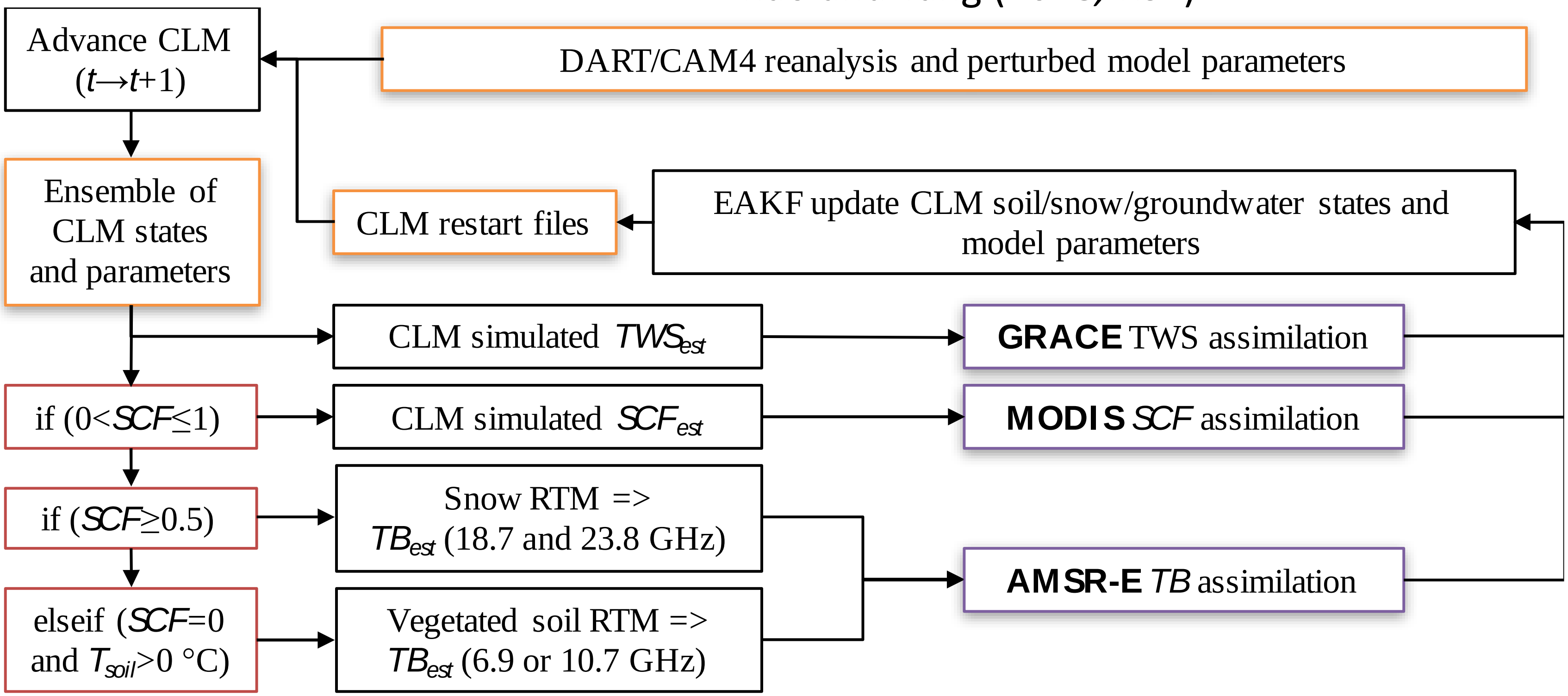
Methodology Development

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

- improves SCF and SWE estimates by assimilating MODIS SCF for unsaturated snow cover areas ($0<SCF\leq1$) (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 ($SCF\geq0.5$) (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, RSE)



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

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

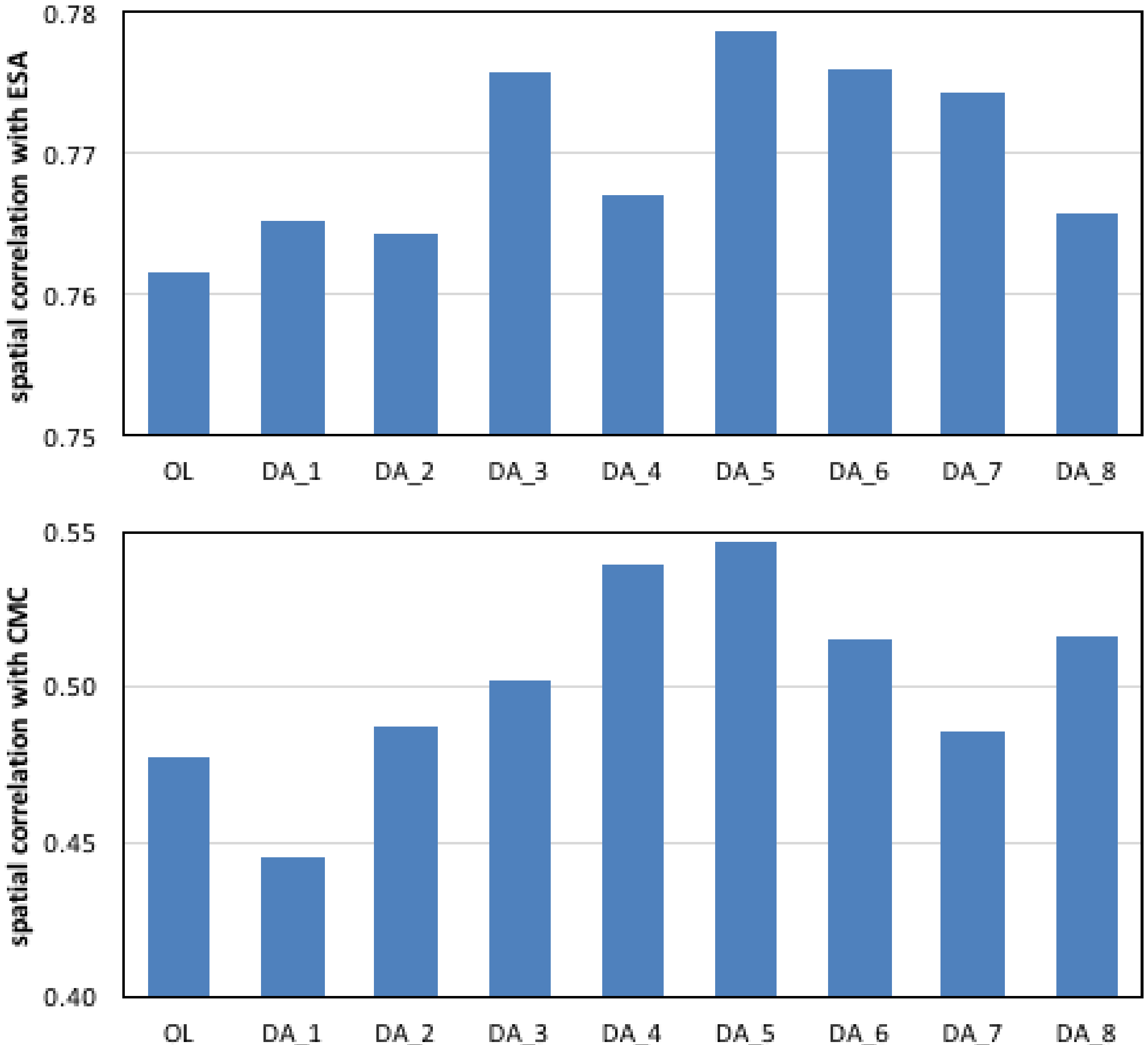
Cases	MOD	GRA	ASO	ASN
OL	Open-loop, no DA			
DA_1_GRA		×		
DA_2_MOD_GRA	×	×		
DA_3_MOD_ASO	×		×	
DA_4_MOD_ASN	×			×
DA_5_MOD_AMR	×		×	×
DA_6_MOD_AMR_GRA	×	×	×	×
DA_7_MOD_ASO_GRA	×	×	×	
DA_8_MOD_ASN_GRA	×	×		×

Eight DA Experiments: Spatial Correlation

Spatial correlation:

Soil moisture (with ESA)

Snow depth (with CMC)

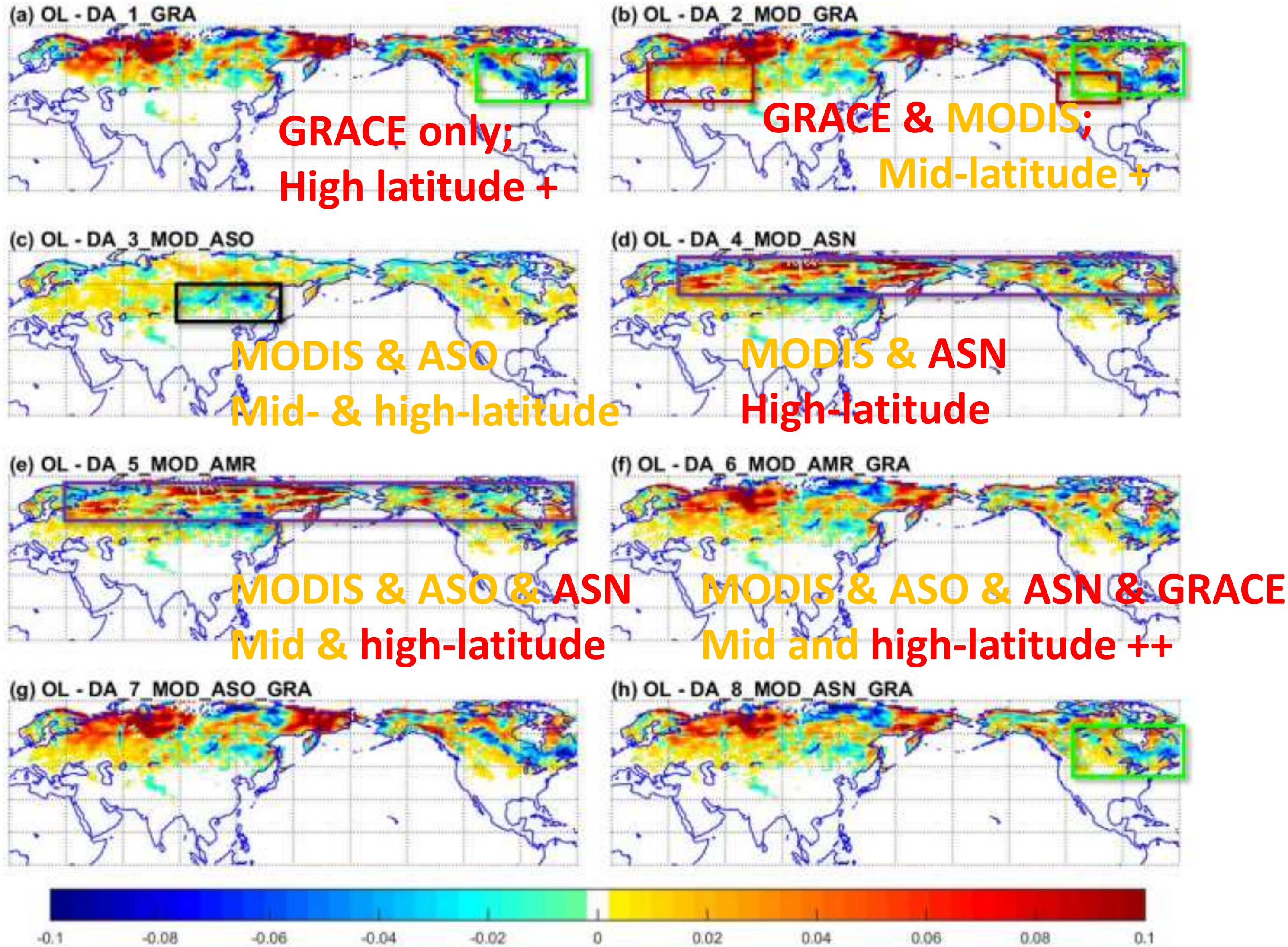


Zhao and Yang (2018; *Remote Sensing of Environment*)

Eight DA Experiments: Snow Depth

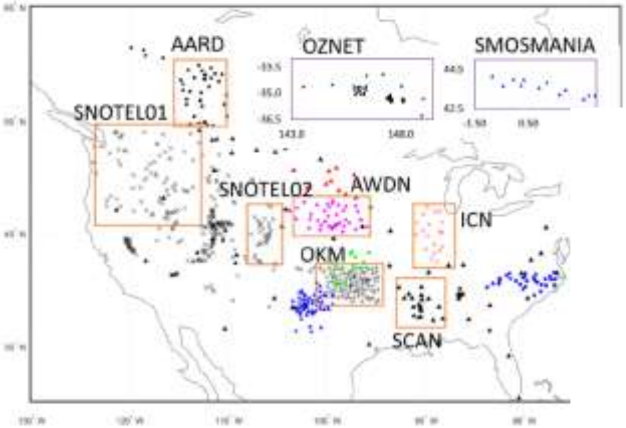
RMSE_diff =
OL – DA

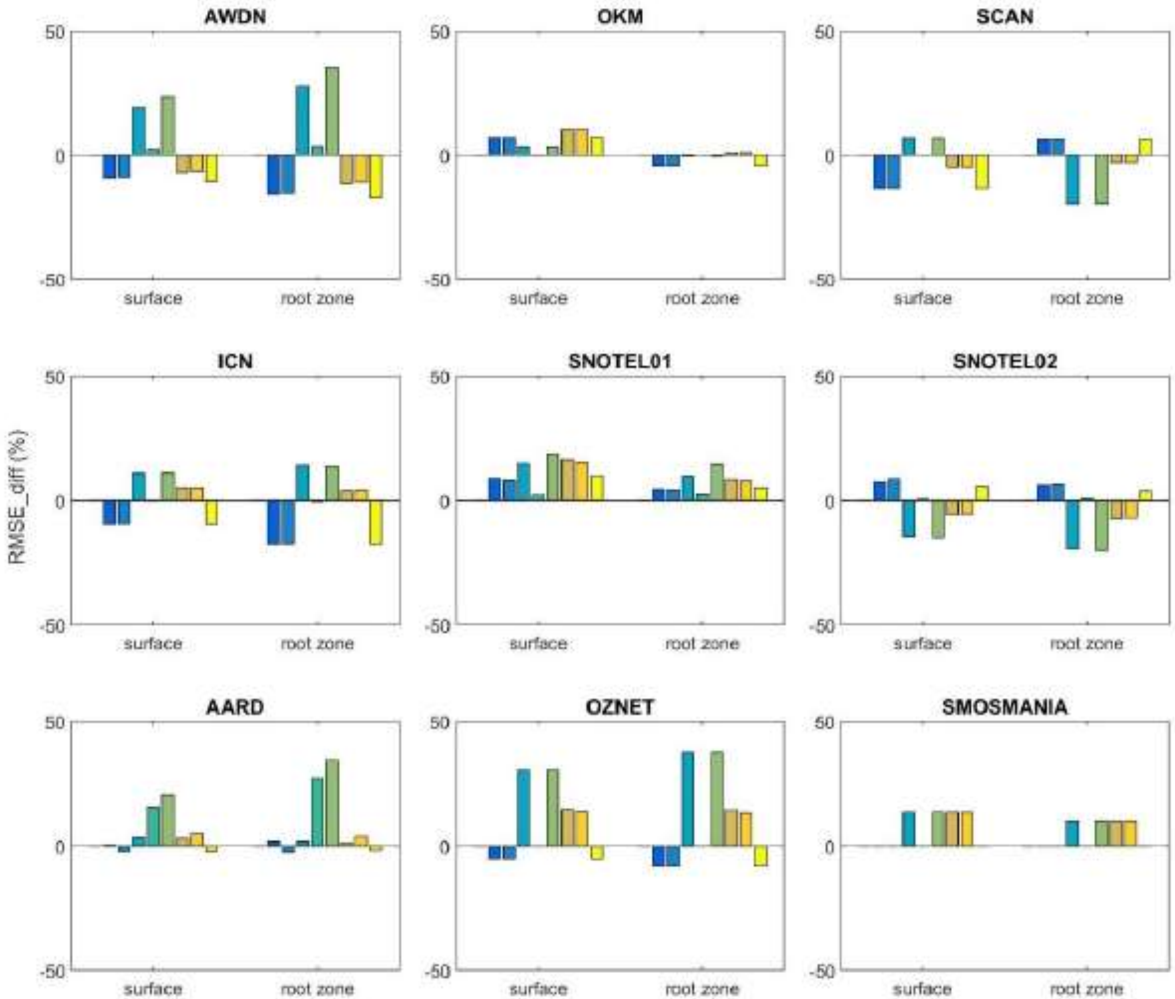
Red colors:
improvements



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

Eight DA Experiments: Soil Moisture



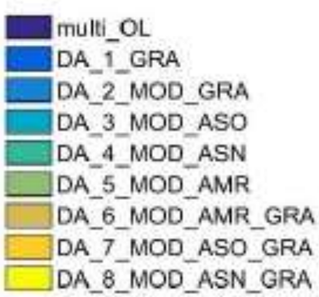


RMSE$_{_diff}$ =

OL – DA

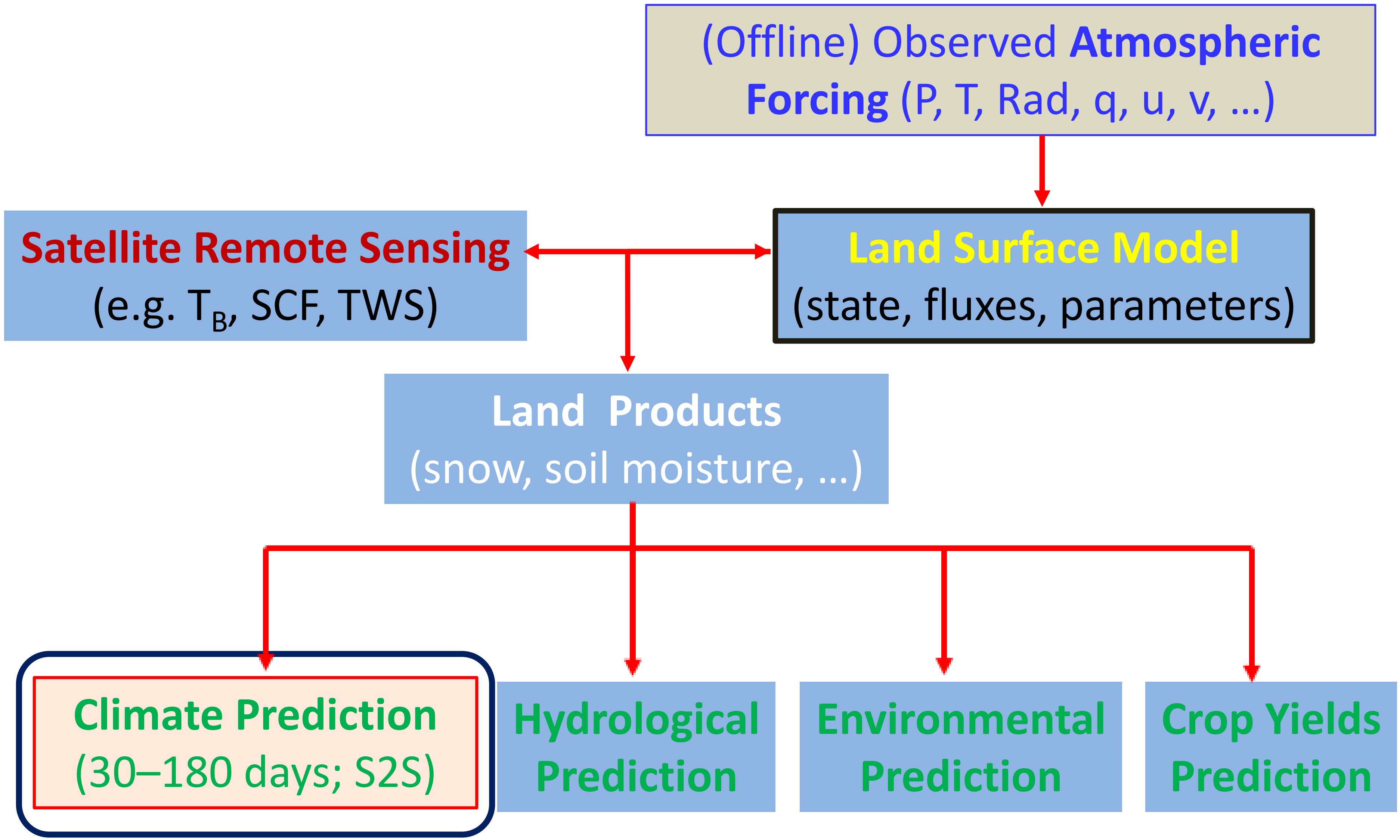
Positive values:

improvements

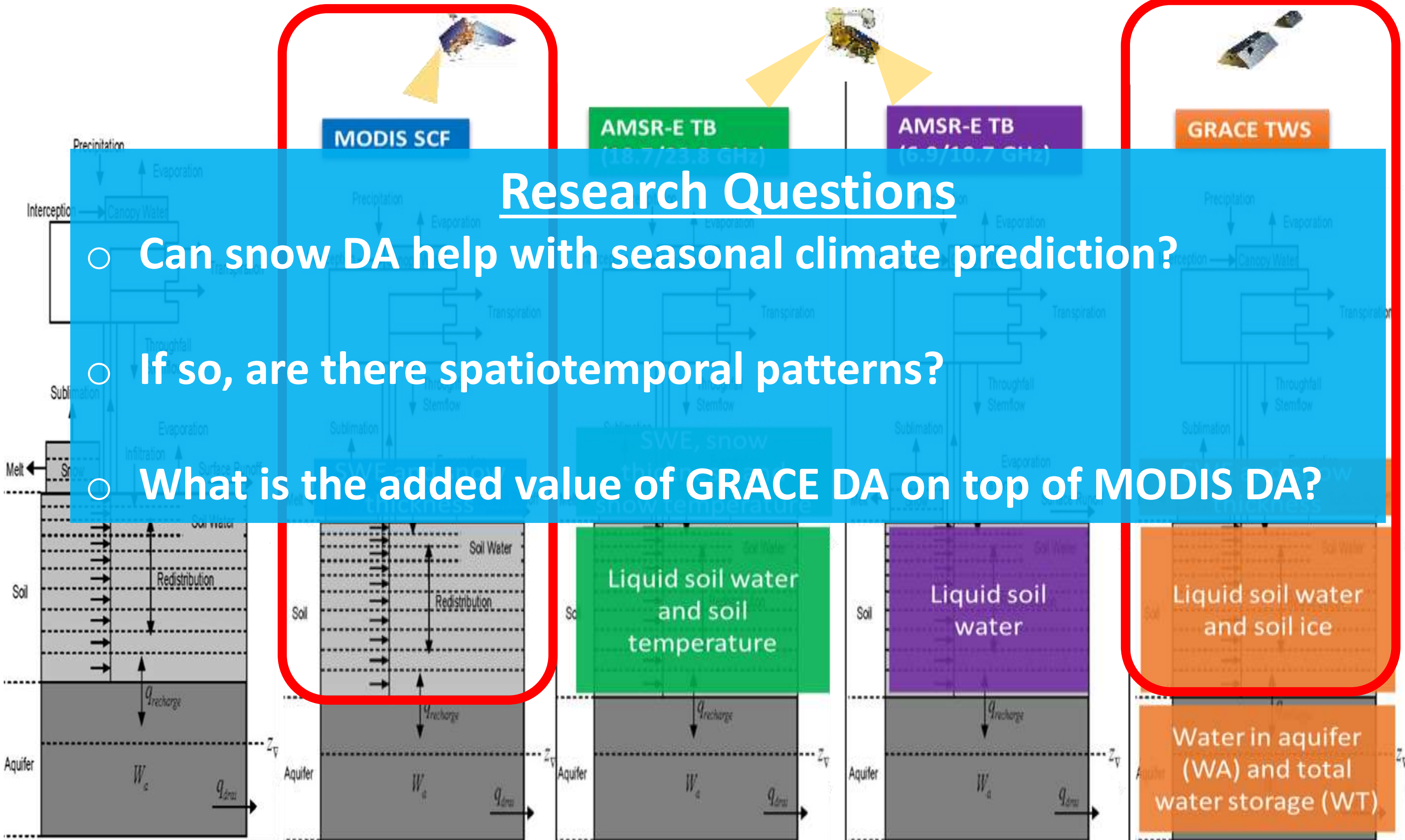


Zhao and Yang (2018; *Remote Sensing of Environment*)

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

- **504 ensemble-based "hindcast" simulations**
  - **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)

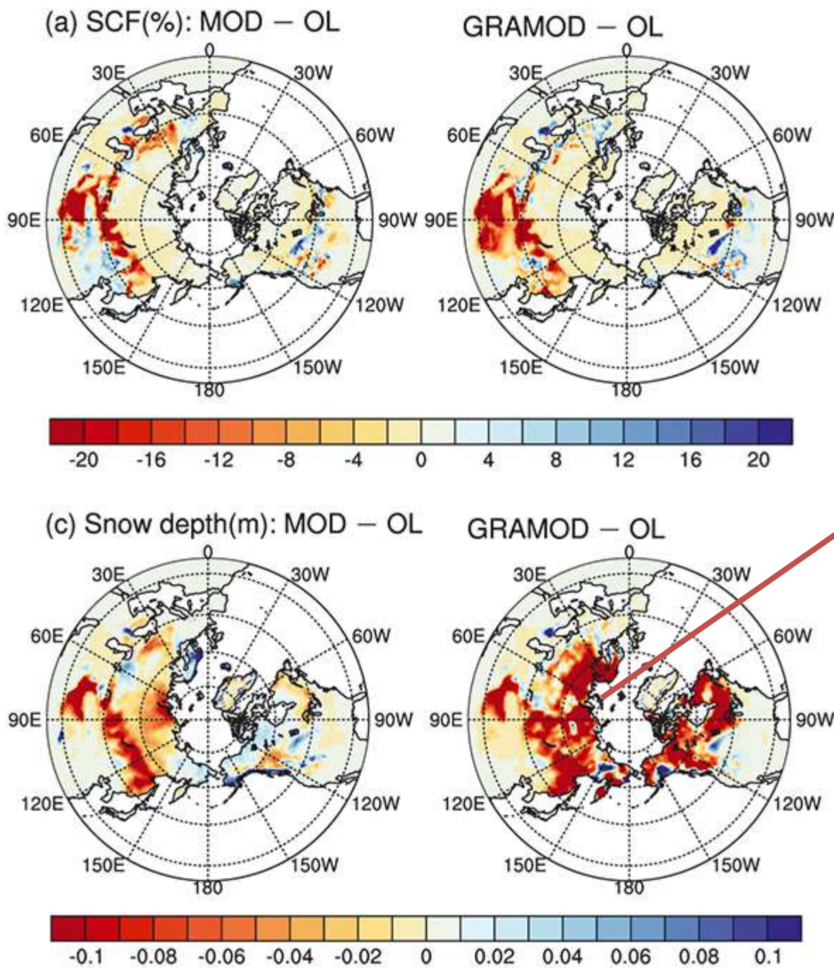
DA-Induced Changes: Initial Snow Conditions

MOD – OL

GRAMOD – OL

Snow Cover Fraction

Snow depth



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

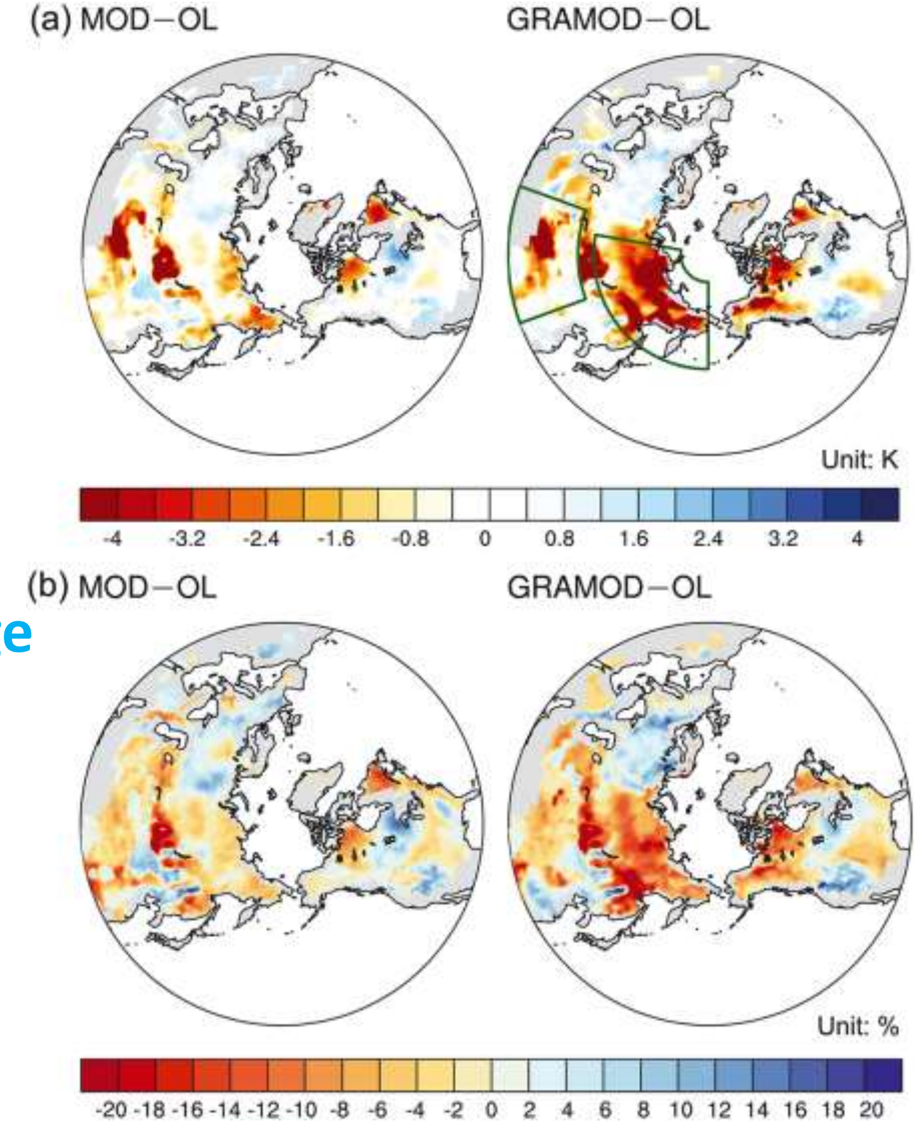
GRACE: additional snow mass information

Lin et al. (2016; GRL)

2-m Temperature Prediction

cRMSE

Percentage change

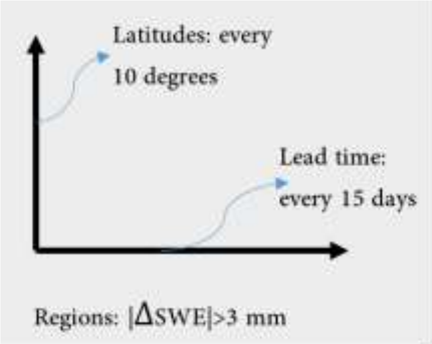


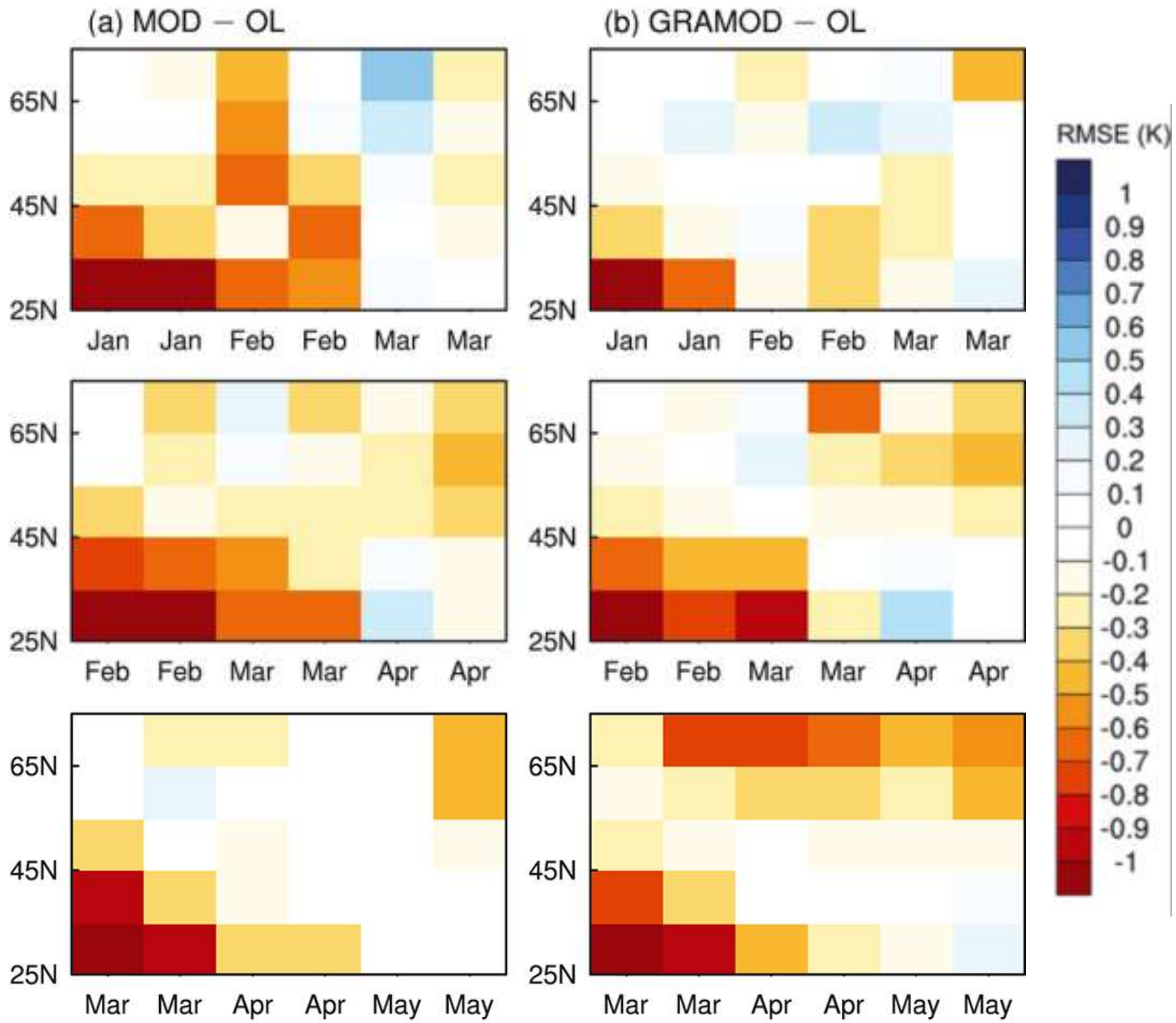
Lin et al. (2016; GRL)

5 – 25% local improvements:

- Tibetan Plateau
- High-latitude (e.g. Siberia)

Interesting Latitudinal Pattern





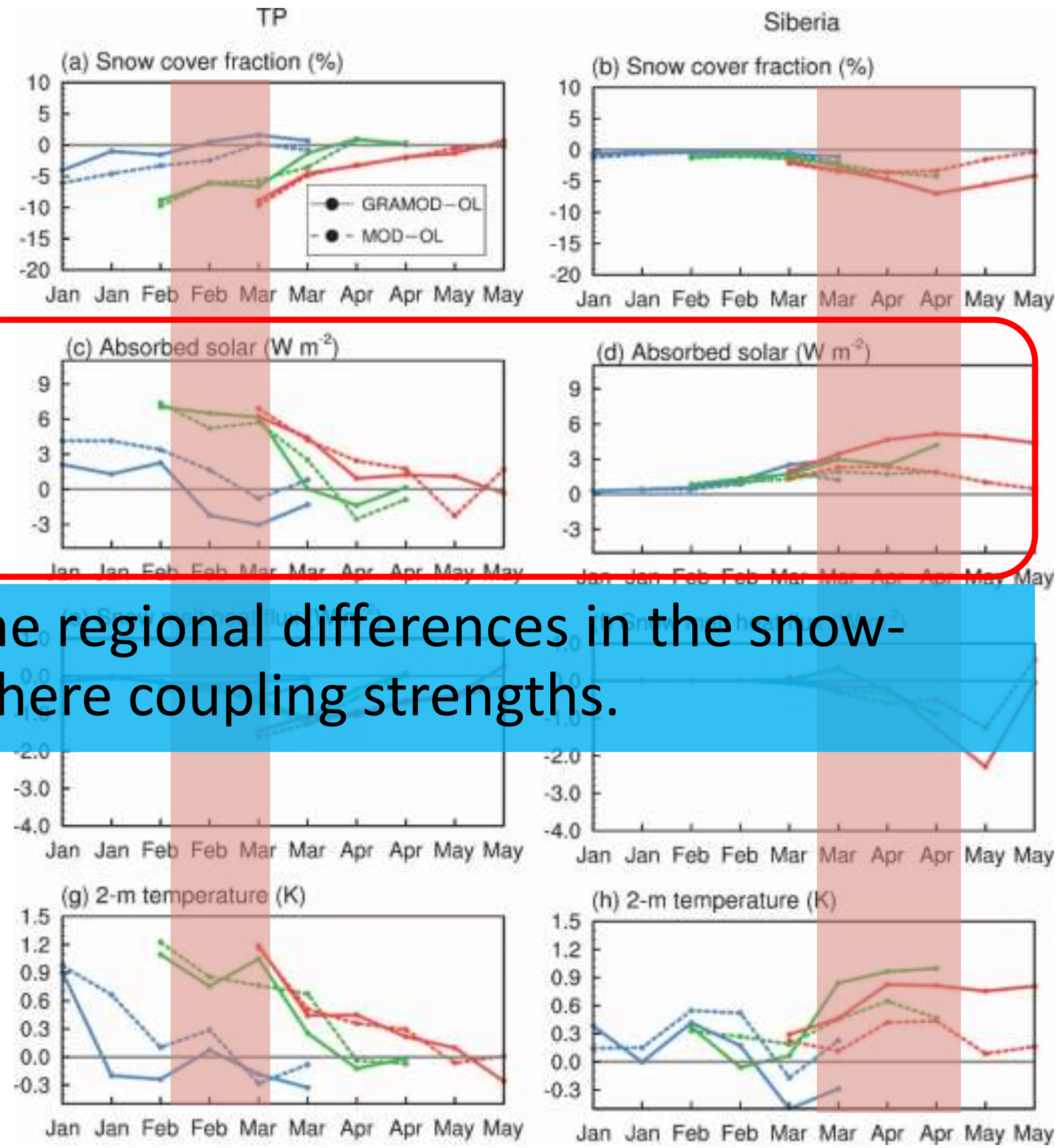
Lower latitude: immediate improvements;

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)

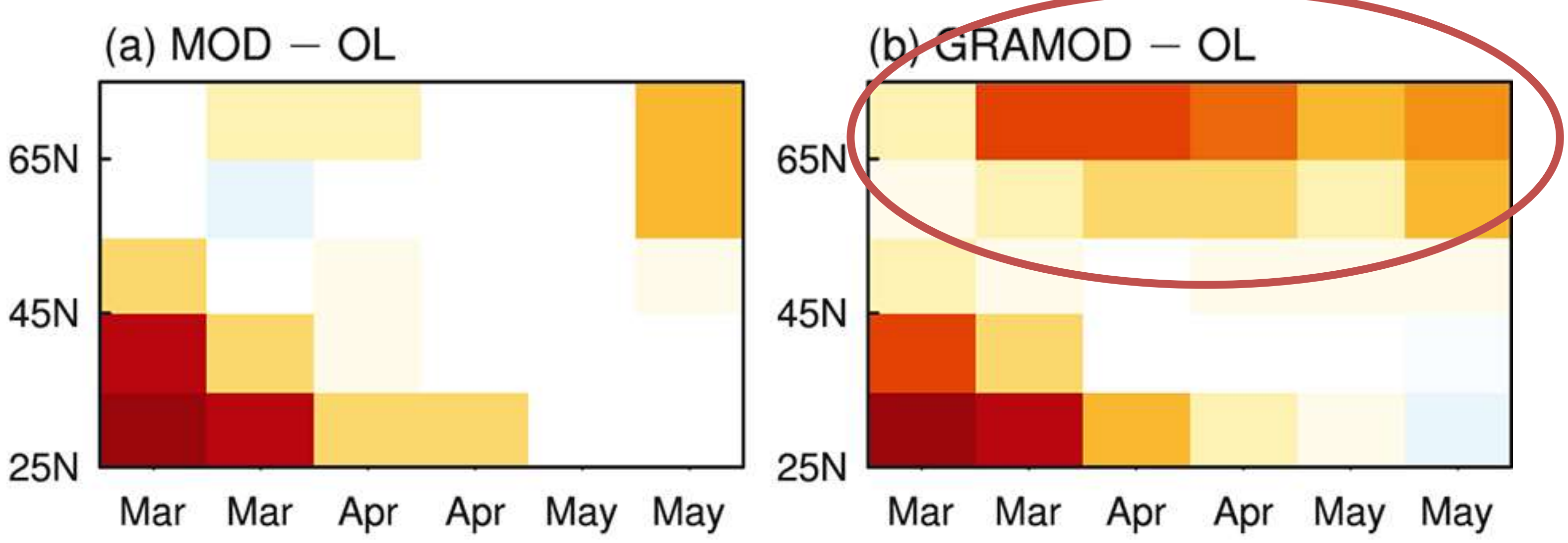


This is related to the regional differences in the snow-atmosphere coupling strengths.

Lin et al. (2016; GRL)

Rebound in Predictability

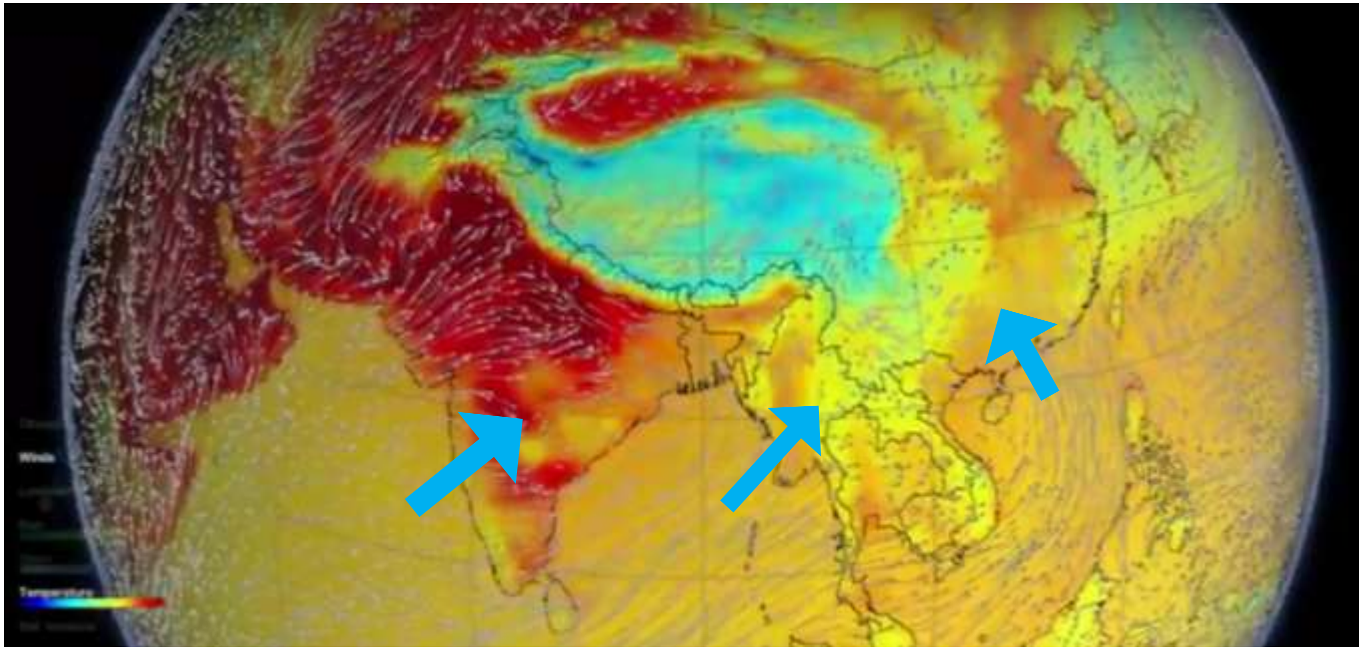
- Higher-latitude such as the Siberia
  - *Improved temperature prediction appears later in warmer months*
  - *Due to strengthened snow-atmosphere coupling*



Lin et al. (2016; GRL)

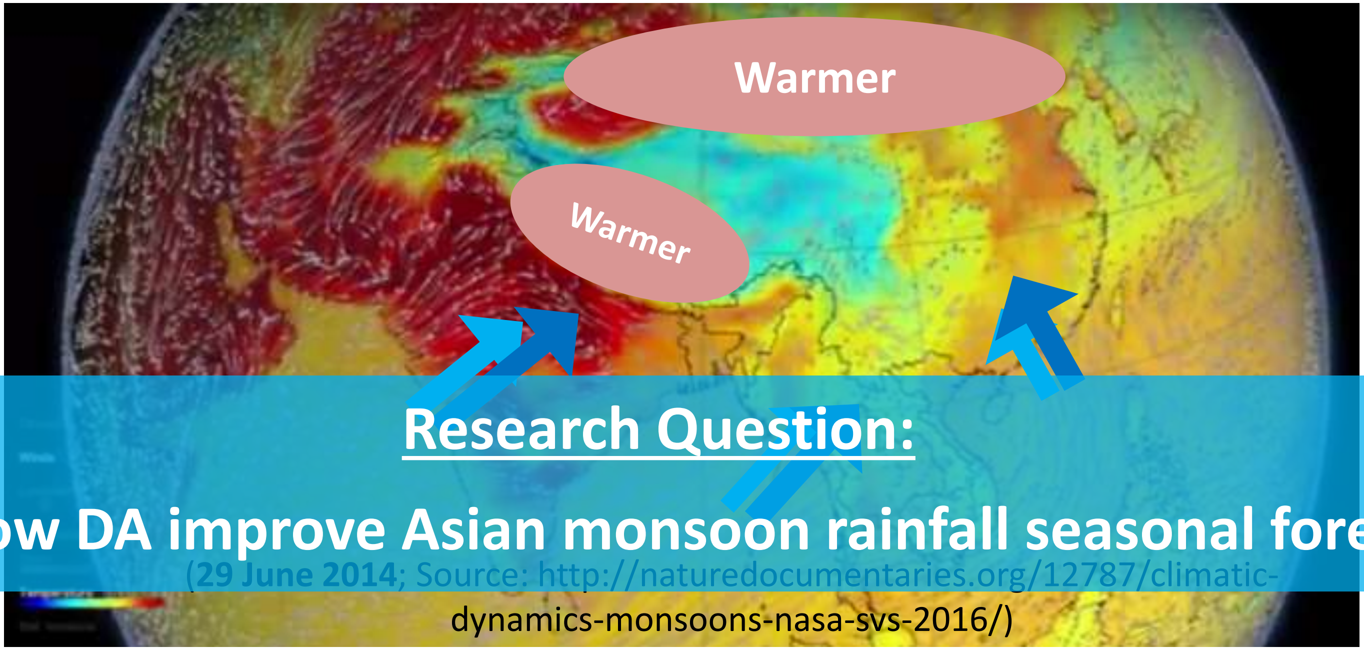
Asian Monsoon

- Affects more than 60% of the world’s population
- Accurate seasonal forecasts are extremely important
- Tropical oceans as the primary source of predictability
- Past studies focus on ocean data assimilation (DA)
- Skill of land-oriented DA has not been demonstrated.



Seasonal Monsoon Rainfall Prediction

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



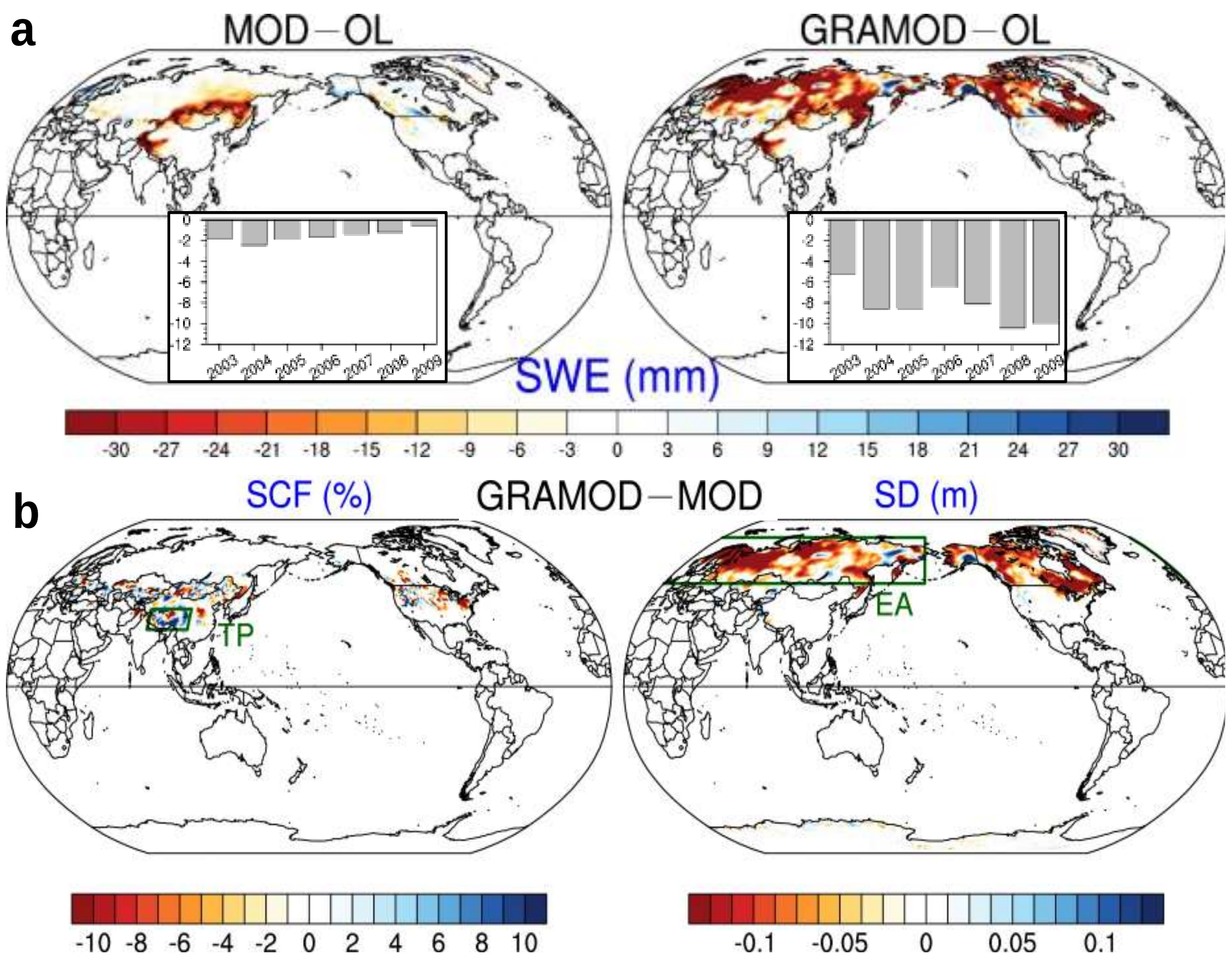
(29 June 2014; Source: http://naturedocumentaries.org/12787/climatic-dynamics-monsoons-nasa-svs-2016/)

<u>Research Question:</u>

Can snow DA improve Asian monsoon rainfall seasonal forecast?

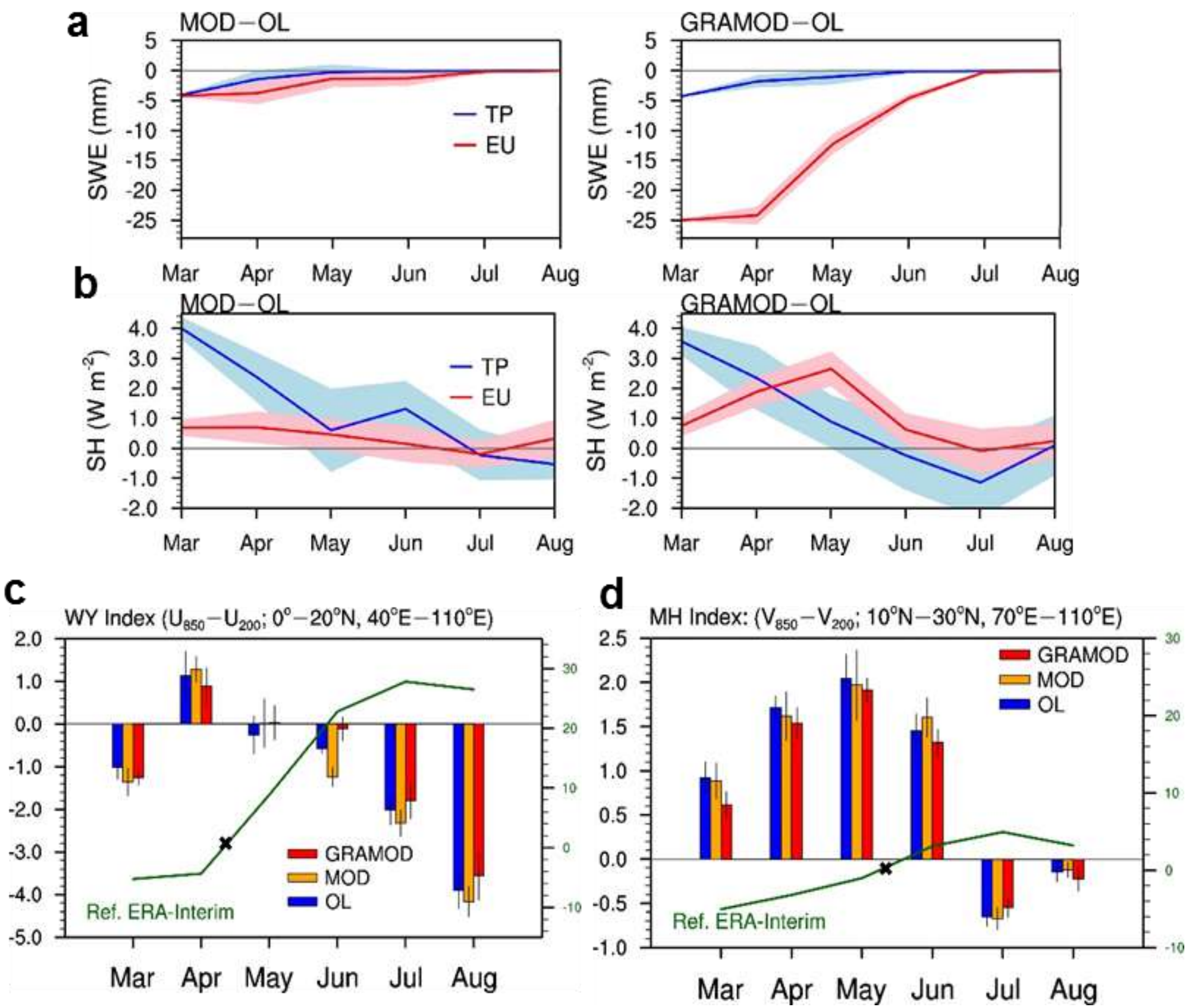
- CLM4-CAM5 experiments initialized on 1 March of 2003 to 2009
- Model runs extended to the end of August

DA-induced Changes in Snow Initializations



Lin et al. (2019)

DA-induced Thermal Forcing and Impacts on Monsoon Circulation



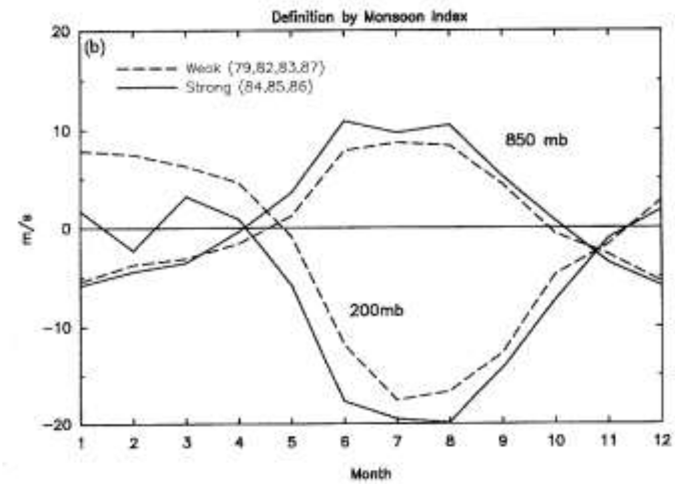
Lin et al. (2019)

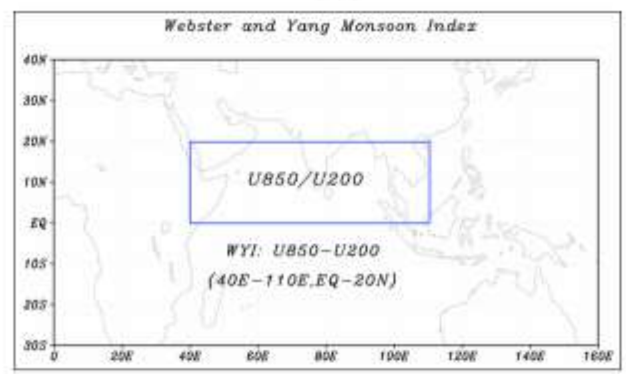
Webster and Yang Monsoon Index

- U winds have anti-phase on 850 hPa and 200 hPa in summer.
- WYM Index:

  U850 (40E–110E, EQ – 20N) – U200 (40E–110E, EQ–20N)

Webster and Yang (1992)

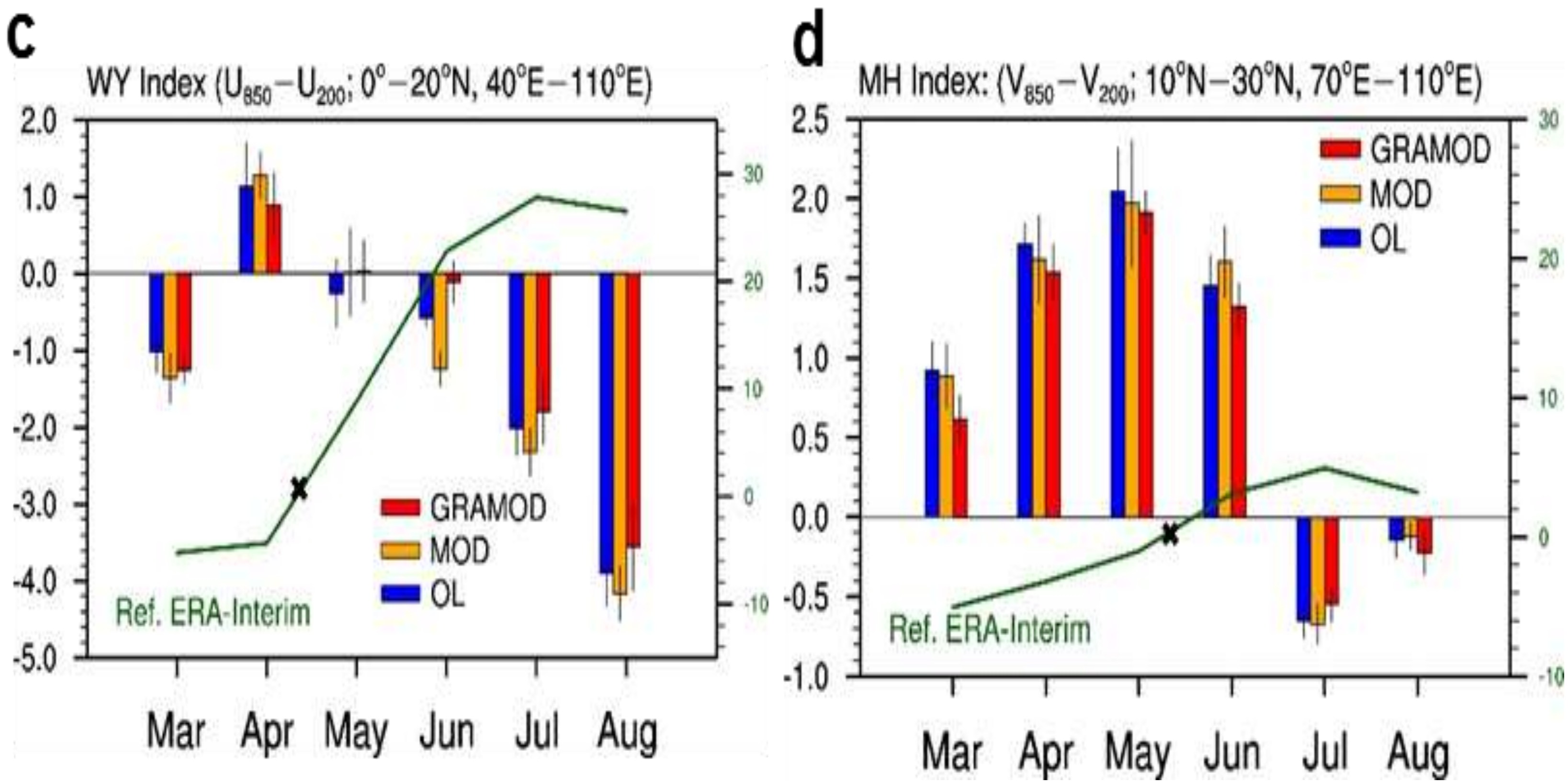




WYM Index = U850(40-110E,EQ-20N)-U200(40-110E,EQ-20N)

http://apdrc.soest.hawaii.edu/projects/monsoon/definition.html

DA-induced Thermal Forcing and Impacts on Monsoon Circulation

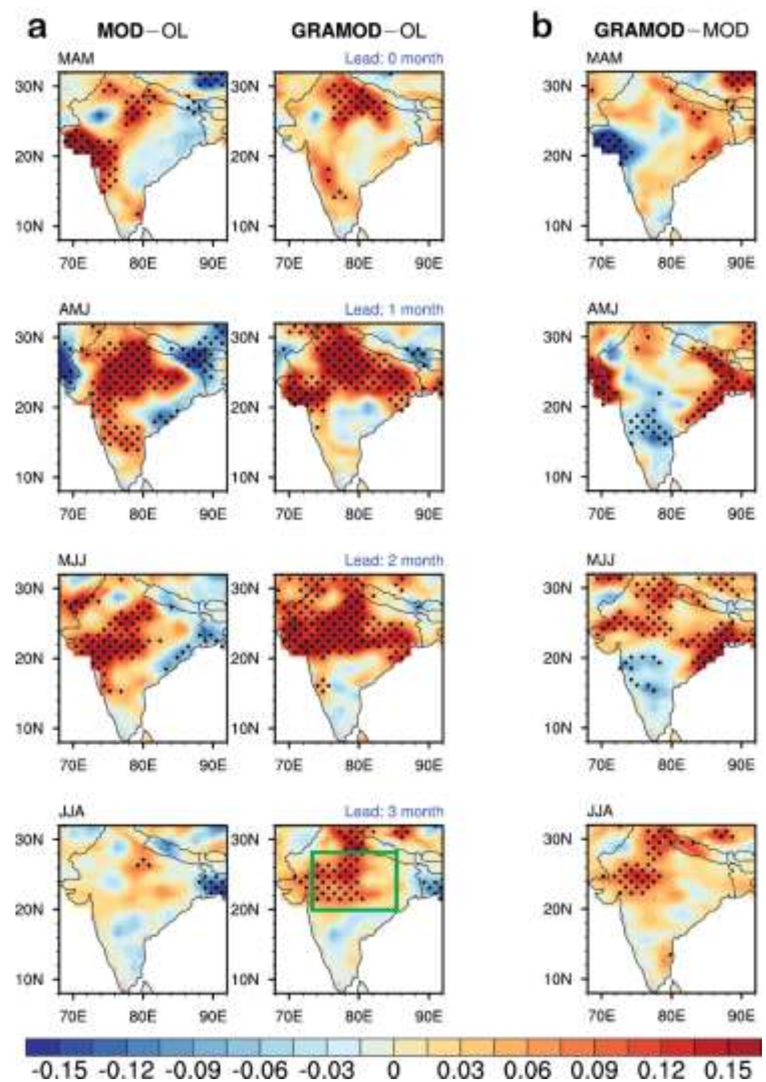


Lin et al. (2019)

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;

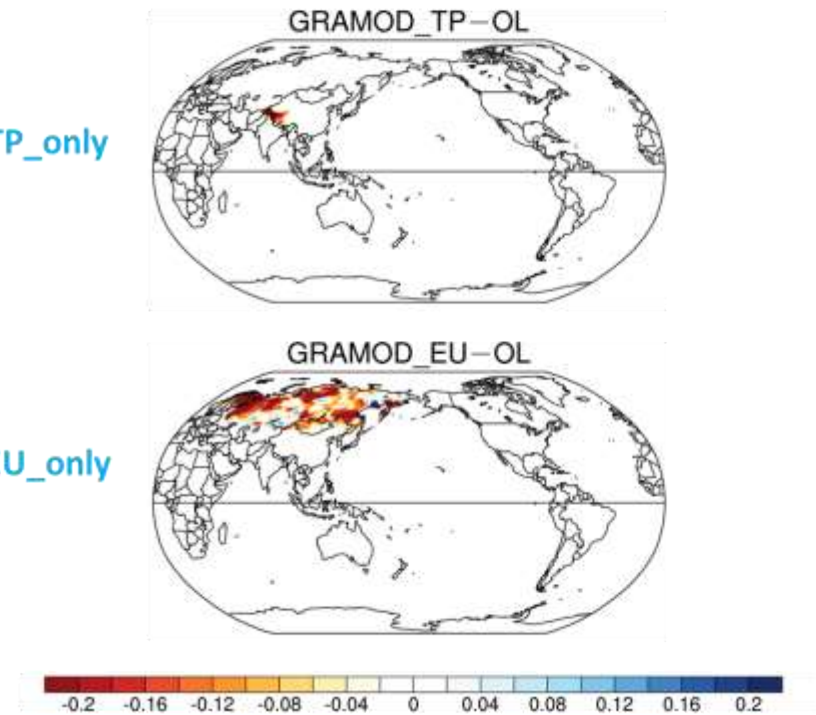


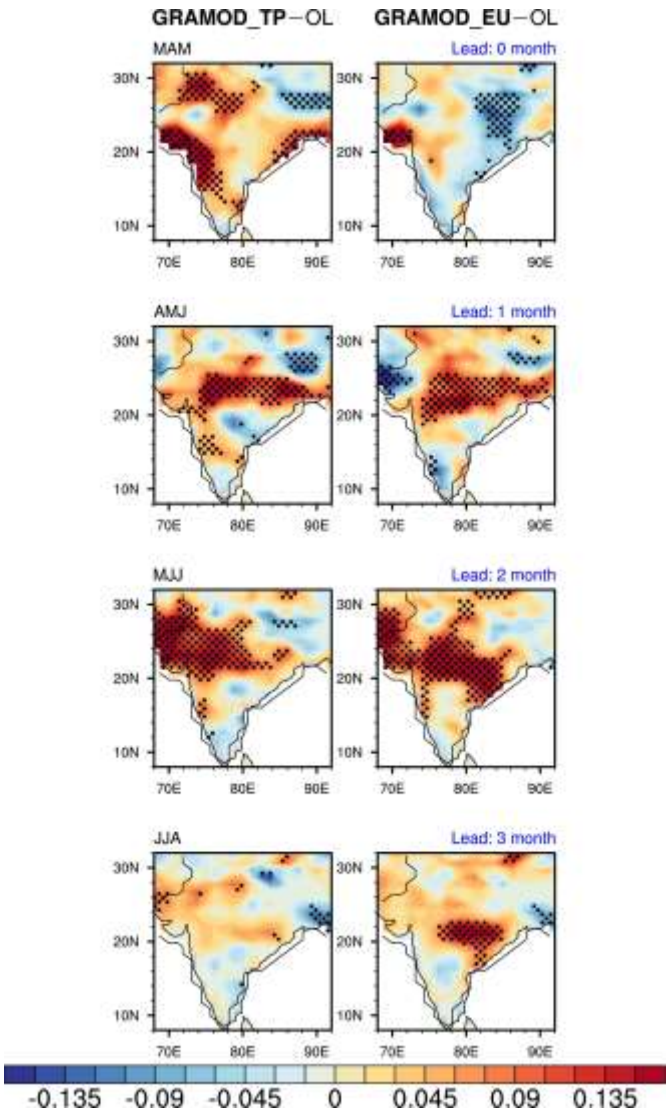
Lin et al. (2019)

Regional Land DA vs. Seasonal Prediction

TP_only

EU_only



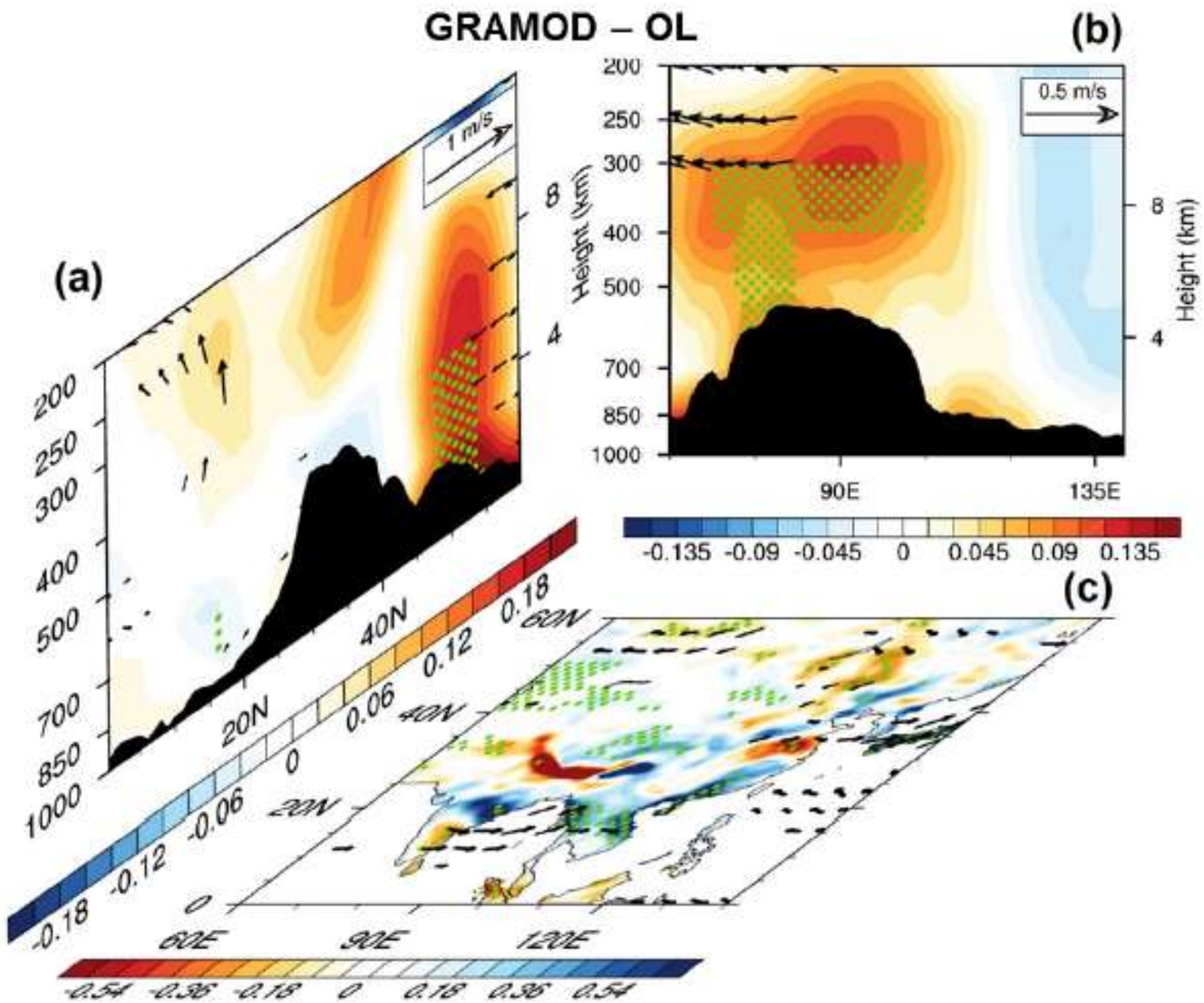


High-latitude Eurasian snow + GRACE DA:

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

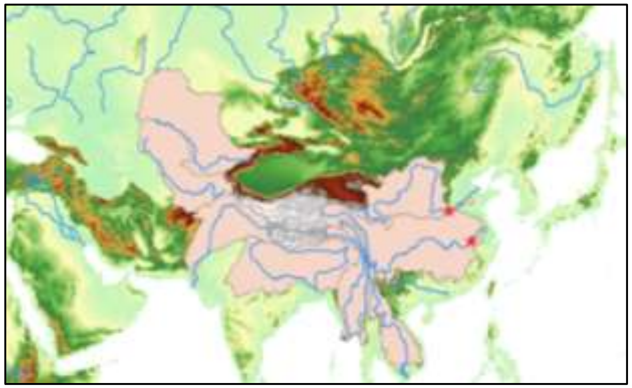
Lin et al. (2019)

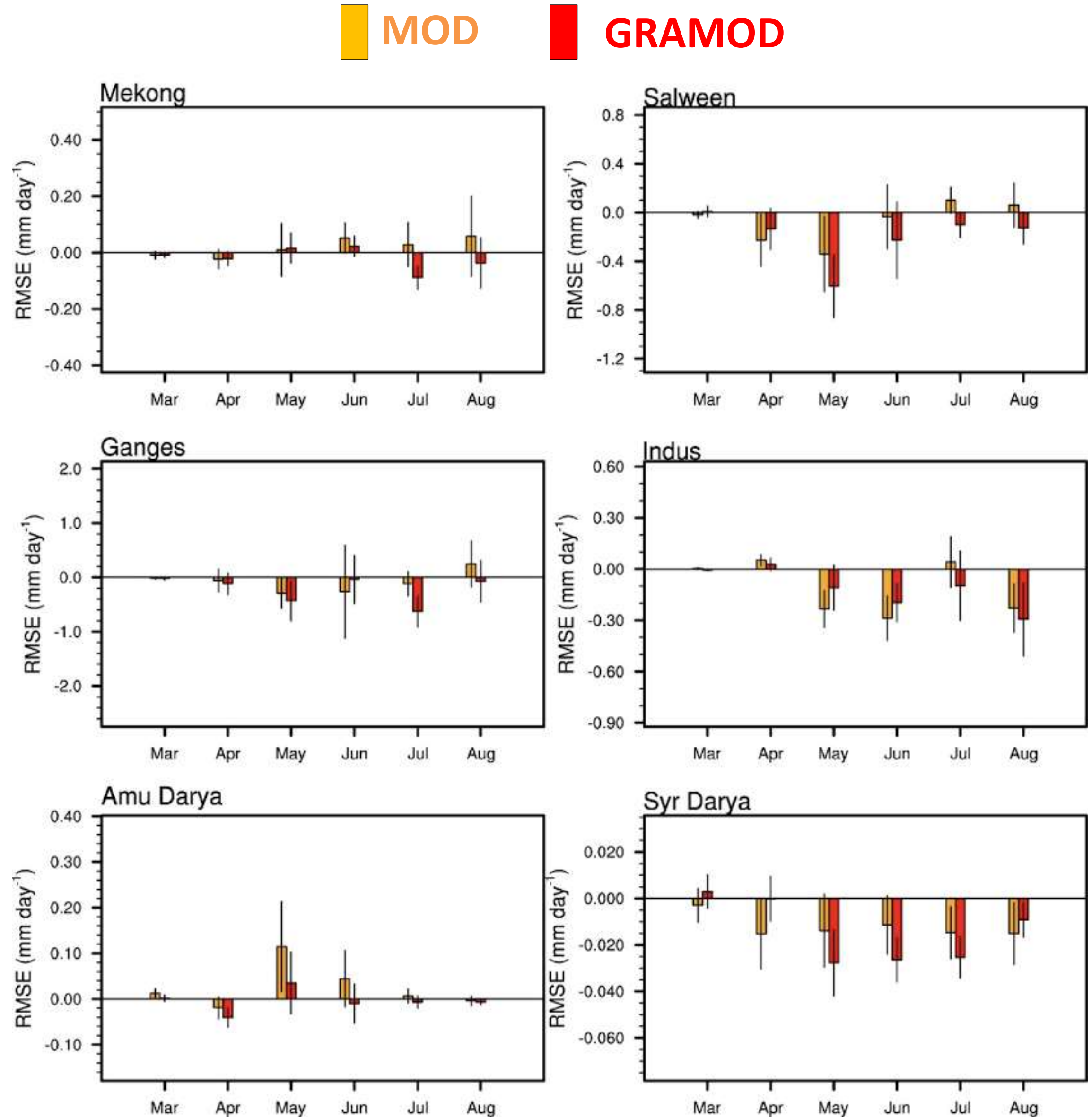
DA-induced Changes in Temperature, Circulation, and Precipitation



Lin et al. (2019)

River Basins Originating from the Tibetan Plateau

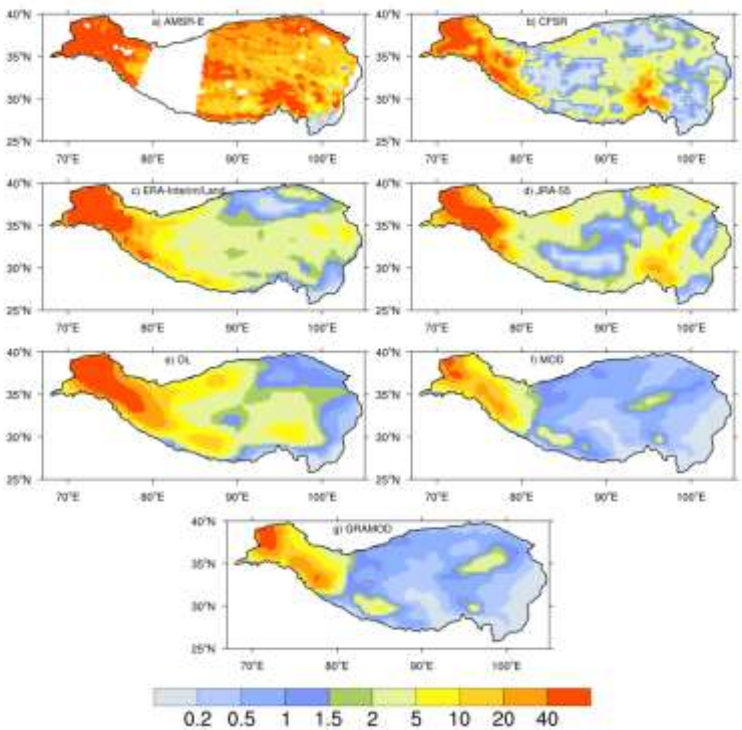


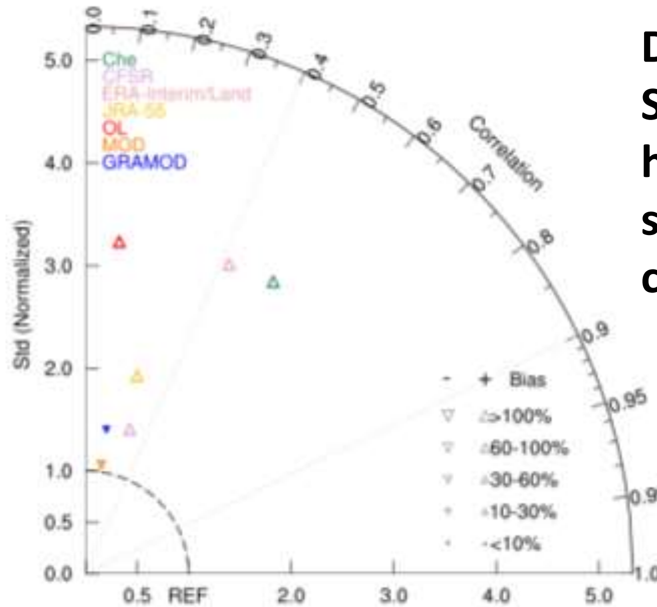


RMSE_diff = DA – OL

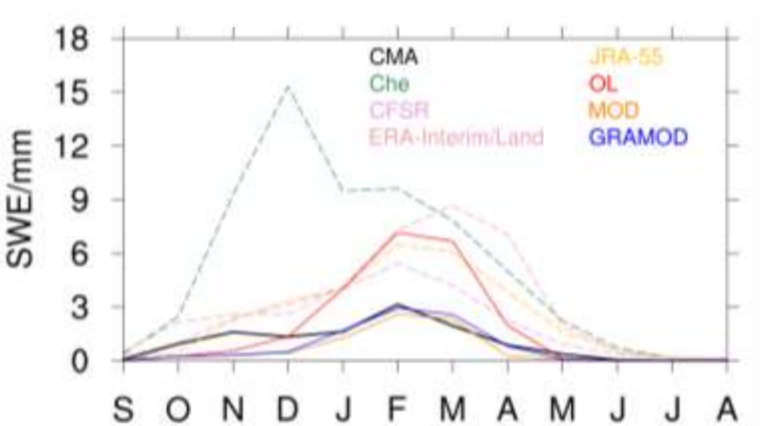
- Basin-averaged runoff against ERA-Land runoff;
- Negative RMSE_diff: improved runoff forecast

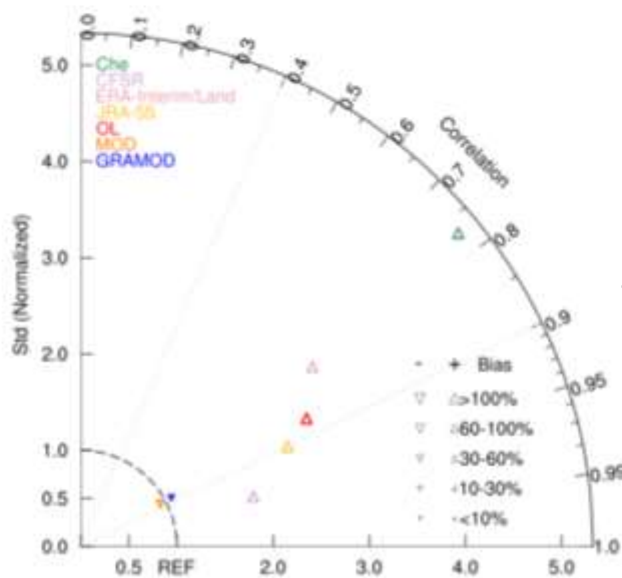
Evaluating Different Datasets of Snow Water Equivalent (SWE)





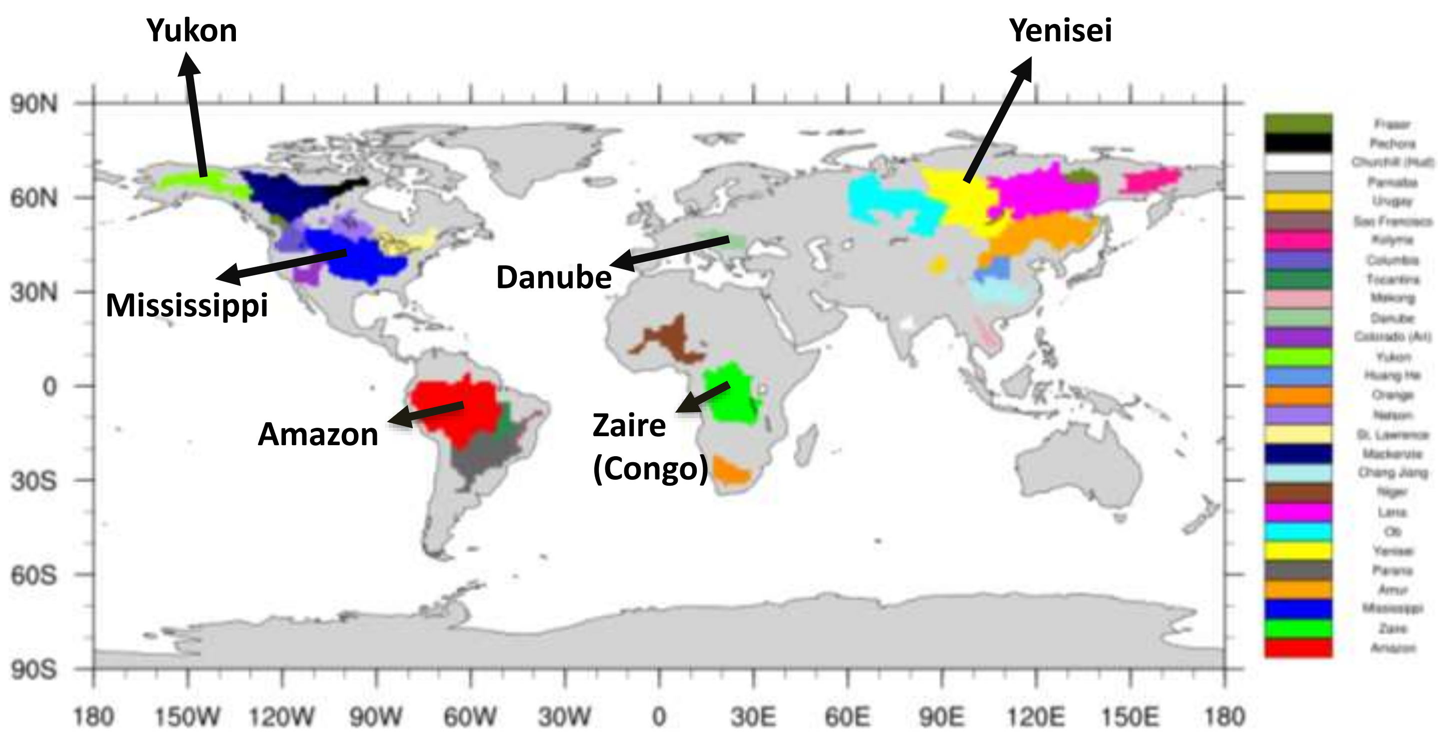
DA products reduce SWE biases, but have a smaller spatial correlation coefficient.

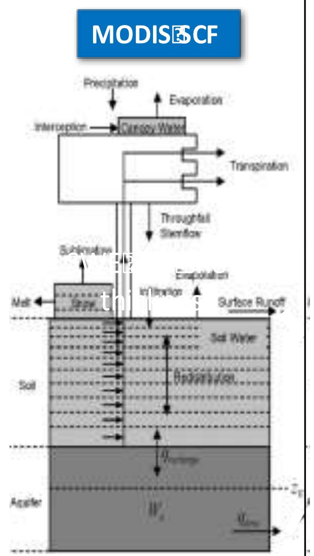


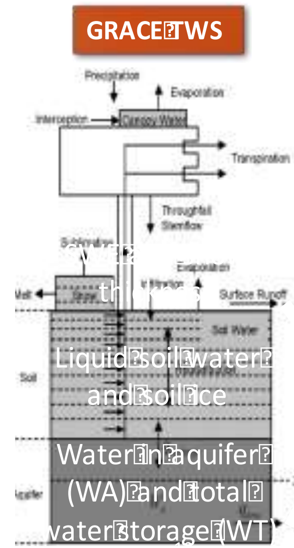


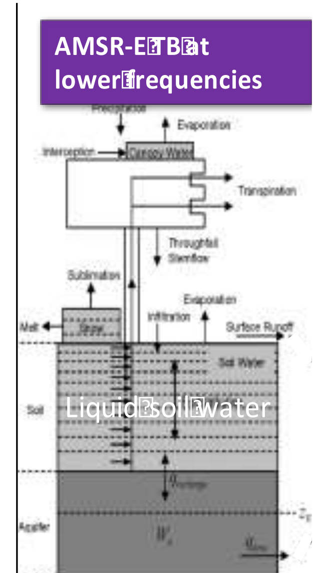
DA products improve seasonal amplitudes and timing.

Selected global large river basins



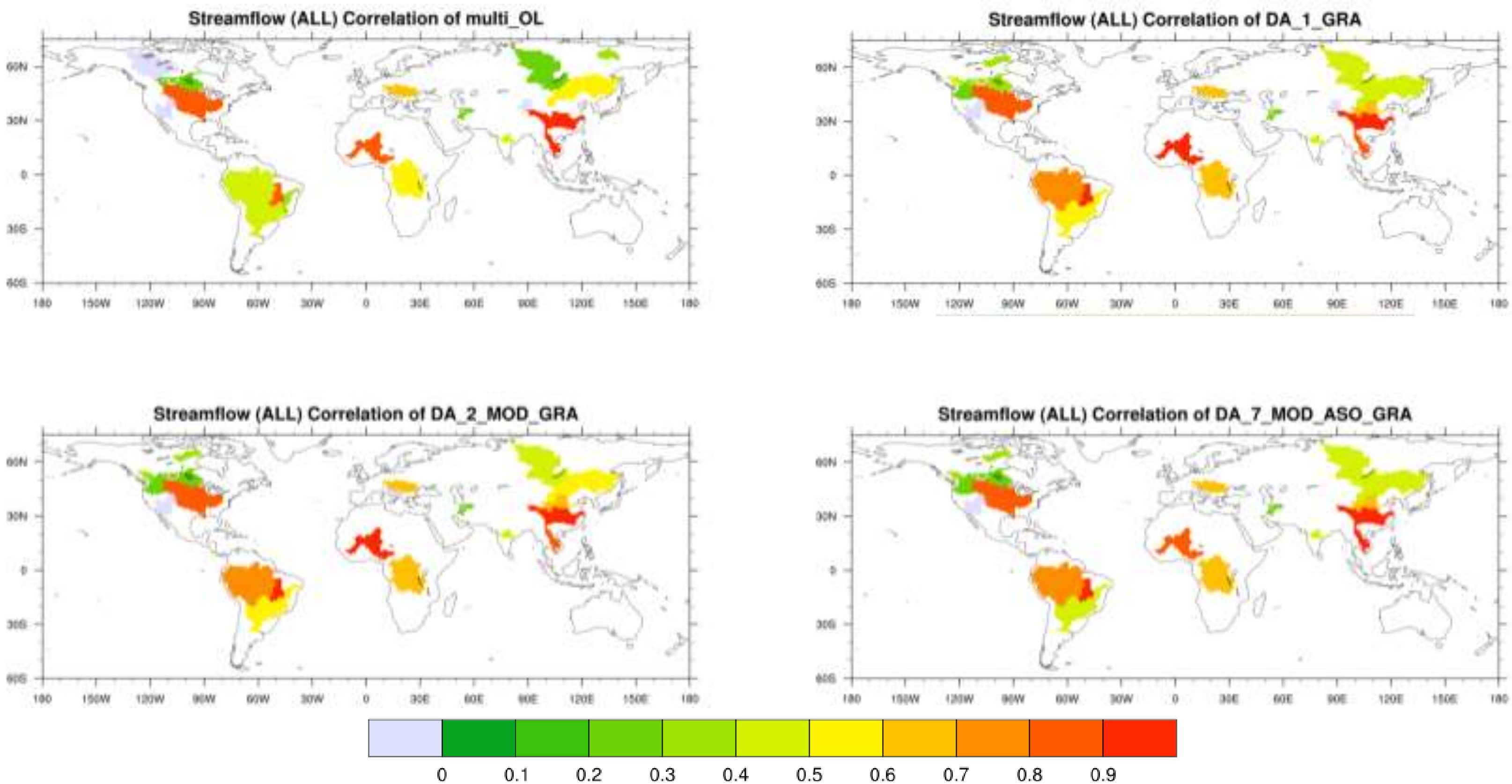






Cases	MODIS SCF	GRACE TWS	AMSR-E TB (6.9/10.7 GHz)
OL	Open-loop, no DA		
DA_1_GRA		x	
DA_2_MOD_GRA	x	x	
DA_7_MOD_ASO_GRA	x	x	x

Improved estimation of monthly streamflow



Summary

- **Developed a global land DA system** capable of assimilating MODIS, GRACE, and AMSR-E observations (40-member multi-year 2003 –2009)
  - 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
  - Mid- to high-latitude Eurasia GRACE DA on March 1 improves summer monsoon forecast skill

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

CLM3.0, 3.5, 4.0, 4.5 (5.0)

- CLM3.0 → 3.5
  - Surface runoff (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 (Lawrence *et al*., 2007)
- CLM3.5 → 4.0, 4.5
  - 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 canopy (Oleson *et al*.)**
  - **BVOC component (MEGAN2) (Guenther *et al*.)**
  - **Dust emissions**
  - Updated hydrology and ground evaporation
  - New (density-based and later revised) snow cover fraction, 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

Co-Chairs: David Lawrence (NCAR), Zong-Liang Yang (Univ of Texas at Austin, 2008-2013)

Noah-MP is unique among LSMs

- **A new paradigm** in land-surface, environmental, and hydrological modeling (Clark et al., 2007; 2011)
- Next-generation LSM for NOAA CFS and GFS
- Already included in WRF
- In a broad sense,
  - Multi-parameterization ≡ Multi-physics ≡ Multi-hypothesis
- **A modular & powerful framework for**
  - Diagnosing differences
  - Identifying structural errors
  - Improving understanding
  - Enhancing data/model fusion and data assimilation
  - Facilitating ensemble forecasts and **uncertainty quantification**

Noah-MP

JOURNAL OF GEOPHYSICAL RESEARCH, VOL. 116, D12109, doi:10.1029/2010JD015139, 2011

The community Noah land surface model with multiparameterization options (Noah-MP): 1. Model description and evaluation with local-scale measurements

Guo-Yue Niu,[1,2] Zong-Liang Yang,[1] Kenneth E. Mitchell,[3] Fei Chen,[4] Michael B. Ek,[3] Michael Barlage,[4] Anil Kumar,[5] Kevin Manning,[4] Dev Niyogi,[6] Enrique Rosero,[1,7] Mukul Tewari,[4] and Youlong Xia[3]

Received 4 October 2010; revised 3 February 2011; accepted 27 March 2011; published 24 June 2011.

JOURNAL OF GEOPHYSICAL RESEARCH, VOL. 116, D12110, doi:10.1029/2010JD015140, 2011

The community Noah land surface model with multiparameterization options (Noah-MP): 2. Evaluation over global river basins

Zong-Liang Yang,[1] Guo-Yue Niu,[1,2] Kenneth E. Mitchell,[3] Fei Chen,[4] Michael B. Ek,[3] Michael Barlage,[4] Laurent Longuevergne,[5] Kevin Manning,[4] Dev Niyogi,[6] Mukul Tewari,[4] and Youlong Xia[3]

Received 4 October 2010; revised 4 February 2011; accepted 25 March 2011; published 24 June 2011.

Noah-MP

1. Leaf area index (prescribed; predicted)
2. Turbulent transfer (Noah; NCAR LSM)
3. Soil moisture stress factor for transpiration (Noah; SSiB; CLM)
4. Canopy stomatal resistance (Jarvis; Ball-Berry)
5. Snow surface albedo (BATS; CLASS)
6. Frozen soil permeability (Noah; Niu and Yang, 2006)
7. Supercooled liquid water (Noah; Niu and Yang, 2006)
8. Radiation transfer:
   Modified two-stream: Gap = F (3D structure; solar zenith angle; ...) ≤ 1-GVF
   Two-stream applied to the entire grid cell: Gap = 0
   Two-stream applied to fractional vegetated area: Gap = 1-GVF
9. Partitioning of precipitation to snowfall and rainfall (CLM; Noah)
10. Runoff and groundwater:
    TOPMODEL with groundwater
    TOPMODEL with an equilibrium water table (Chen&Kumar,2001)
    Original Noah scheme
    BATS surface runoff and free drainage

More to be added

Niu et al. (2011)

Collaborators: Yang, Niu (UT), Chen (NCAR), Ek/Mitchell (NCEP/NOAA), and others

Maximum # of Combinations

1. Leaf area index (prescribed; predicted) 2
2. Turbulent transfer (Noah; NCAR LSM) 2
3. Soil moisture stress factor for transp. (Noah; SSiB; CLM) 3
4. Canopy stomatal resistance (Jarvis; Ball-Berry) 2
5. Snow surface albedo (BATS; CLASS) 2
6. Frozen soil permeability (Noah; Niu and Yang, 2006) 2
7. Supercooled liquid water (Noah; Niu and Yang, 2006) 2
8. Radiation transfer: 3
Modified two-stream: Gap = F (3D structure; solar zenith angle; ...) ≤ 1-GVF
Two-stream applied to the entire grid cell: Gap = 0
Two-stream applied to fractional vegetated area: Gap = 1-GVF
9. Partitioning of precipitation to snow- and rainfall (CLM; Noah) 2
10. Runoff and groundwater: 4
TOPMODEL with groundwater
TOPMODEL with an equilibrium water table (Chen&Kumar,2001)
Original Noah scheme
BATS surface runoff and free drainage

2x2x3x2x2x2x2x3x2x4 = 4608 combinations

Process understanding, probabilistic forecasting, quantifying uncertainties

Integrated Hydrological Framework

Meteorology
(NLDAS/GLDAS)

e.g. precipitation, temperature, wind, radiation

Hydrology
(Noah-MP)

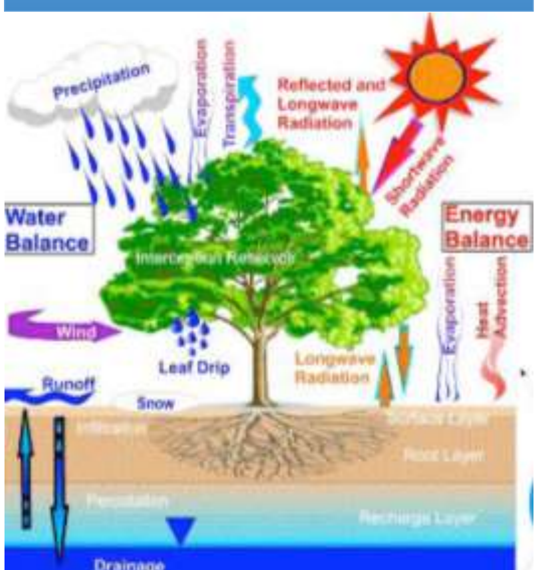
Runoff

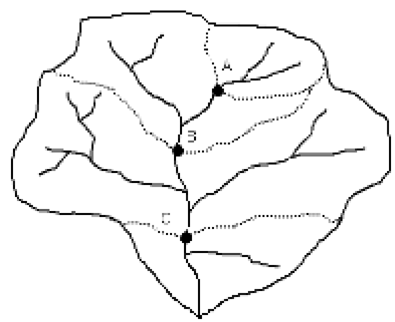
R

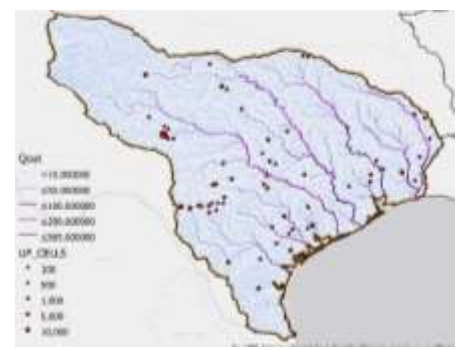
Hydraulics
(RAPID)

Streamflow

Q





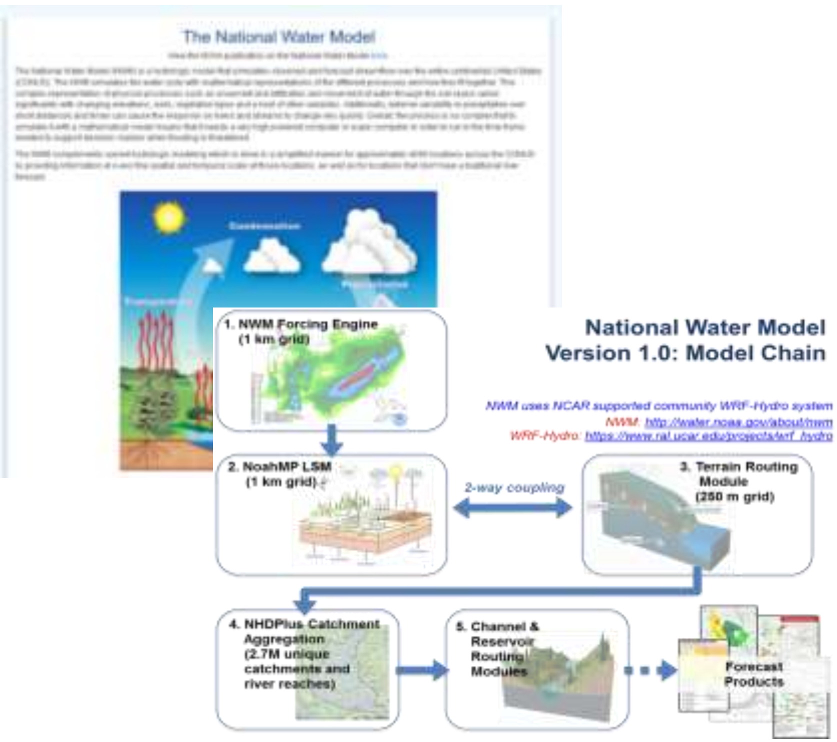


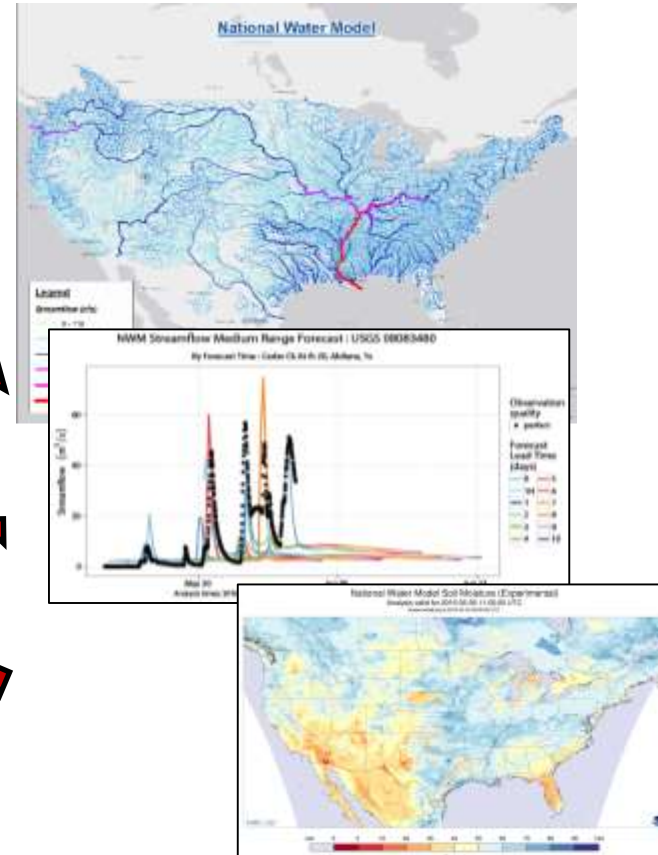
Regional Studies: Texas *[David+ 2011; David+ 2013b]*
Mississippi River *[Cai+ 2014; David+ 2013a; Tavakoly+ 2017]*
Global

The NOAA National Water Model

Development Team: NCAR, NOAA/OWP/NWC, USGS, UT-Austin, CUAHSI, Universities

Sponsor: NOAA Office of Water Prediction





http://water.noaa.gov/about/nwm

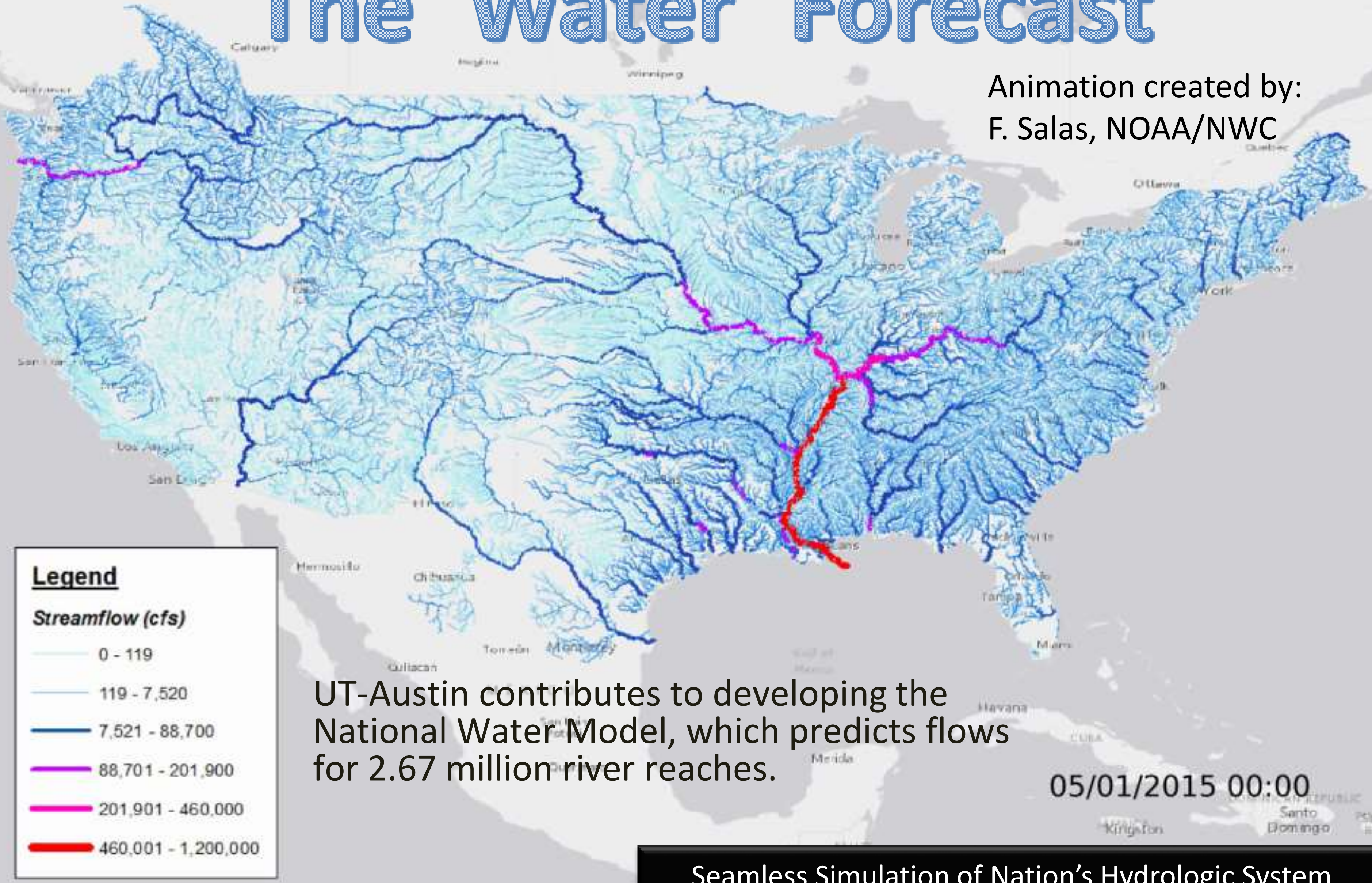
System become fully operational beginning Aug. 16, 2016

- Real-time verification since June 2016
- Multiple operational products created by NOAA, academia, private sector

National Water Model

The 'Water' Forecast

Animation created by:
F. Salas, NOAA/NWC

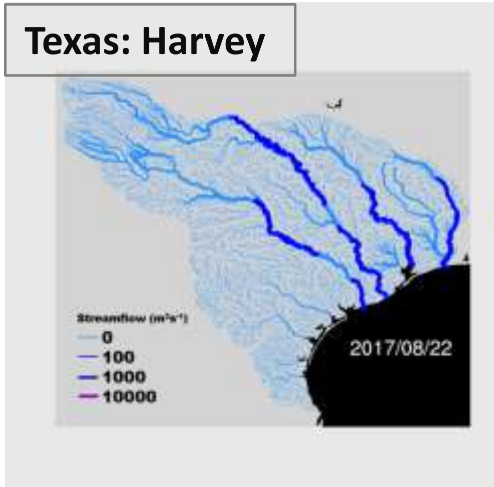


UT-Austin contributes to developing the National Water Model, which predicts flows for 2.67 million river reaches.

05/01/2015 00:00

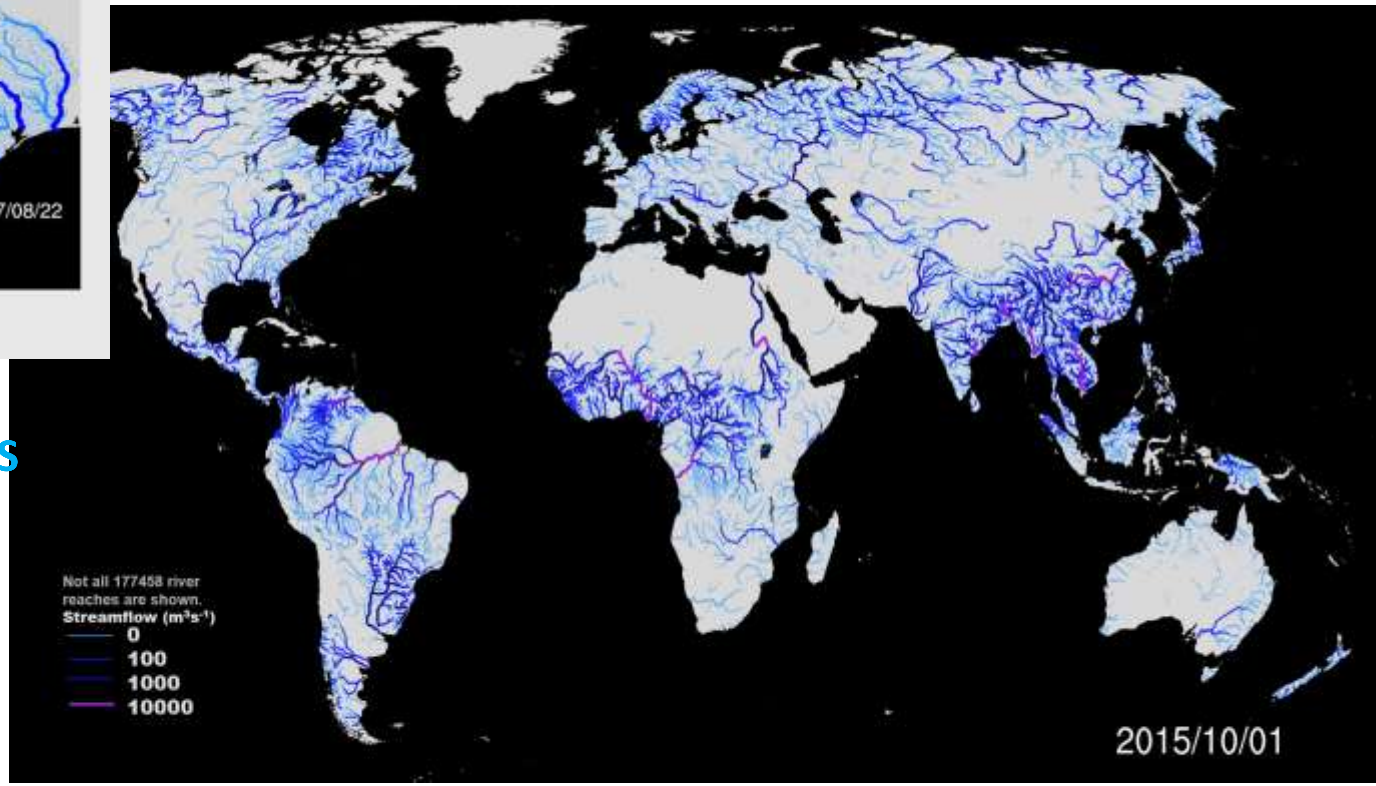
Seamless Simulation of Nation's Hydrologic System

River Discharge Modeling with Vector-Based Routing



1/8° Noah-MP +
15 sec HydroSHEDS

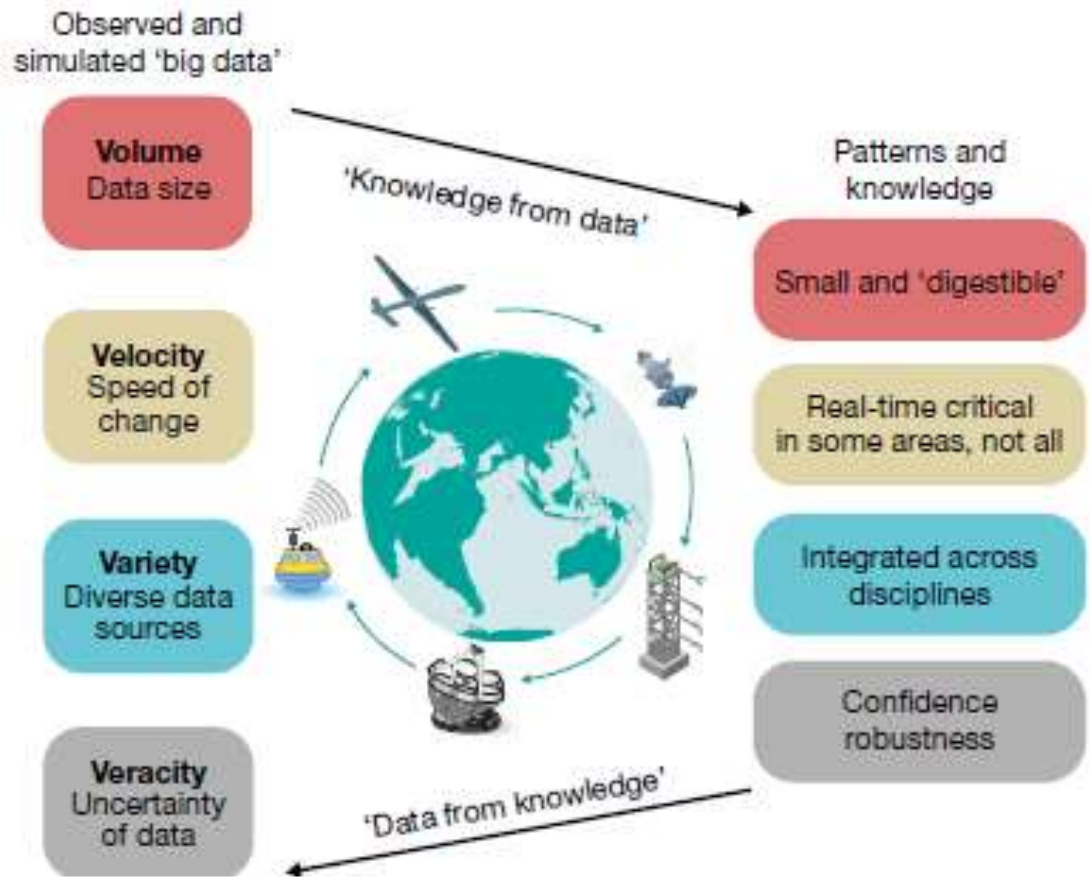
25 km GLDAS + Hydro1K



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

Big Data Challenges in the Geoscientific Context

Deep learning and process understanding for data-driven Earth system science



(Reichstein et al. Nature, 2019)

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 land state datasets have been lacking
- Therefore, 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)
- Future directions
  - Linking land DA with multi-physics and parameter estimation
  - DA with coupled land–atmosphere system
  - DA with fully coupled earth system
  - 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.*
10. ……

Create knowledge. Foster change.

Thank you for your attention!

Q & A

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

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

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