Land surface data assimilation using SMAP, SMOS, and AMSR observations

Rolf Reichle

With contributions from:

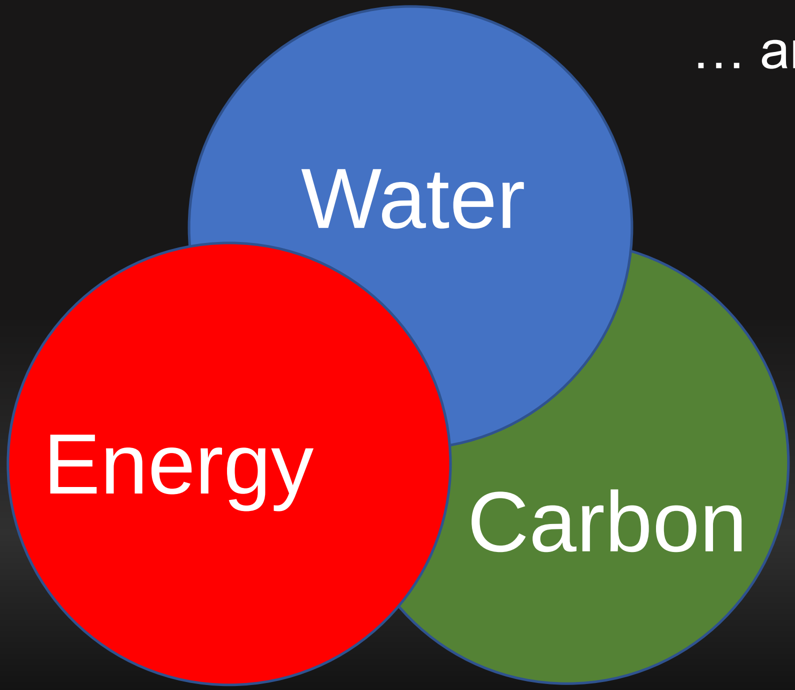
Wade Crow, Gabrielle De Lannoy, Bart Forman, Lucas Jones, John Kimball, Jana Kolassa, Randy Koster, Hans Lievens, Qing Liu, Yuan Xue, and many others.

Motivation

Low-frequency passive microwaves are sensitive to the terrestrial water cycle (soil moisture, snow)

… and the energy cycle (via ET)

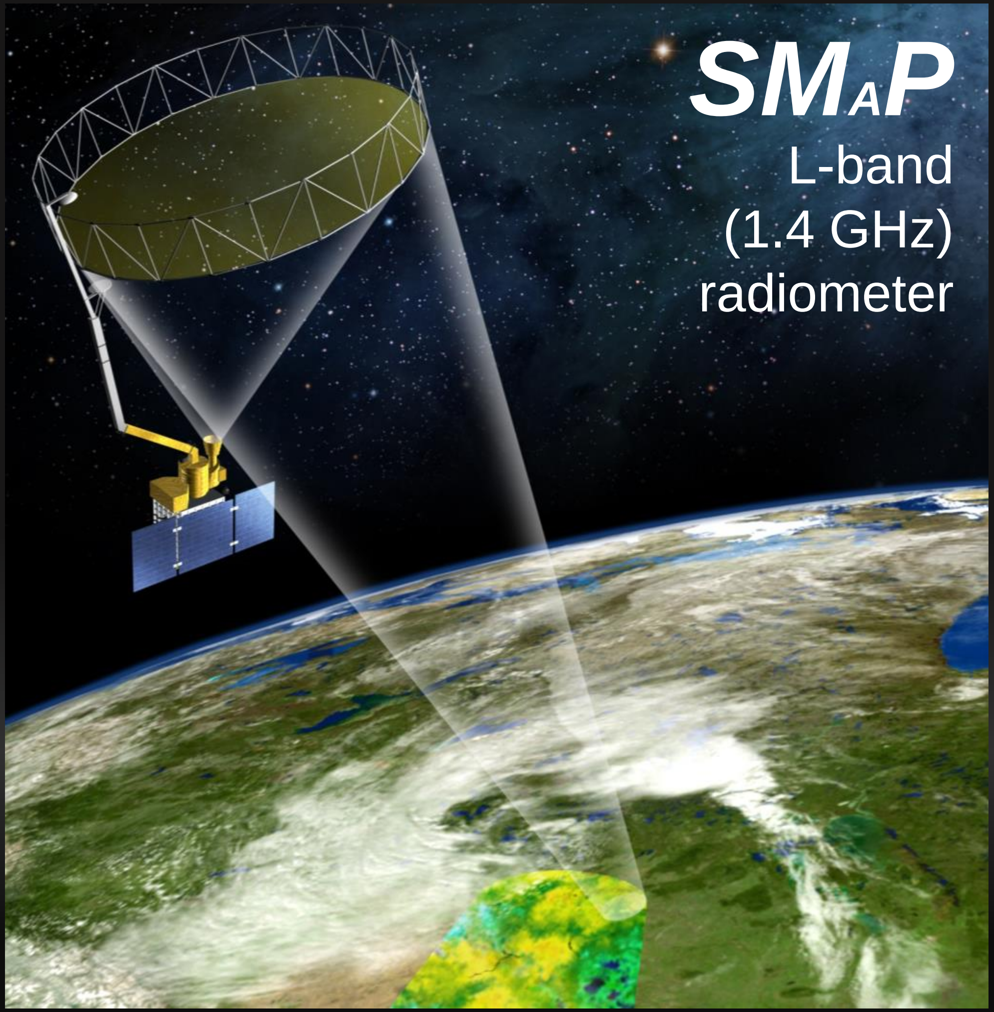
… and the carbon cycle (via ET, F/T).



Outline

1. Motivation and Introduction
   - SMAP Level-4 Soil Moisture Algorithm
2. Soil Moisture
   - Assimilation of AMSR-E, SMOS, and SMAP
   - Model Diagnosis & Calibration, Flood Forecasting, Carbon Fluxes
3. Snow Data Assimilation
   - AMSR-E
4. Summary

Limitations of low-frequency PMW observations

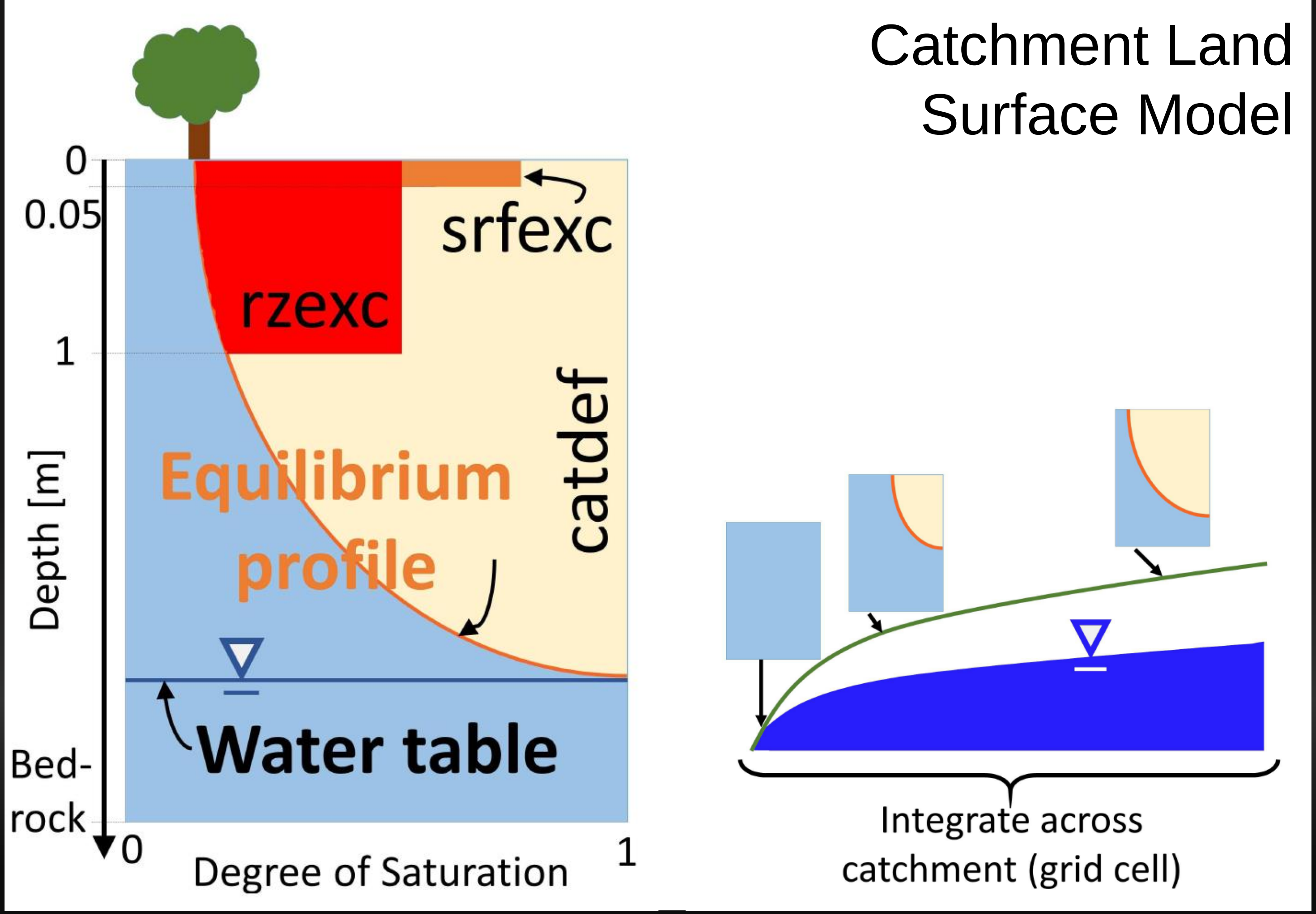


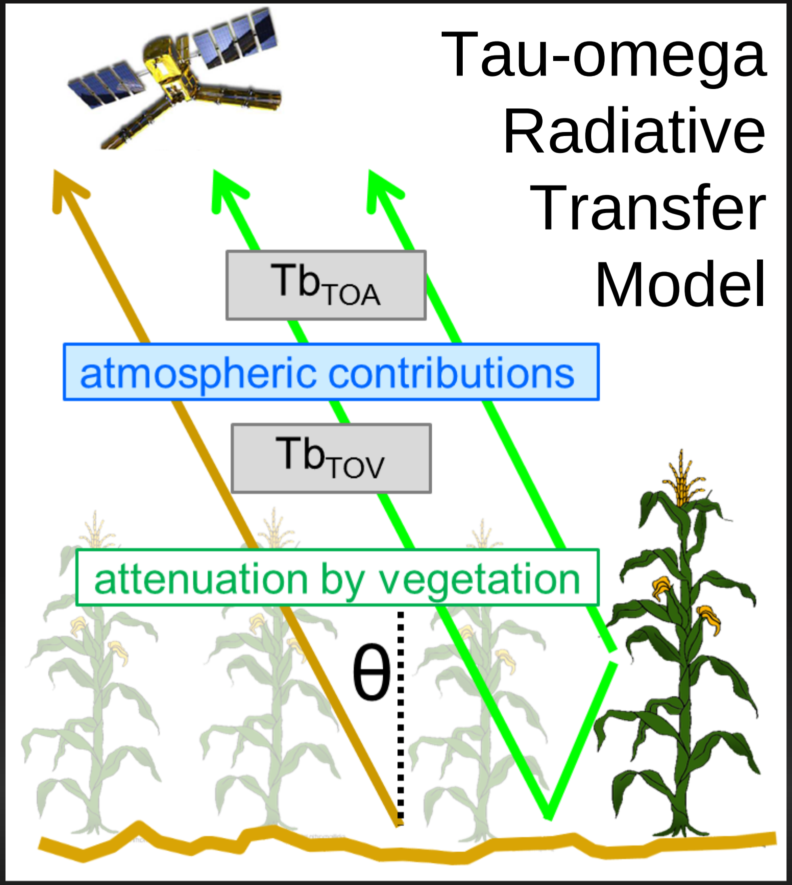
1. Sensitive only to surface soil moisture (~0-5 cm).
2. Available only in swaths.
3. Coarse resolution (~40 km).
4. Subject to errors.

→ **Need data assimilation for many applications.**

Example: SMAP Level-4 Soil Moisture (L4_SM) algorithm.

SMAP L4_SM modeling system



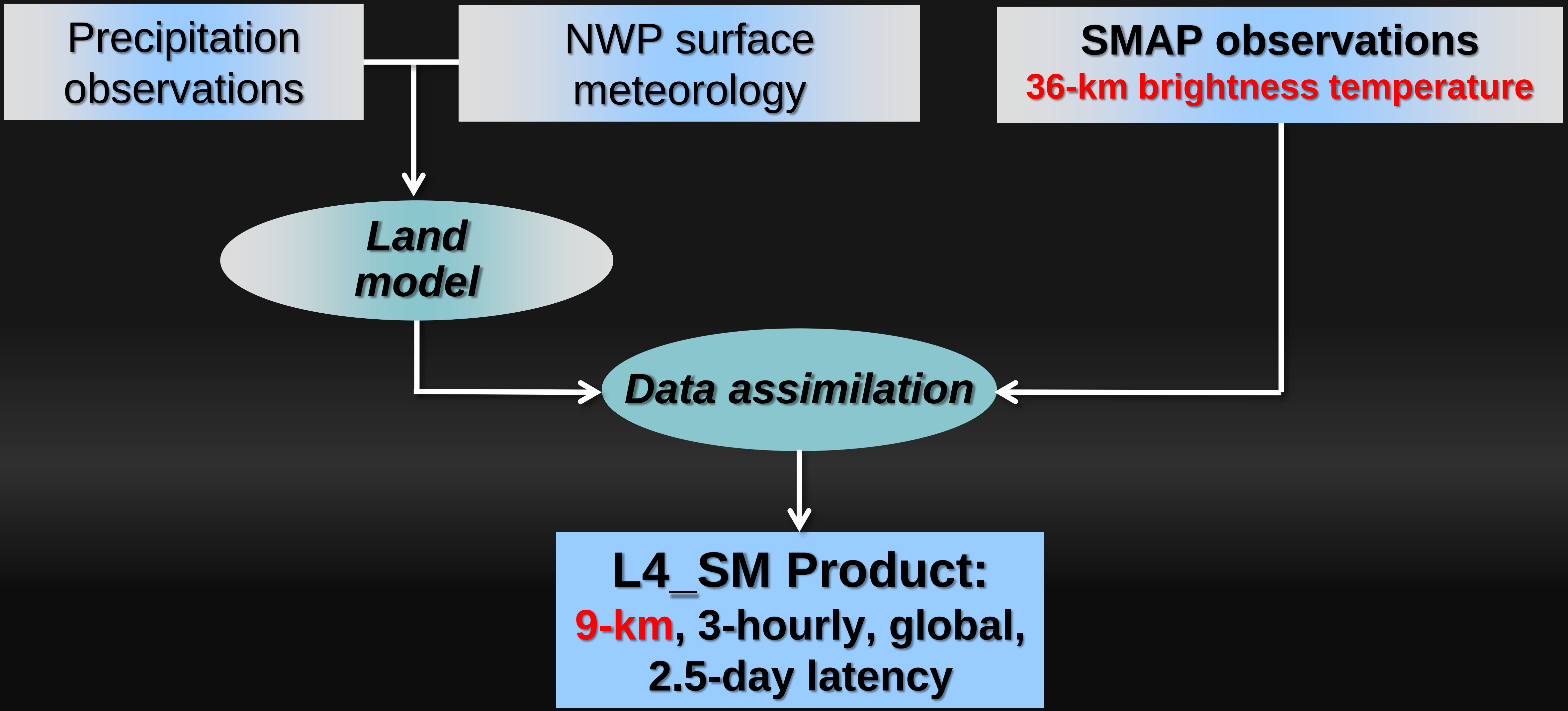


Surface soil moisture & temperature

Model estimates are **also subject to errors** (in model structure, parameters, and forcing).

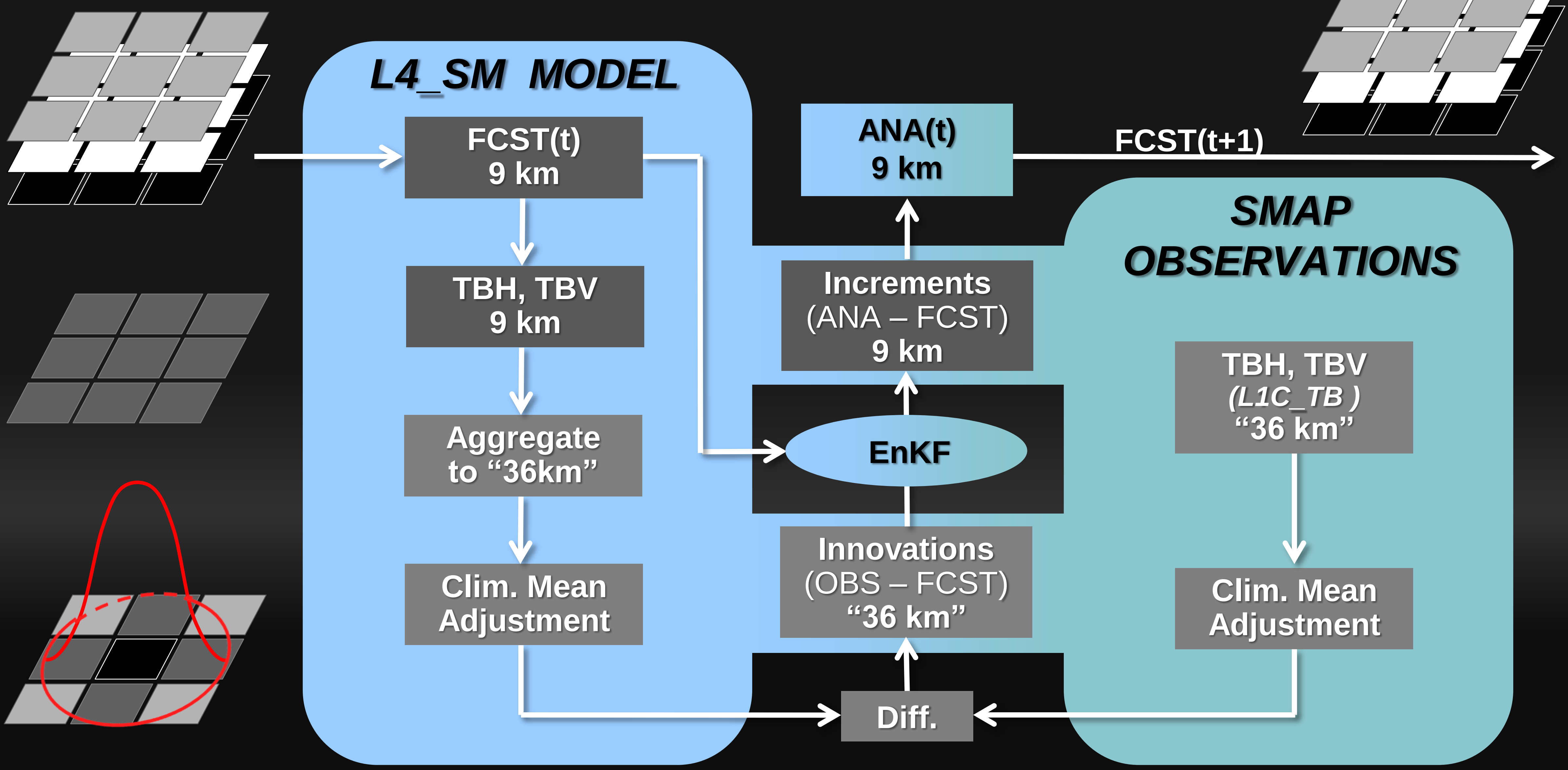
Koster et al. (2000), *JGR*, doi:10.1029/2000JD900327.
De Lannoy et al. (2013), *JHM*, doi:10.1175/JHM-D-12-092.1.

SMAP L4_SM soil moisture assimilation algorithm



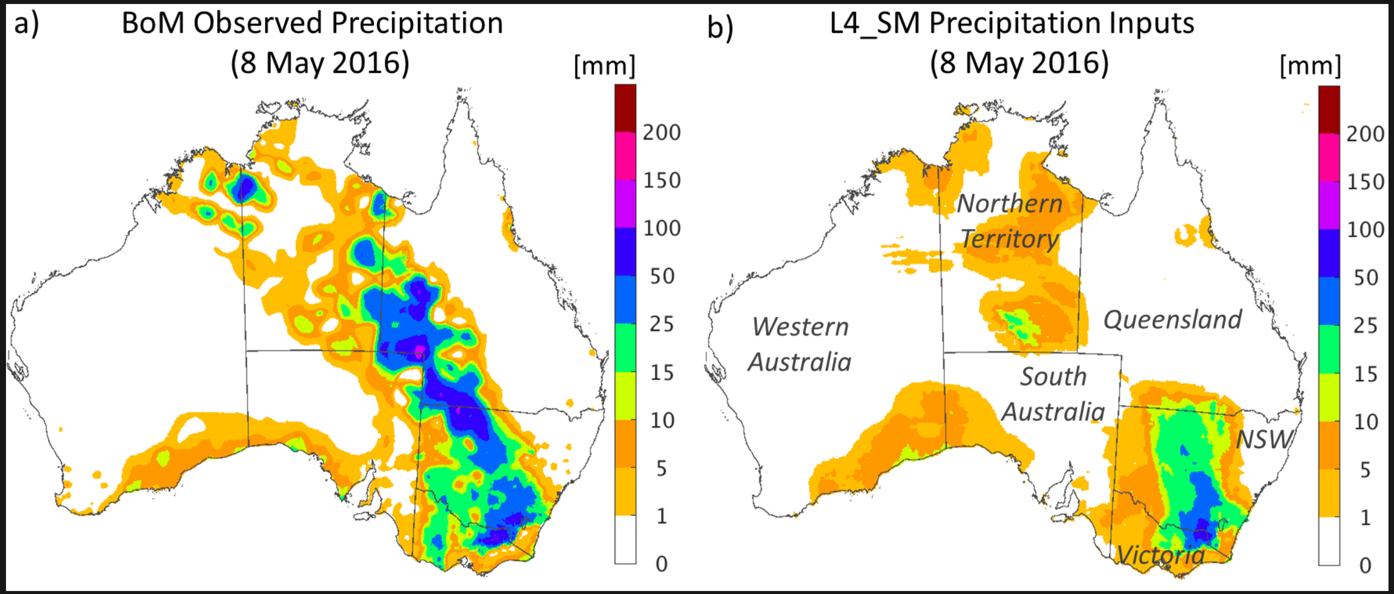
Reichle et al. (2017), *JHM*, doi:10.1175/JHM-D-17-0130.1.

SMAP L4_SM soil moisture analysis



Reichle et al. (2017), *JHM*, doi:10.1175/JHM-D-17-0130.1.

SMAP L4_SM analysis – 2100 UTC 8 May 2016



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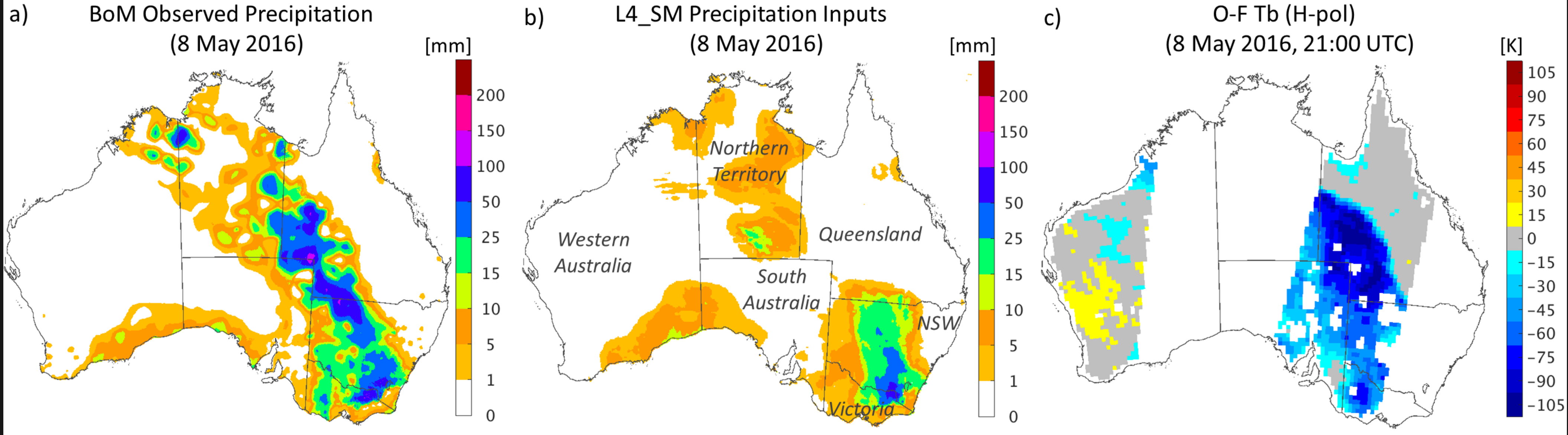

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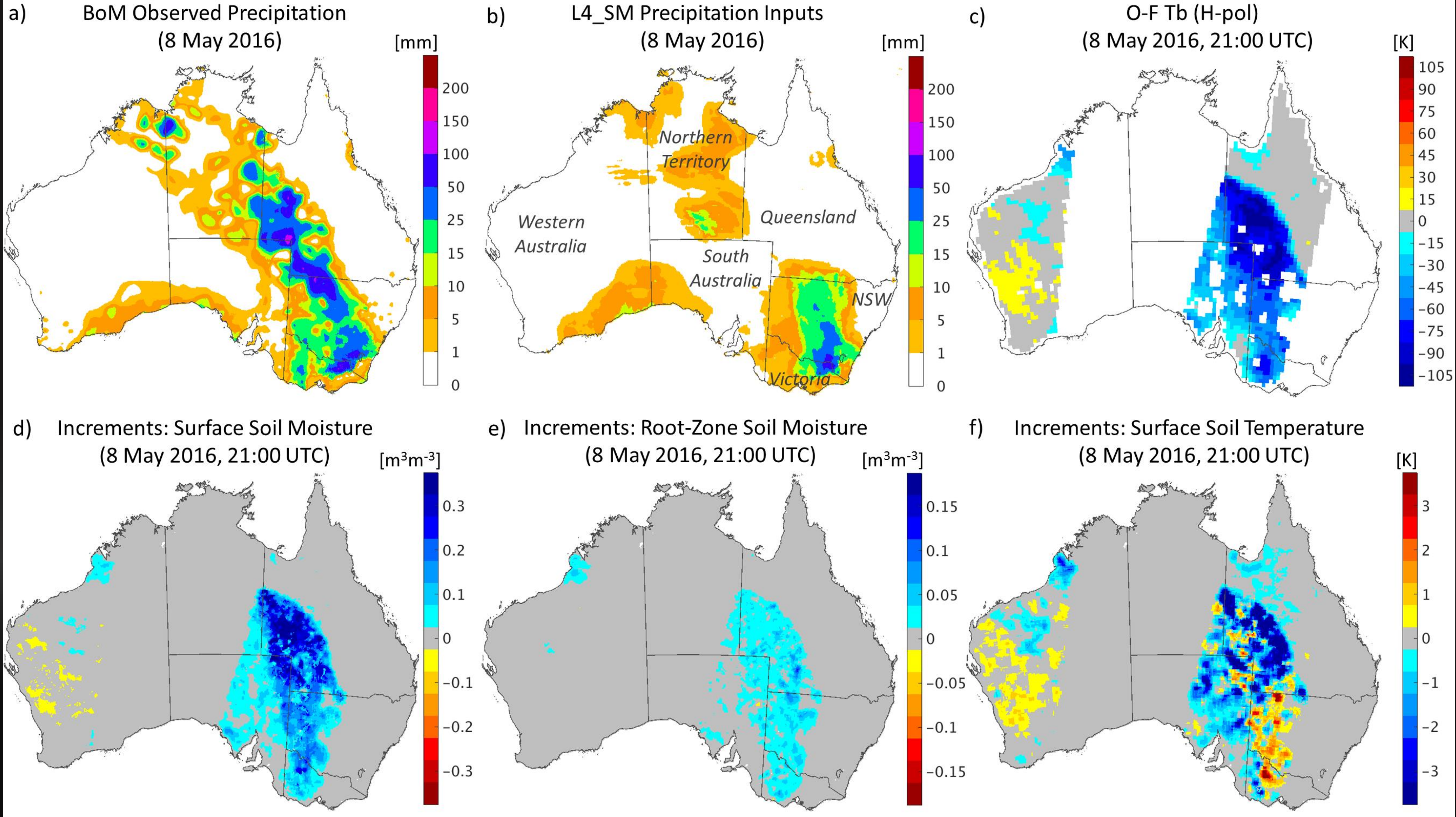

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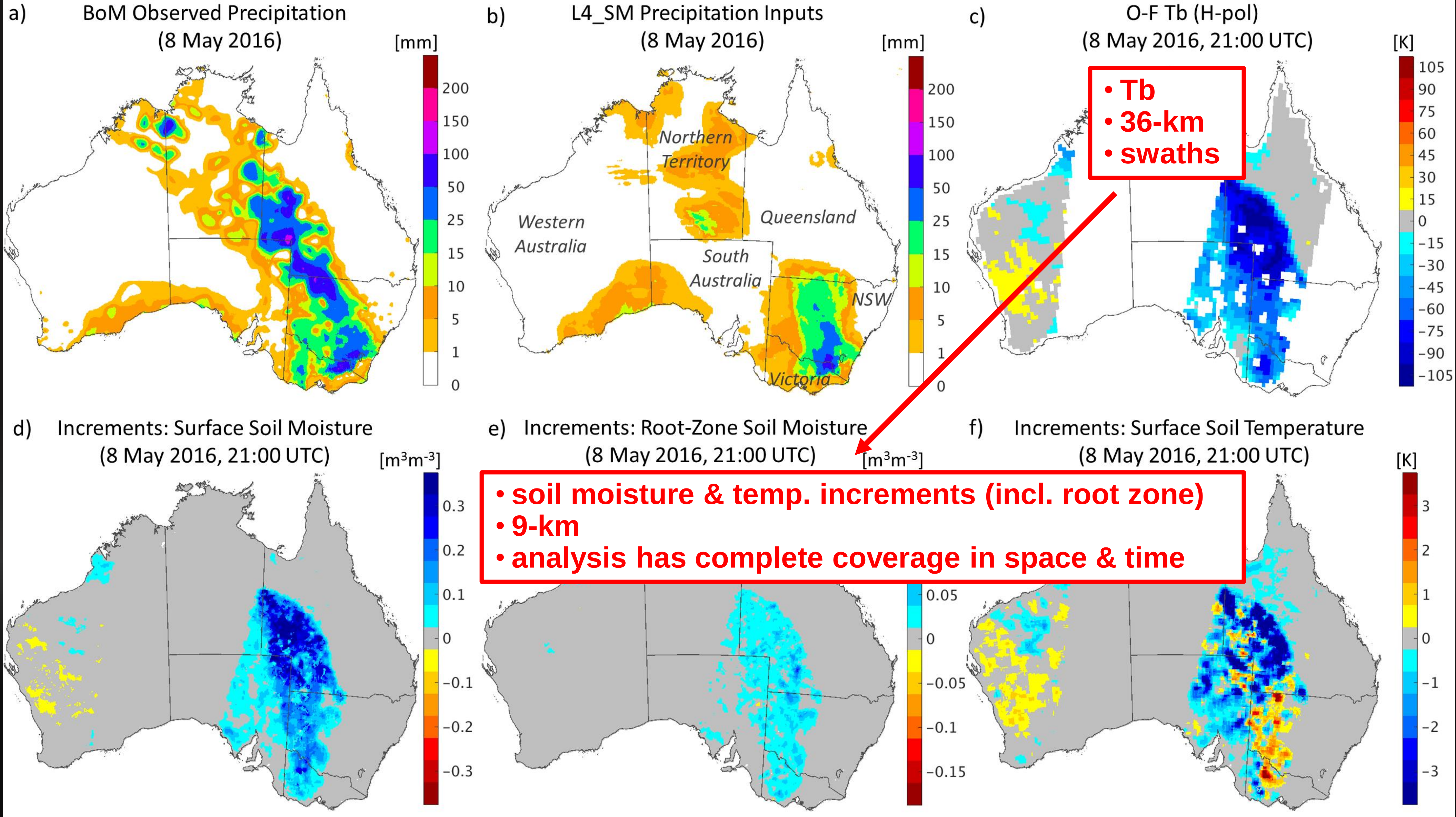
SMAP L4_SM analysis – 2100 UTC 8 May 2016



Reichle et al. (2017), *JHM*, doi:10.1175/JHM-D-17-0130.1.

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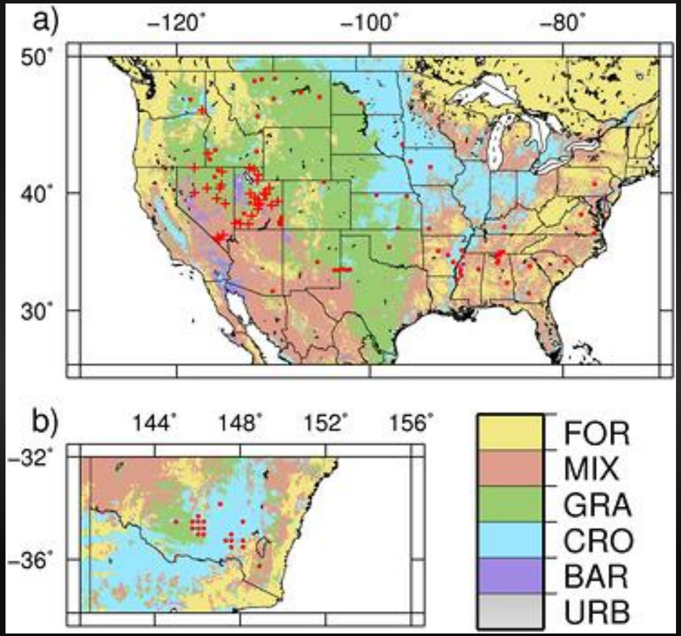
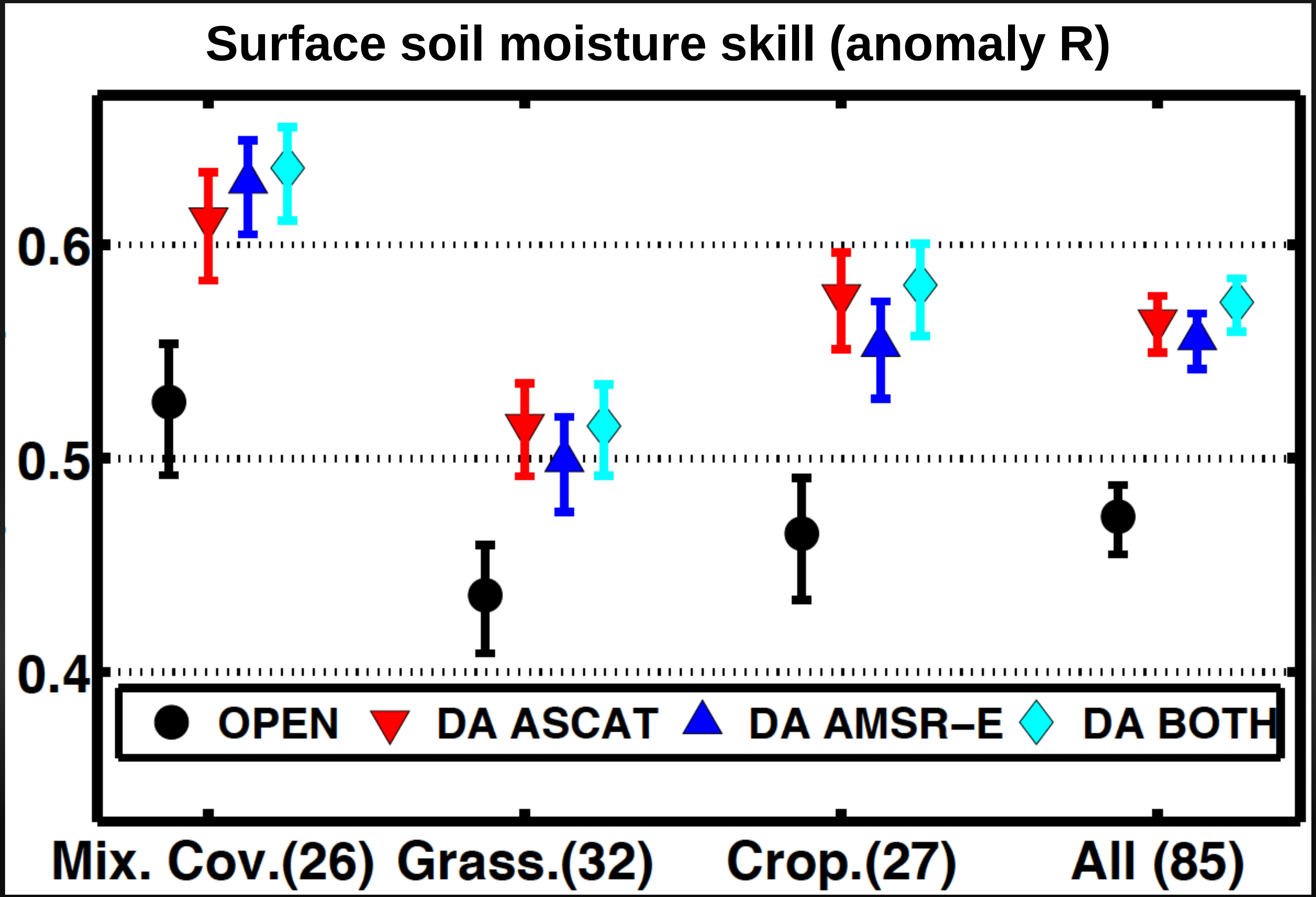
Assimilate passive and/or active microwave soil moisture retrievals?

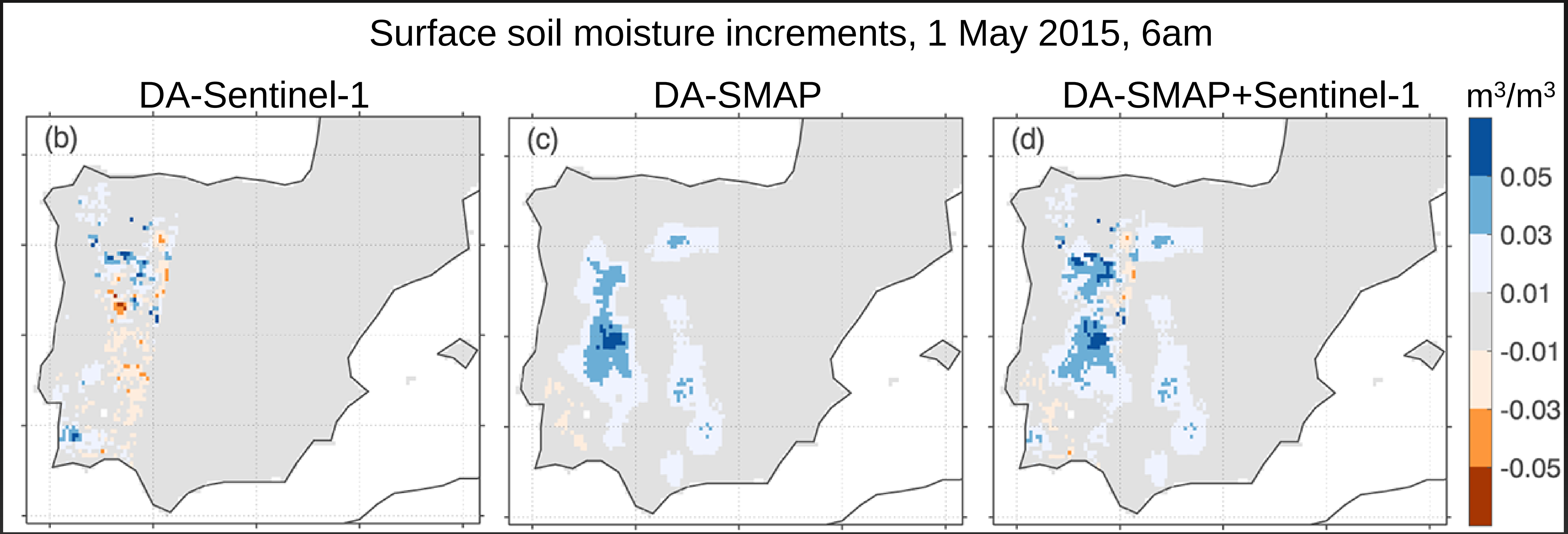
Best results with joint assimilation of passive (AMSR-E) *and* active (ASCAT) retrievals.





Draper et al. (2012), *GRL*, doi:10.1029/2011GL050655.

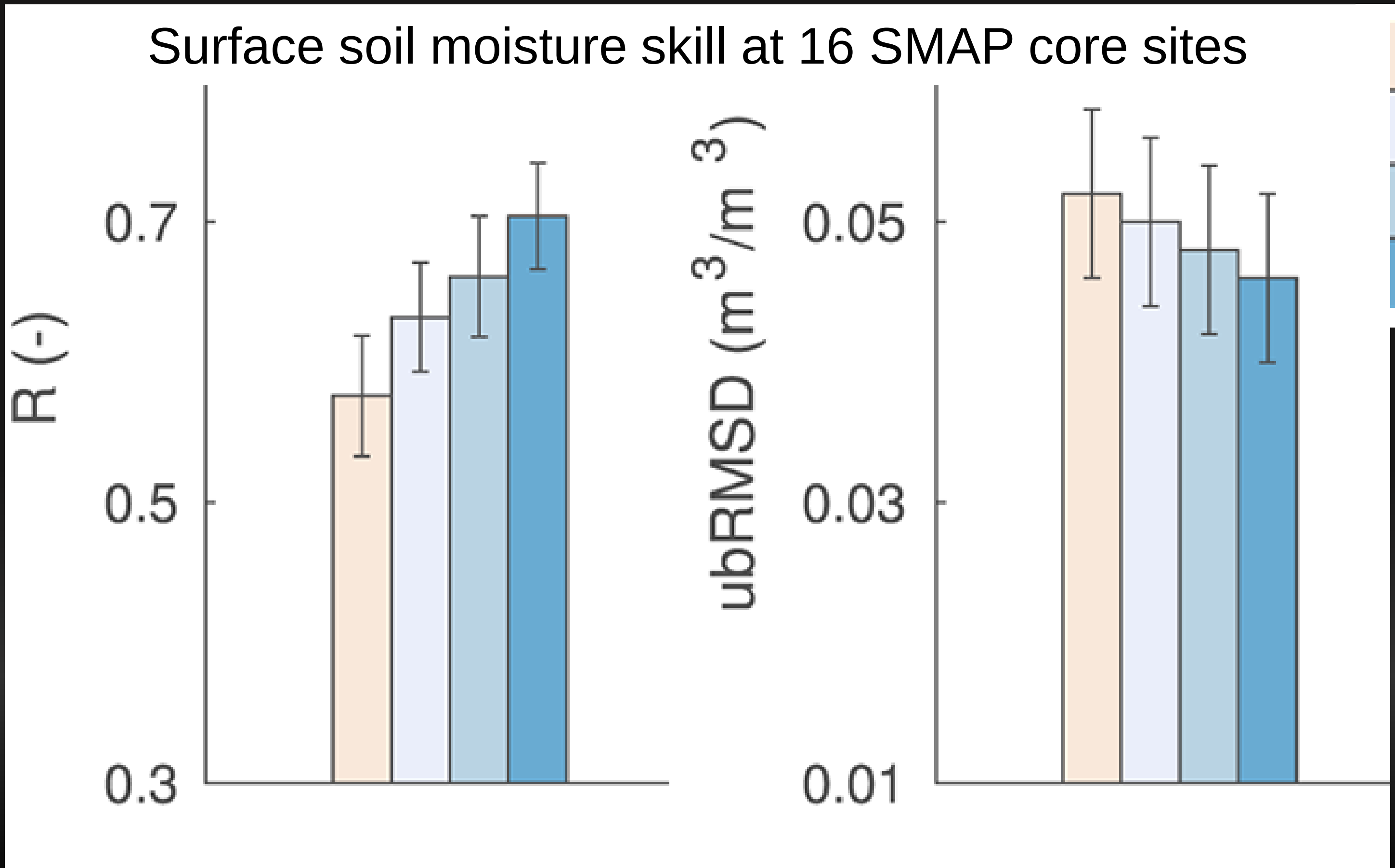
Assimilate brightness temperature and/or backscatter?

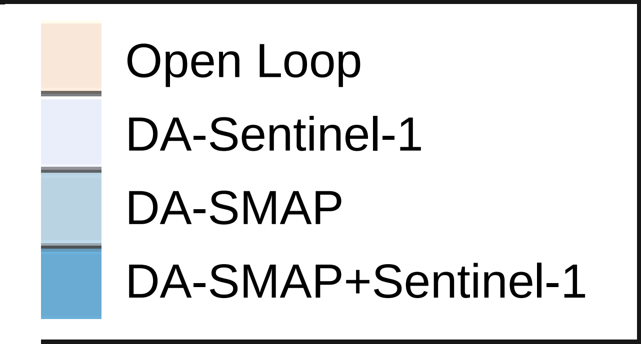


DA-Sentinel-1:	Based on water cloud model and 1d. Has more spatial detail.
DA-SMAP:	As in L4_SM. Inter-/extrapolates over unobserved grid cells.
DA-SMAP+Sentinel-1:	Combines advantages of both.

Lievens et al. (2017), *GRL*, doi:10.1002/2017GL073904.

Assimilate brightness temperature and/or backscatter?

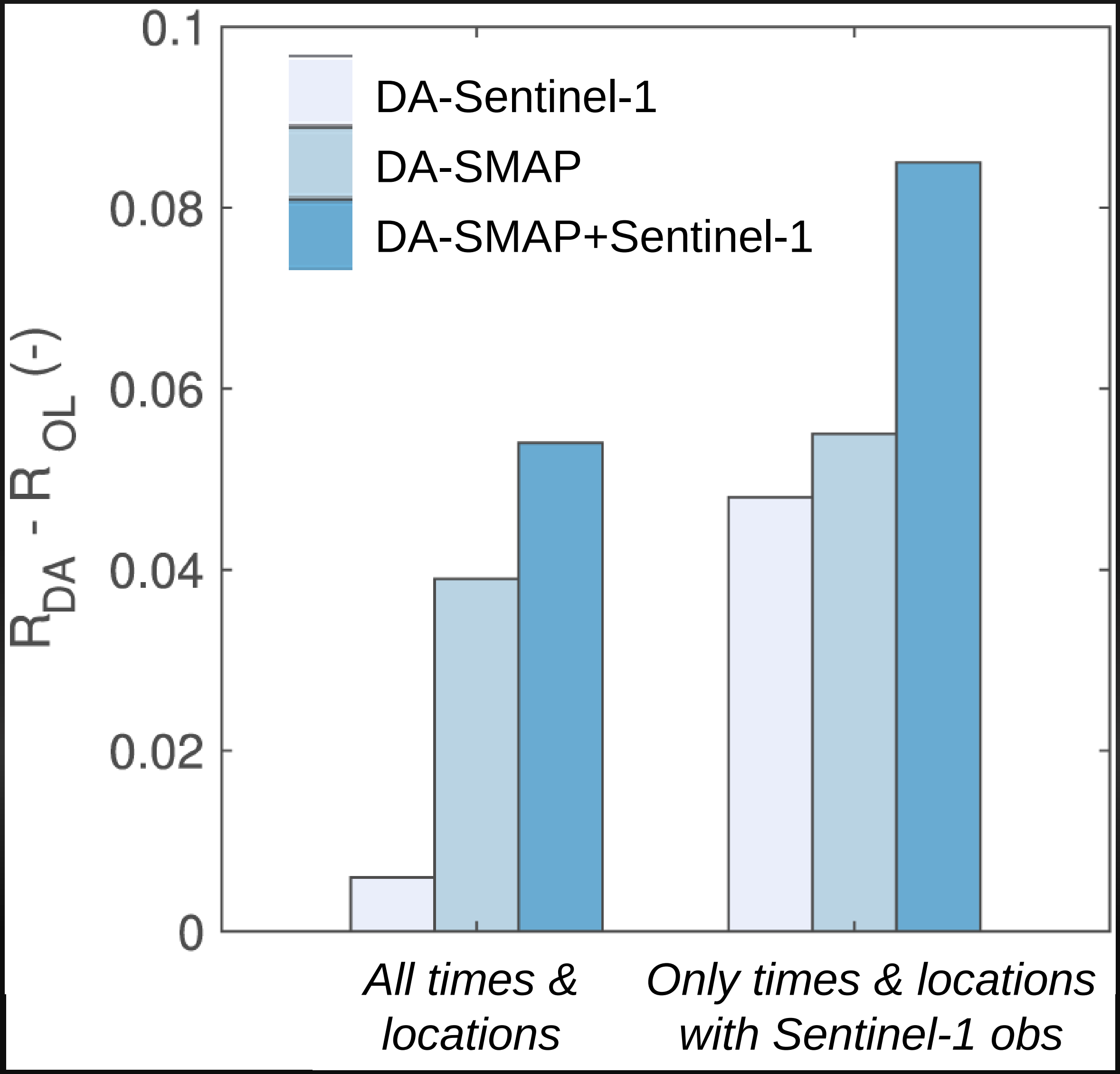




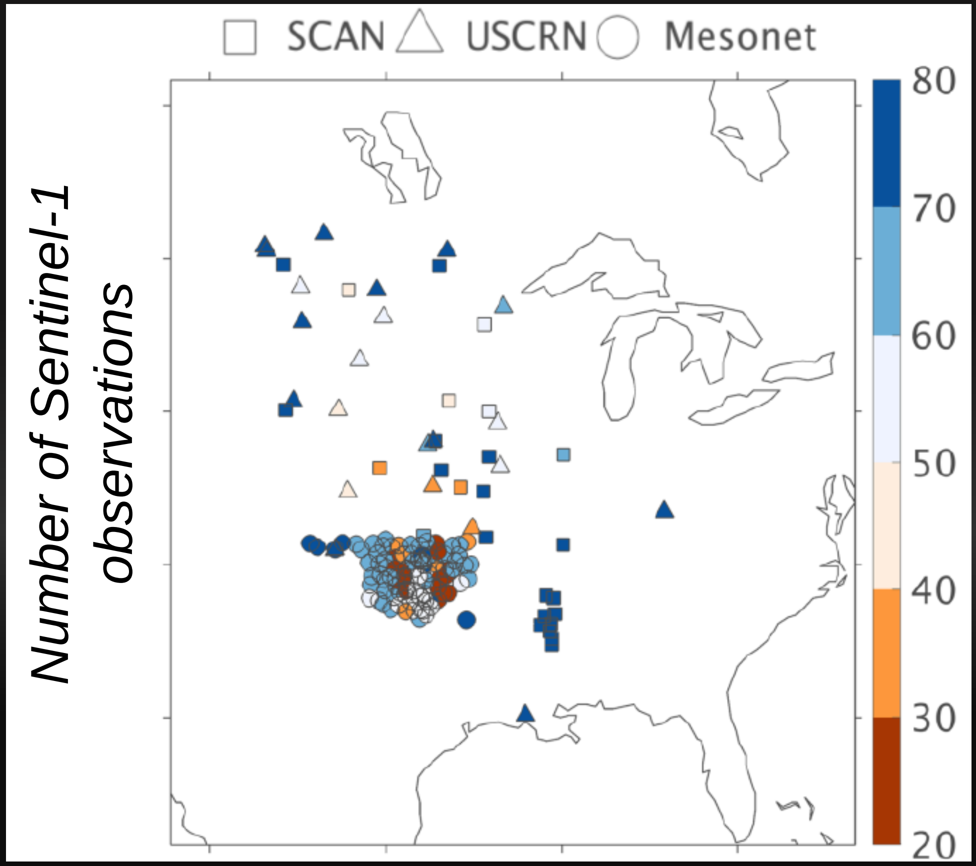
Joint SMAP+Sentinel-1 assimilation yields largest skill improvements.

Lievens et al. (2017), *GRL*, doi:10.1002/2017GL073904.

Assimilate brightness temperature and/or backscatter?



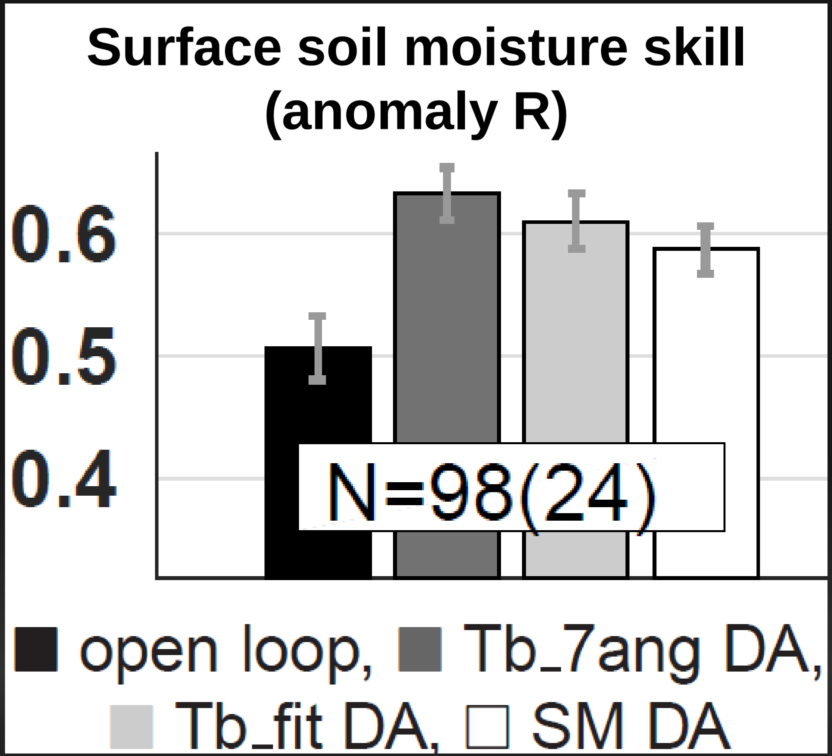
Increased ***spatial*** correlation vs. in situ soil moisture.

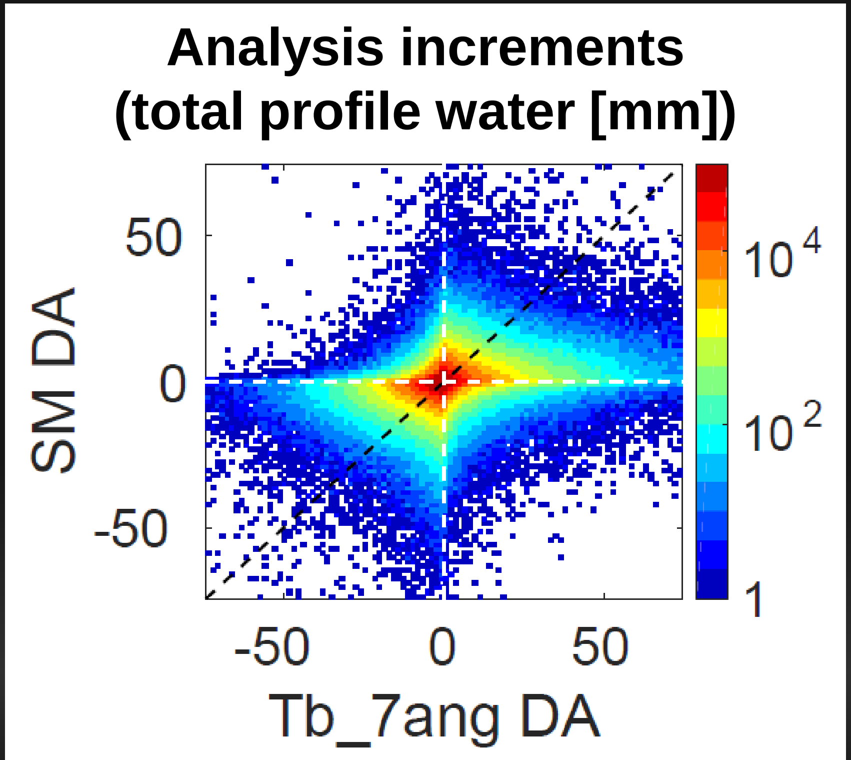


Lievens et al. (2017), *GRL*, doi:10.1002/2017GL073904.

Assimilate brightness temperature or soil moisture retrievals?

- Assimilate SMOS Tbs (7 angles), Tbs fitted to 40°, or soil moisture retrievals



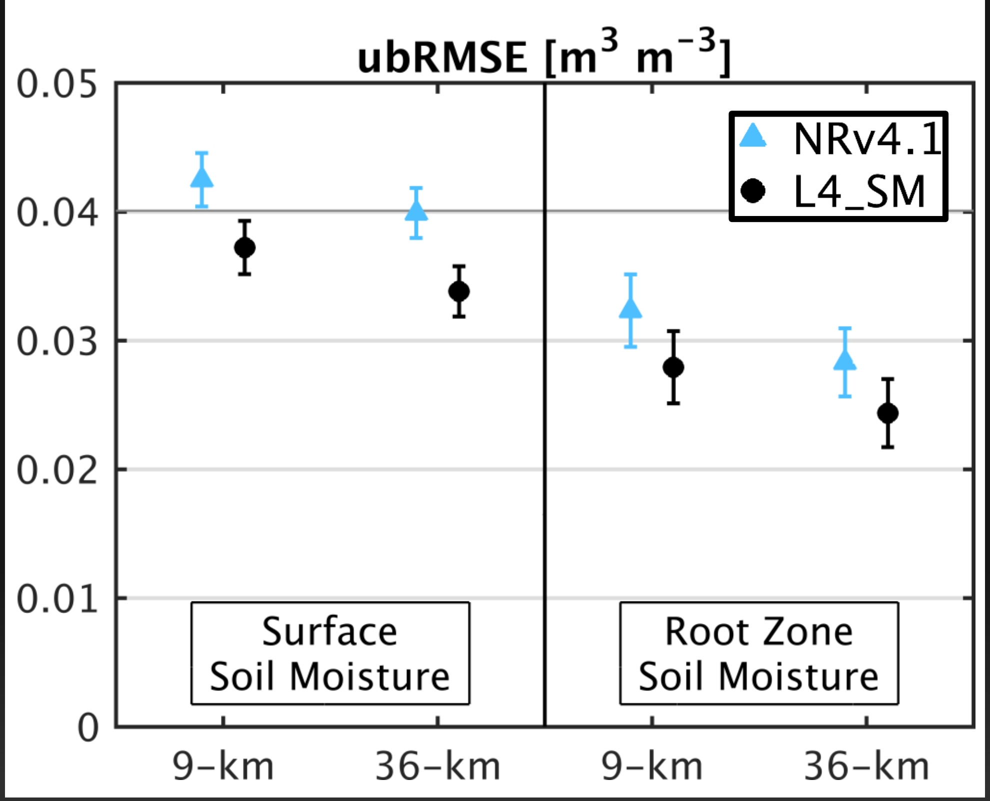


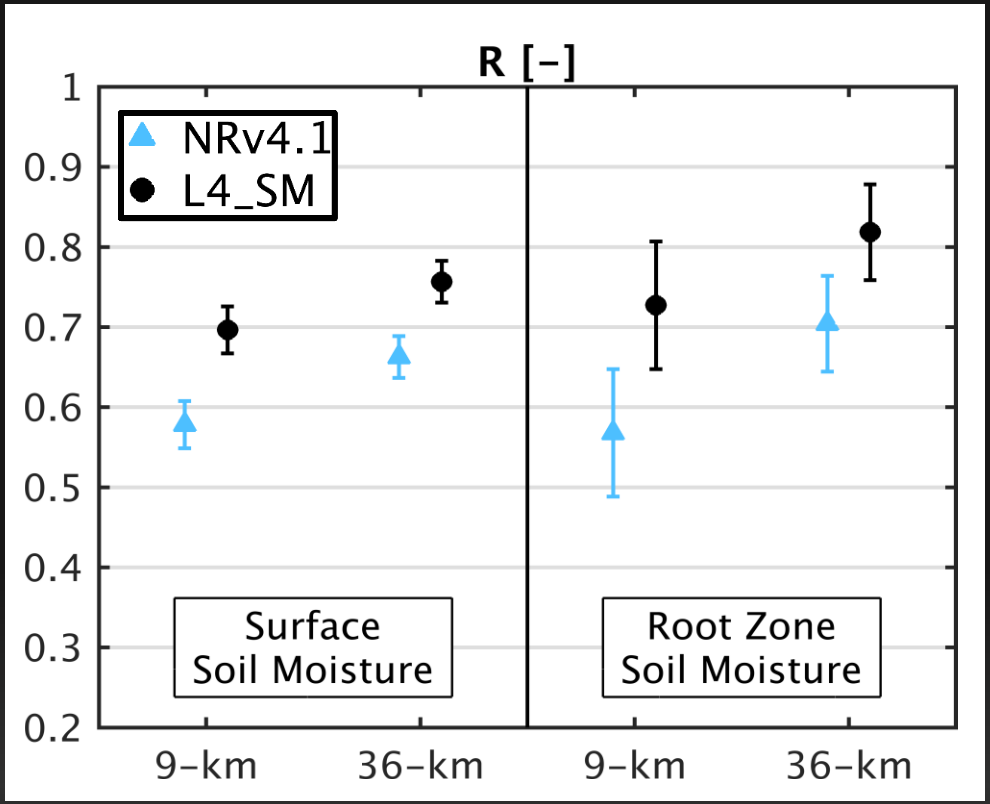
Similar skill vs. in situ measurements…

… but very different increments (i.e., information extraction).

De Lannoy et al. (2016), *HESS*, doi:10.5194/hess-20-4895-2016.

Can we improve root-zone soil moisture?





L4_SM root-zone estimates improved over model-only data (NRv4.1).

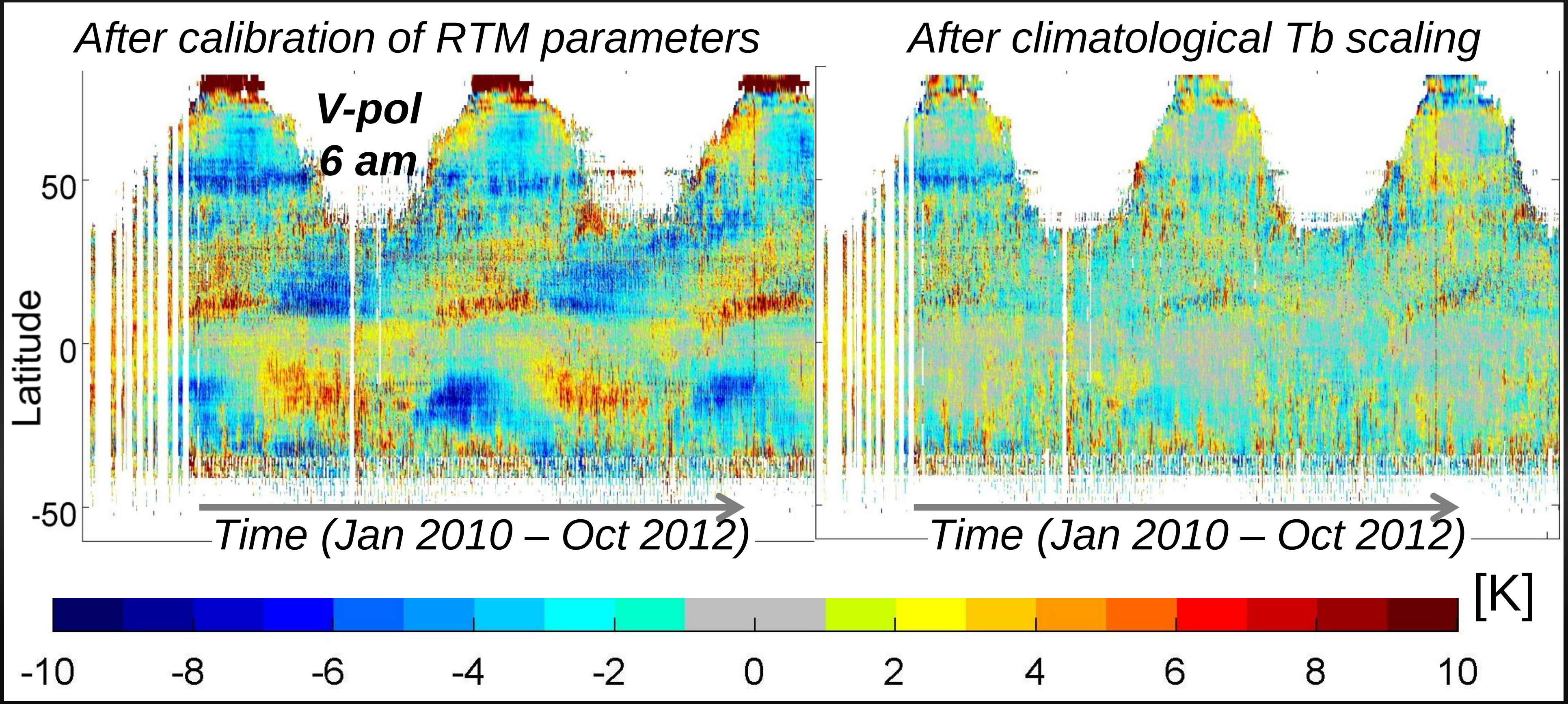
# Ref. Pixels	
SFSM 9 km	26
SFSM 36 km	17
RZSM 9 km	9
RZSM 36 km	7

Reichle et al. (2017), *JHM,* doi:10.1175/JHM-D-17-0063.1.

How do we address model bias?

Step 1: Calibrate microwave radiative transfer model to match long-term mean and std-dev of SMOS Tbs.

Step 2: Rescale assimilated Tbs to match seasonally varying climatology of SMOS (or SMAP) Tbs.



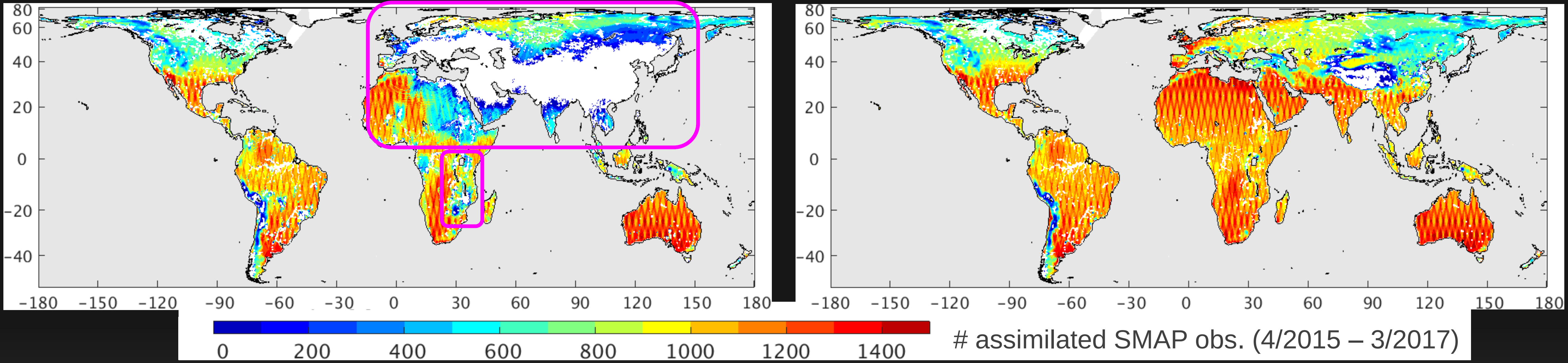
Put differently: Assimilate anomalies. Requires knowledge of Tb climatology.

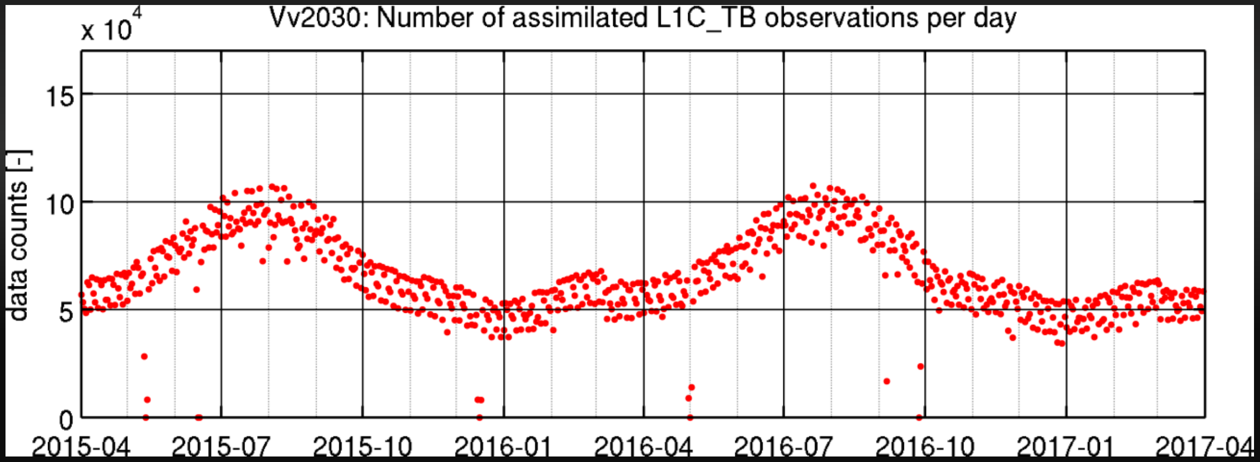
De Lannoy et al. (2013), *JHM*, doi:10.1175/JHM-D-12-092.1.

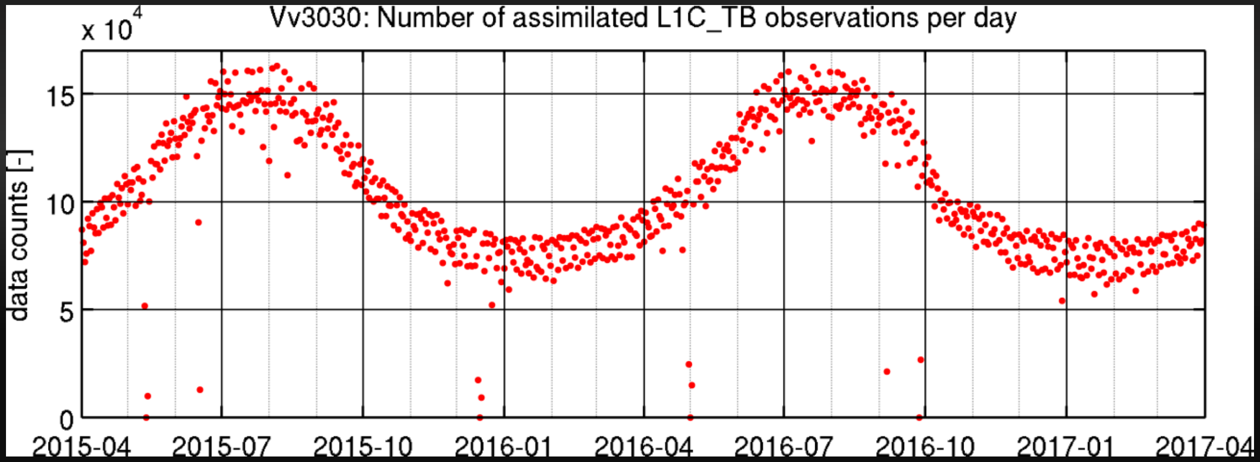
How do we address model bias?

SMAP L4_SM **v2** – rescaling w/ SMOS only

SMAP L4_SM **v3** – rescaling with SMOS & SMAP





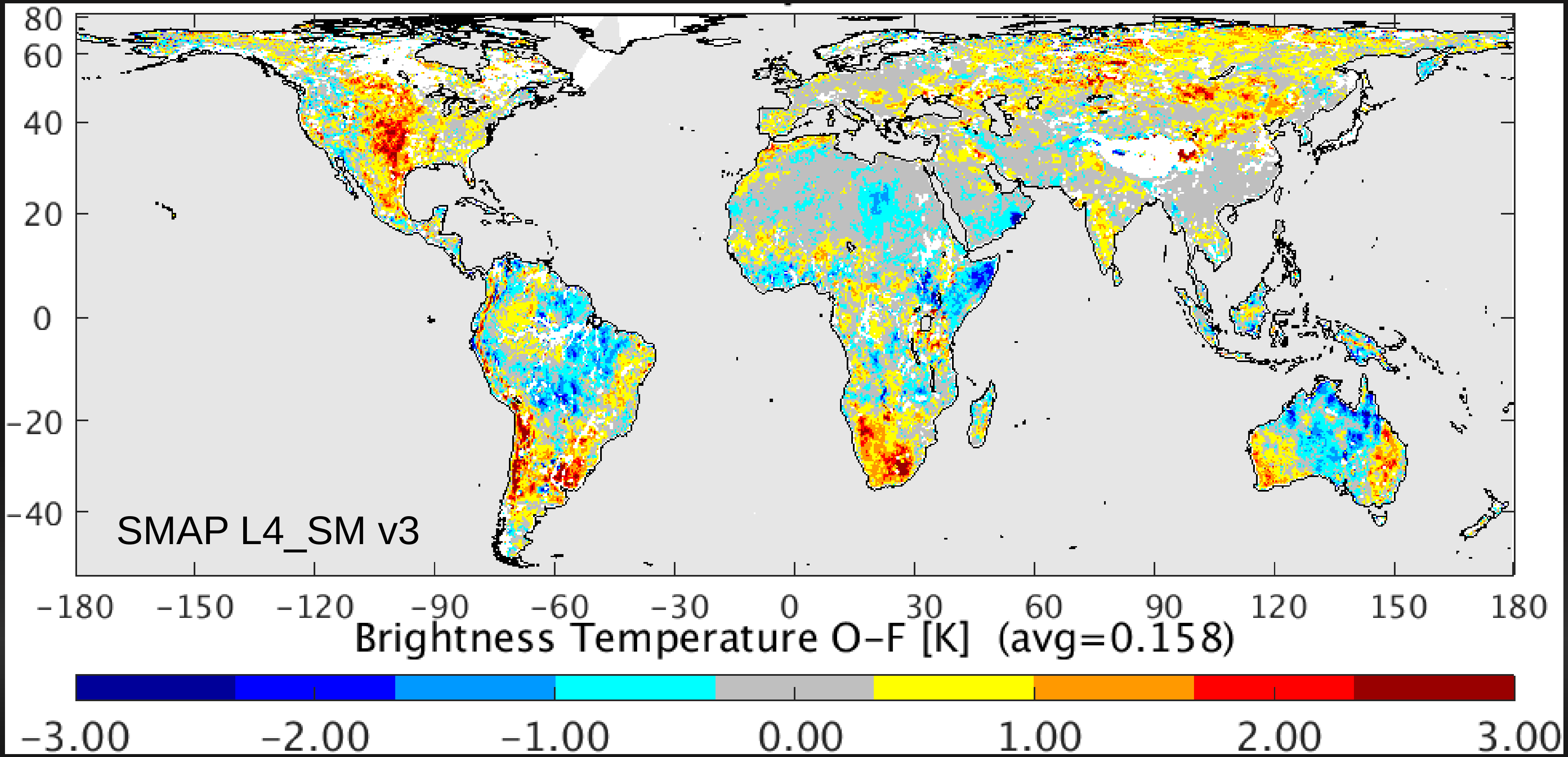


Average: 65,000 / day

Average: 104,000 / day

Reichle et al. (2017), *JHM*, doi:10.1175/JHM-D-17-0130.1.

How do we address model bias?



SMAP L4_SM analysis mostly unbiased.

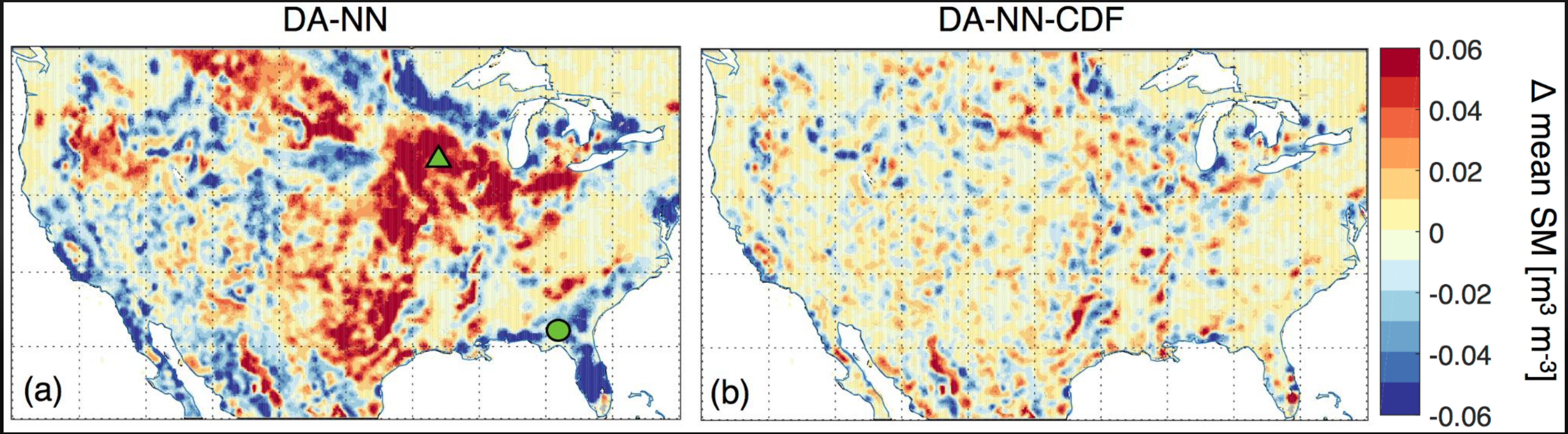
Reichle et al. (2017), *JHM*, doi:10.1175/JHM-D-17-0130.1.

Do we need to address model bias?

Constructed SMAP Neural Network (NN) retrievals in the *global* climatology of the Catchment model.

Experiments:

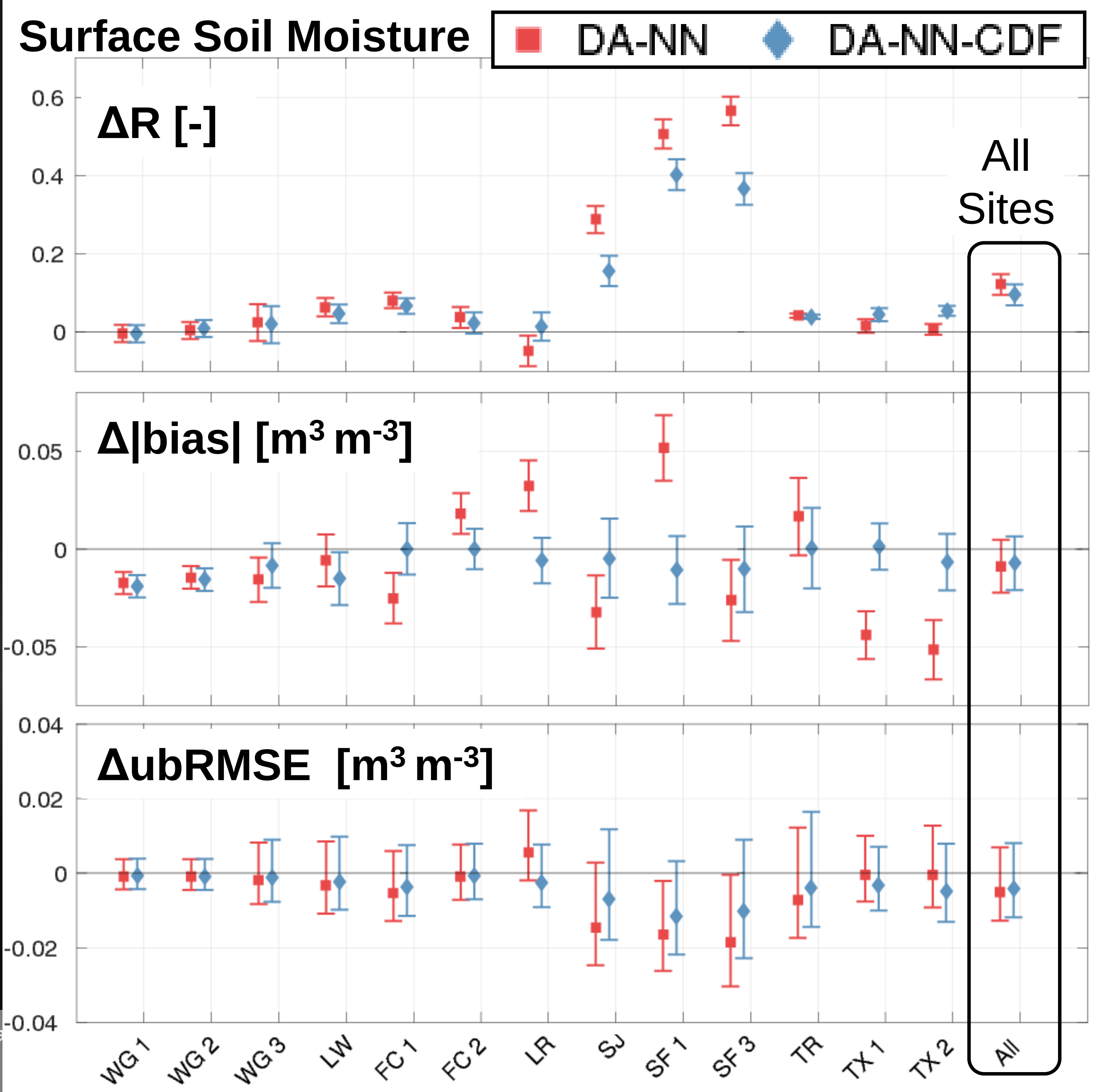
OL:	Model-only simulation (no assimilation)
DA-NN:	Assimilate NN retrievals **without further bias correction**
DA-NN-CDF:	Assimilate NN retrievals **with local bias correction**



Difference (OL minus DA) in mean soil moisture.

Kolassa et al. (2017), *Rem. Sens.*, doi:10.3390/rs9111179.

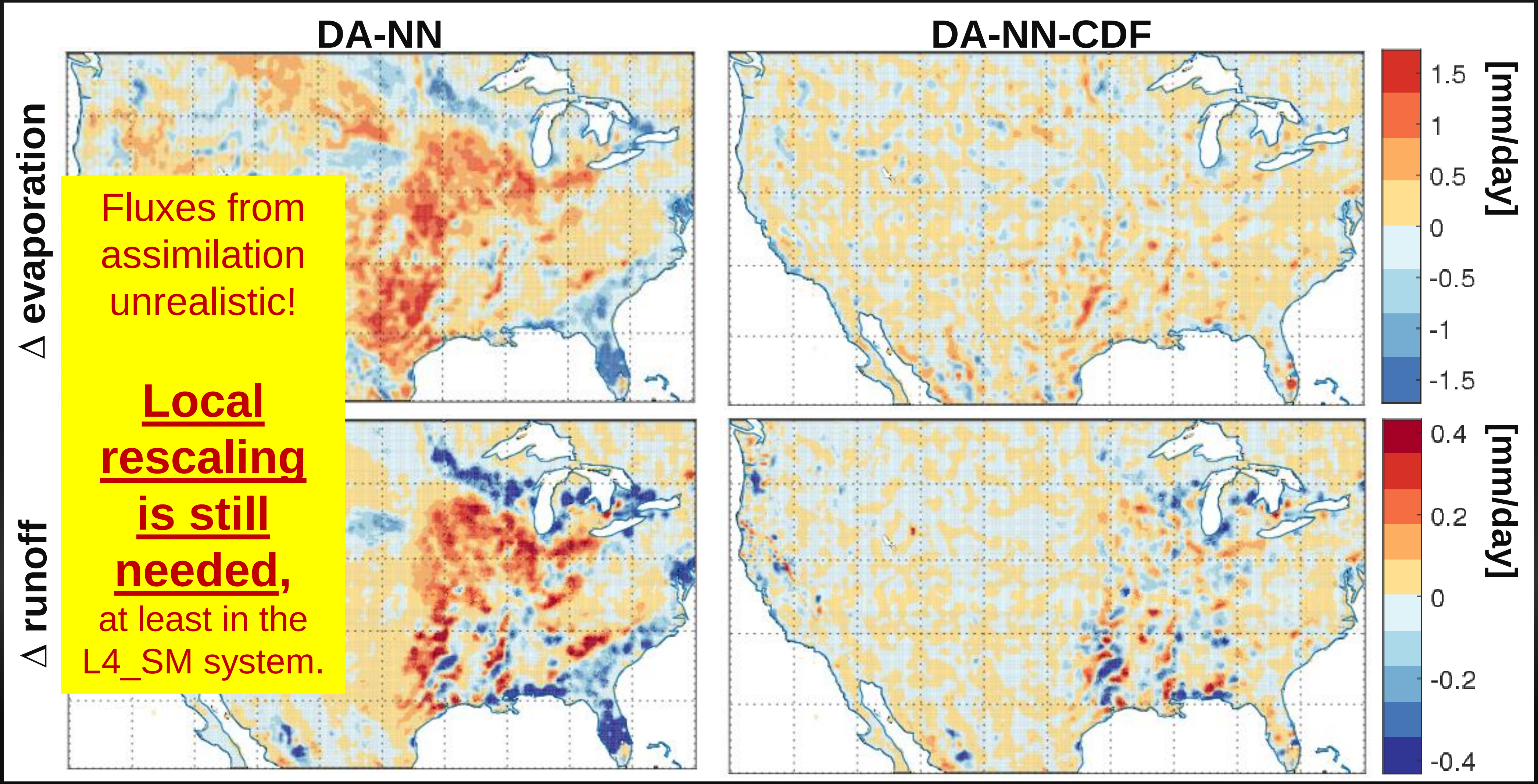
Do we need to address model bias?



Similar results for root-zone soil moisture.

Kolassa et al. (2017), *Rem. Sens.*, doi:10.3390/rs9111179.

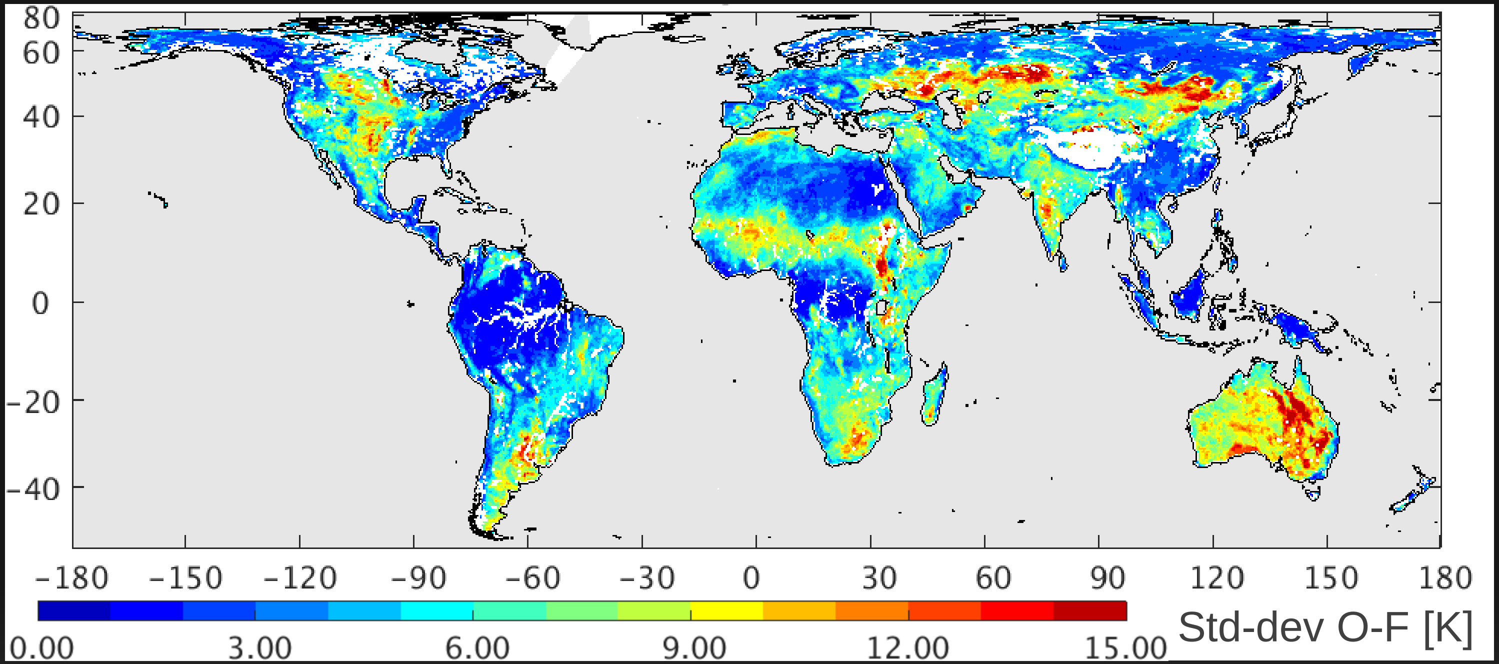
Do we need to address model bias?

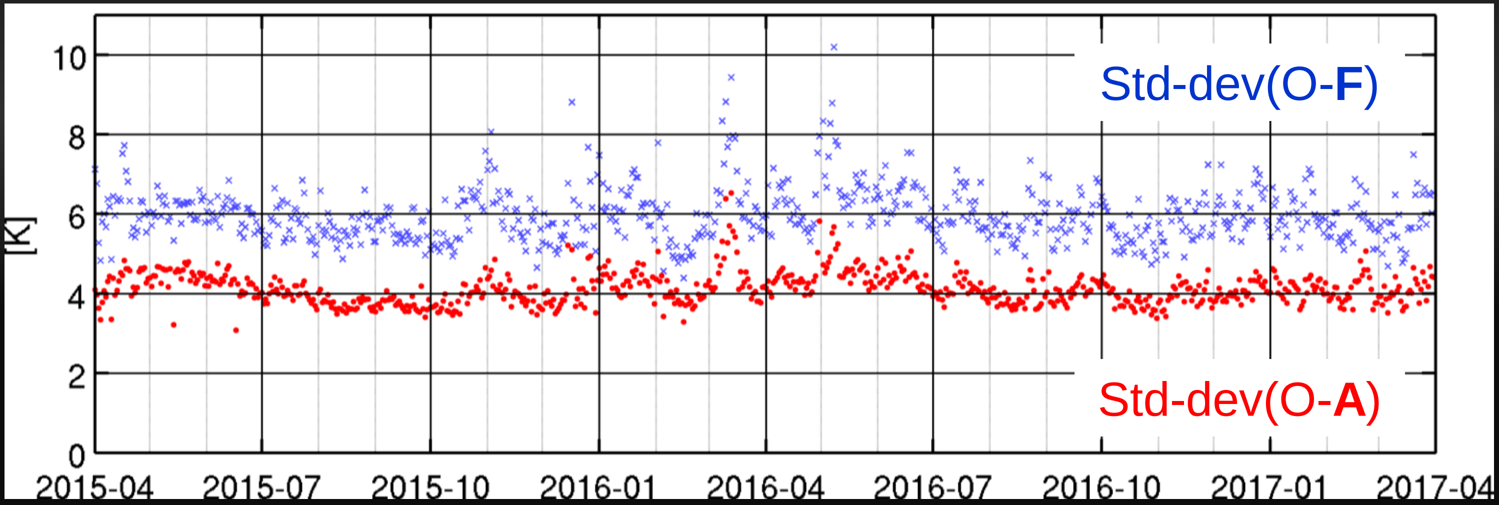


Difference (OL minus DA) in <u>mean</u> (top) evaporation and (bottom) runoff.

Kolassa et al. (2017), *Rem. Sens.*, doi:10.3390/rs9111179.

What is the quality of the uncertainty estimates?





Average:
O-F: 6 K
O-A: 4 K

cf. Tb obs error = 4 K

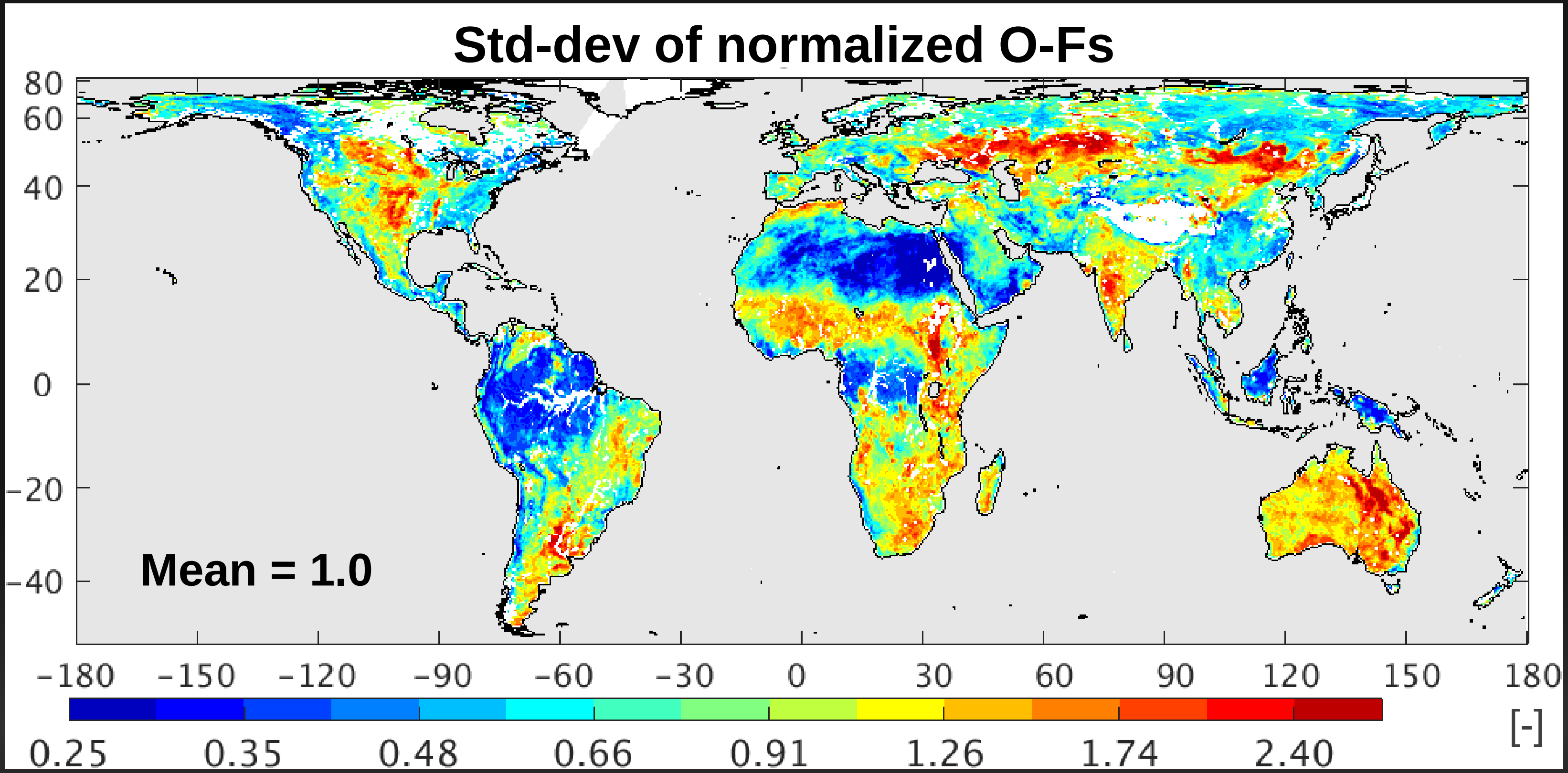
includes

instrument error = 1.3 K
&
representative-ness error = 3.8 K

Reichle et al. (2017), *JHM*, doi:10.1175/JHM-D-17-0130.1.

What is the quality of the uncertainty estimates?

Normalize O-Fs with (assumed) error std-devs supplied to the analysis.

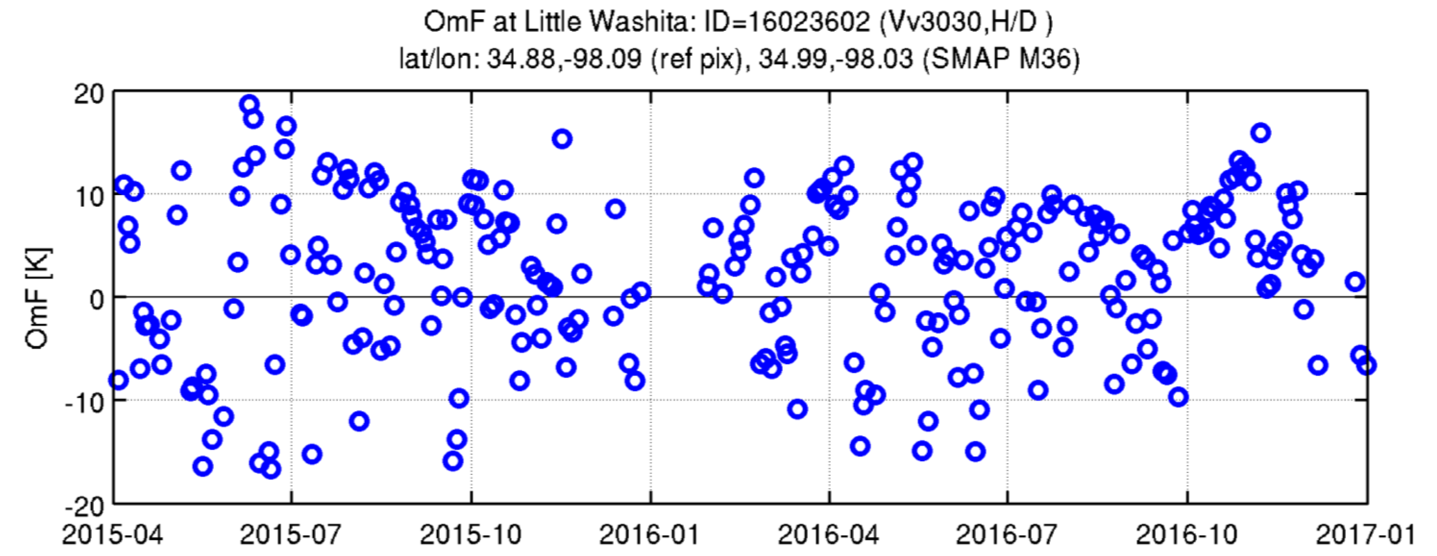


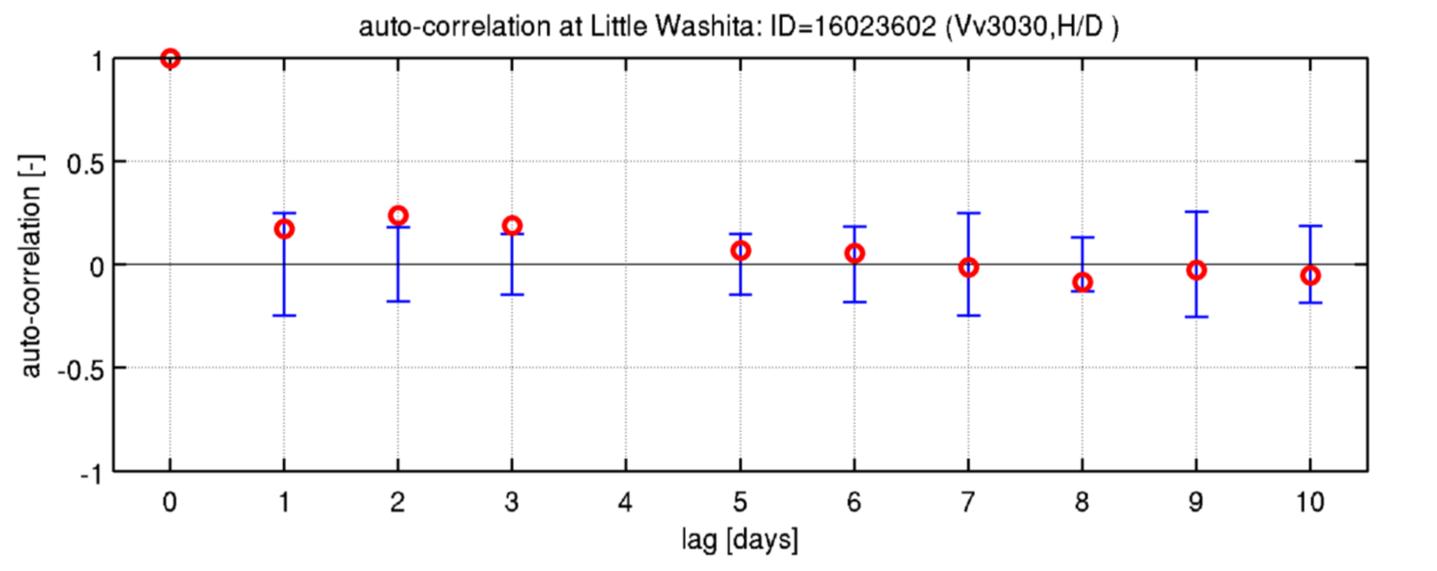
over-estimation **under-estimation**

of actual O-F errors

Reichle et al. (2017), *JHM*, doi:10.1175/JHM-D-17-0130.1.

How efficiently do we use the observations?





O-F time series at Little Washita, Oklahoma.

O-F auto-correlation measures “efficiency” of assimilation system.

Reichle et al. (2017), *JHM*, doi:10.1175/JHM-D-17-0130.1.

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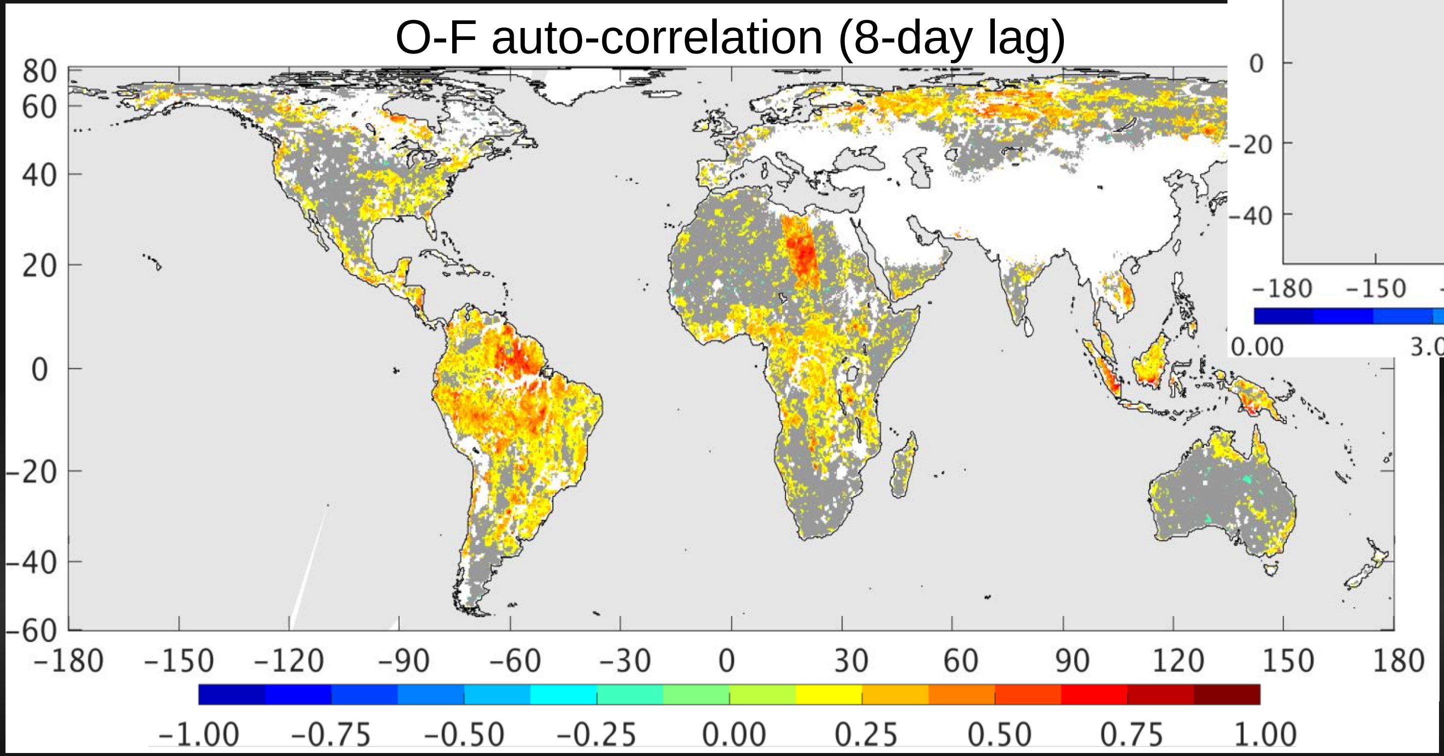

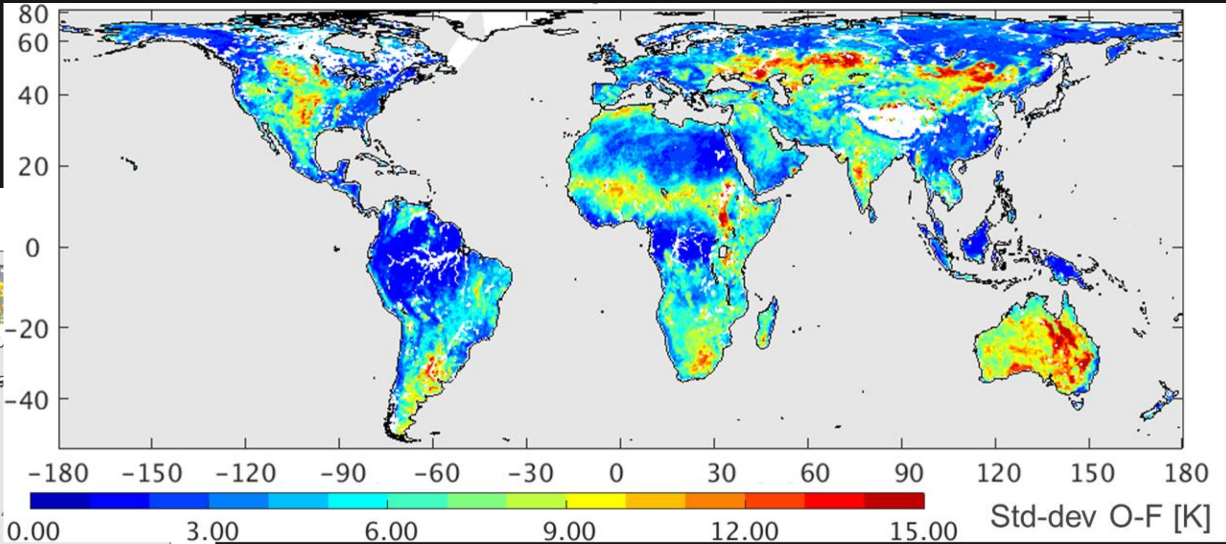

Observations *are* used efficiently where it matters.

Reichle et al. (2017), *JHM*, doi:10.1175/JHM-D-17-0130.1.

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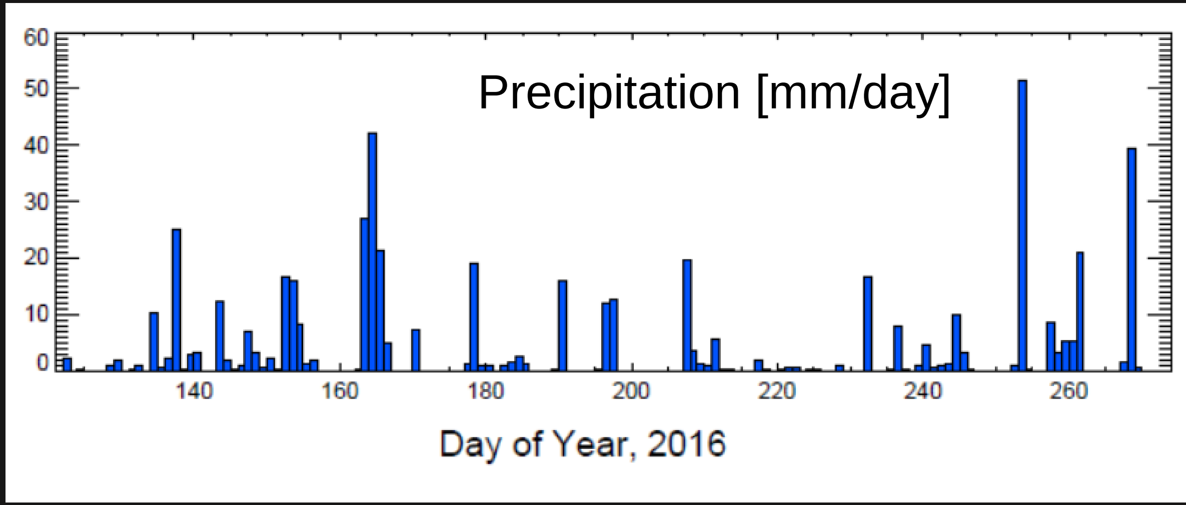
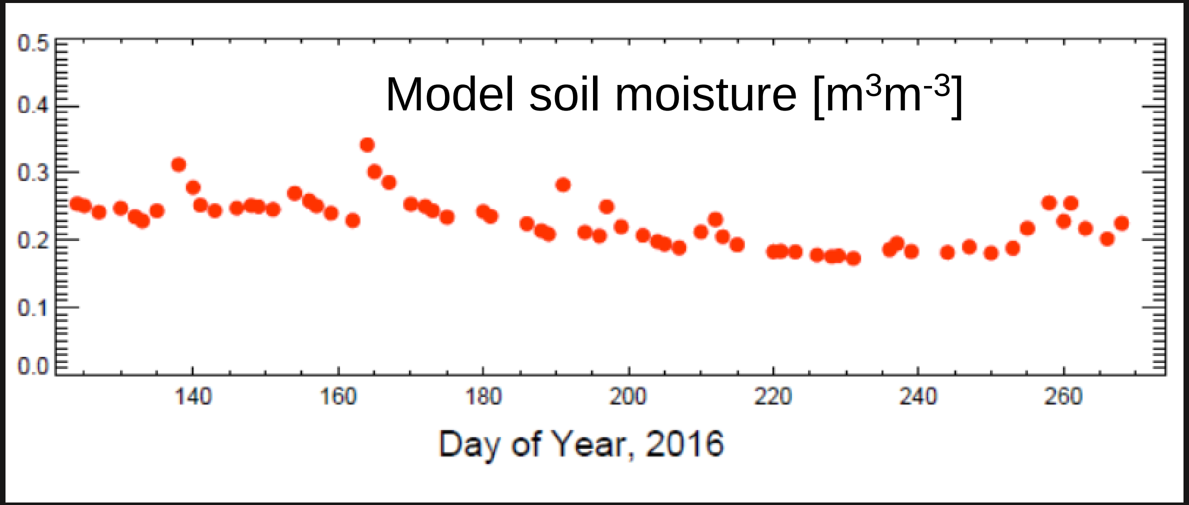
Can we use PMW information for land model calibration?





Koster et al. (2017), *JHM*, submitted.

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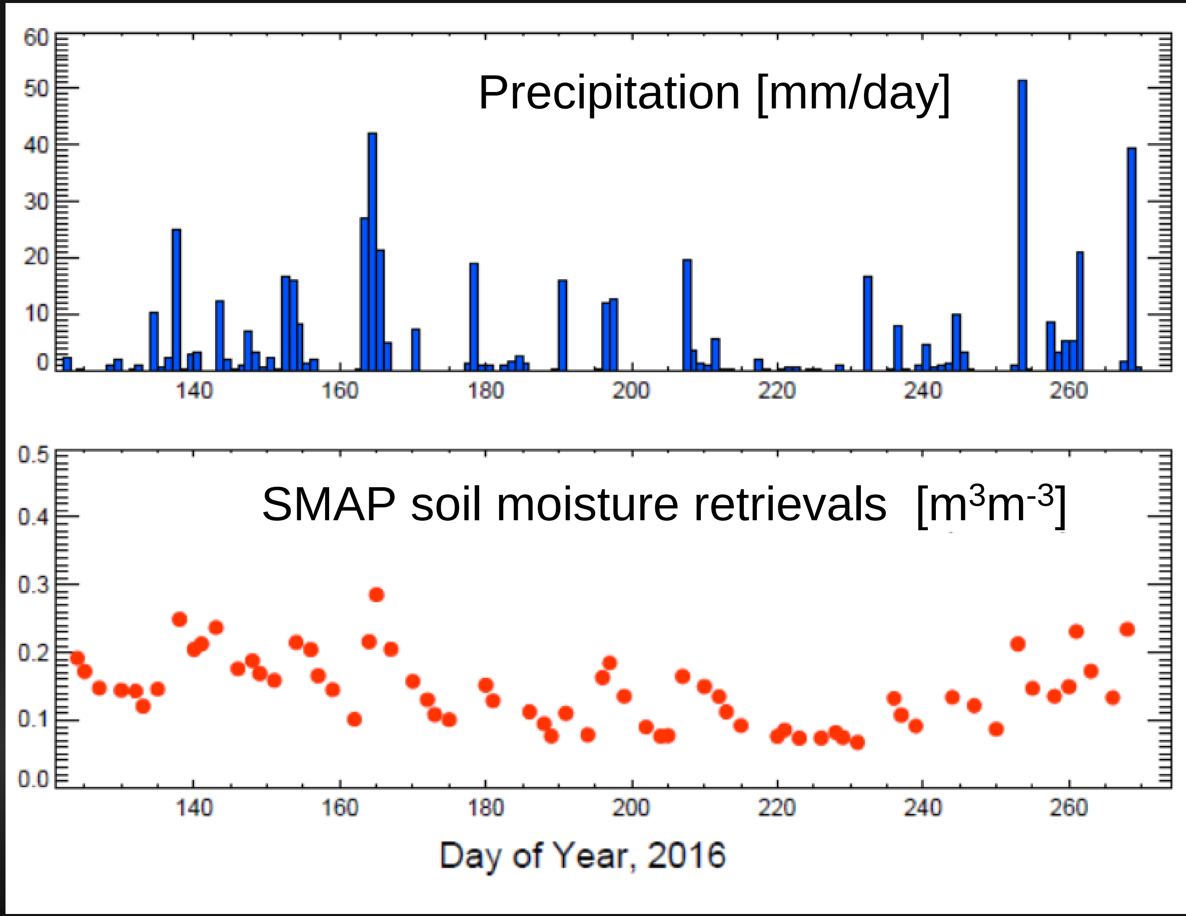

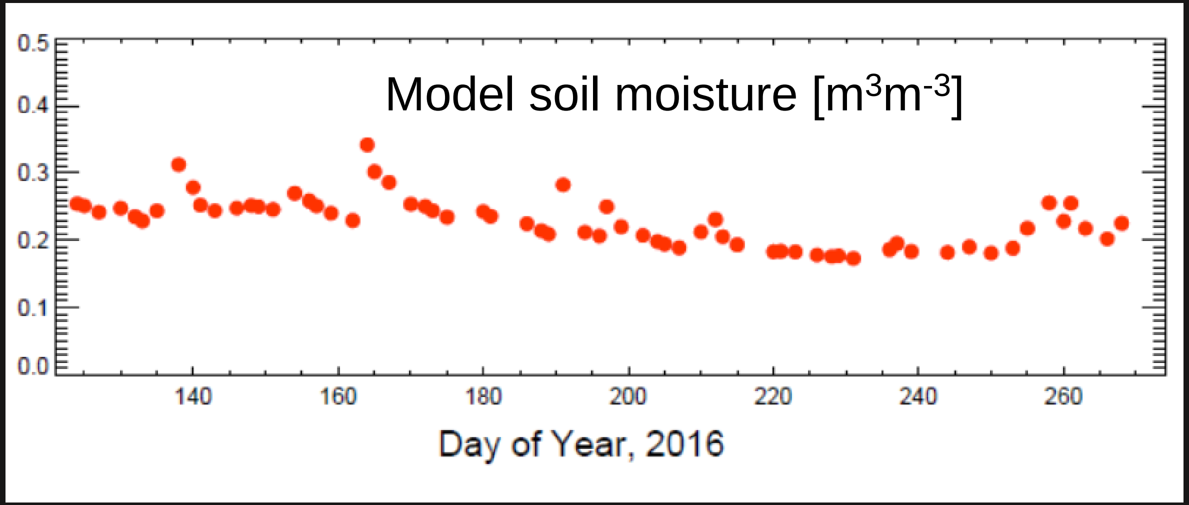

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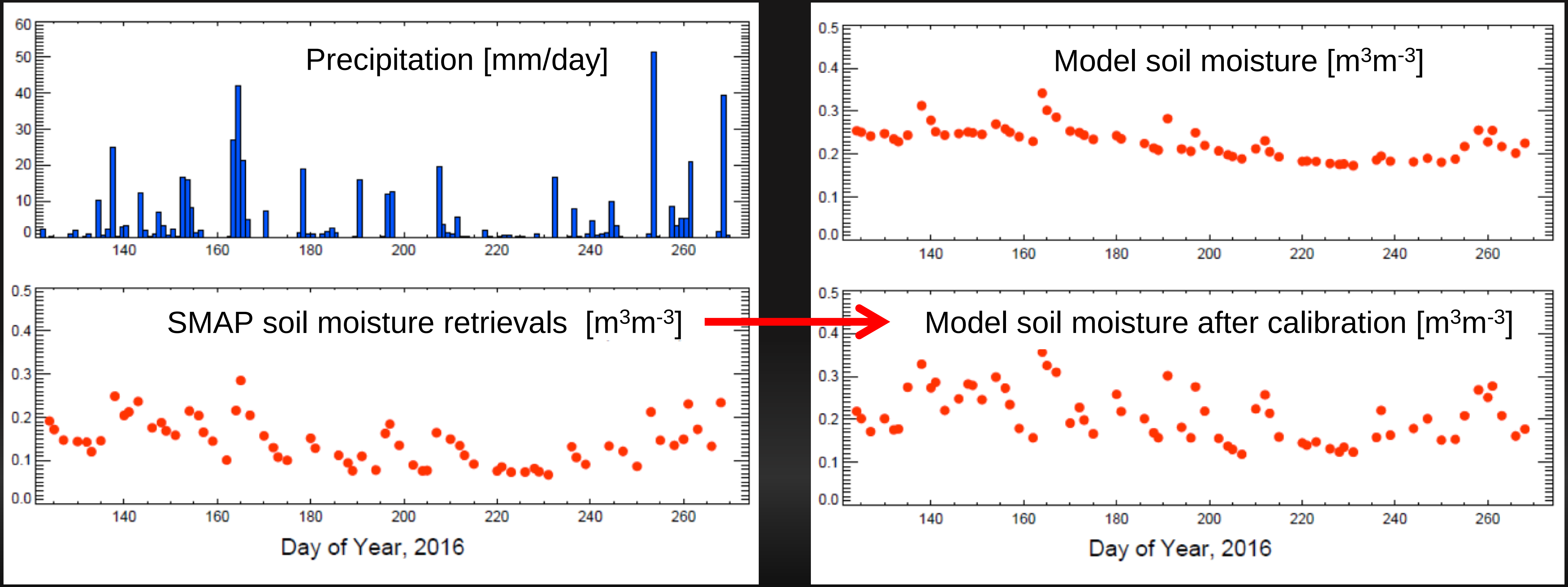
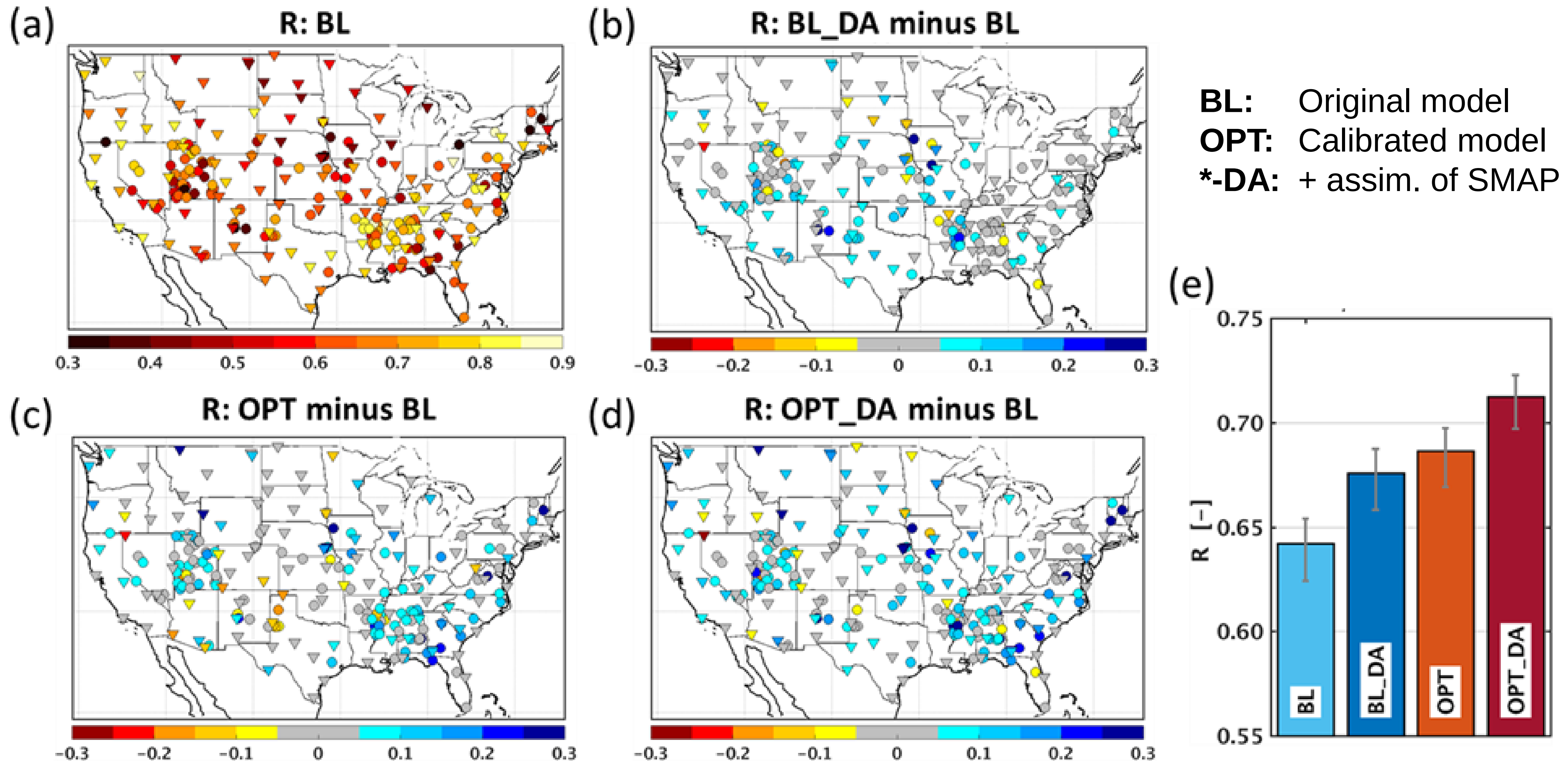


How about model calibration vs. data assimilation?

Koster et al. (2017), *JHM*, submitted.

Can we use PMW information for land model calibration?

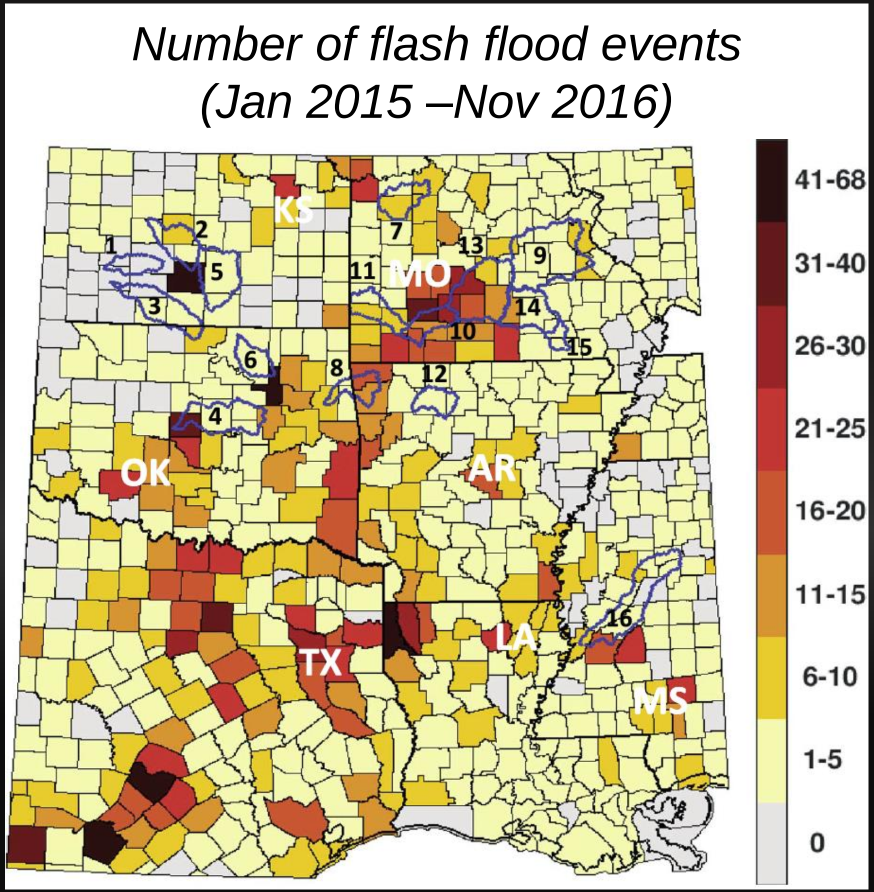


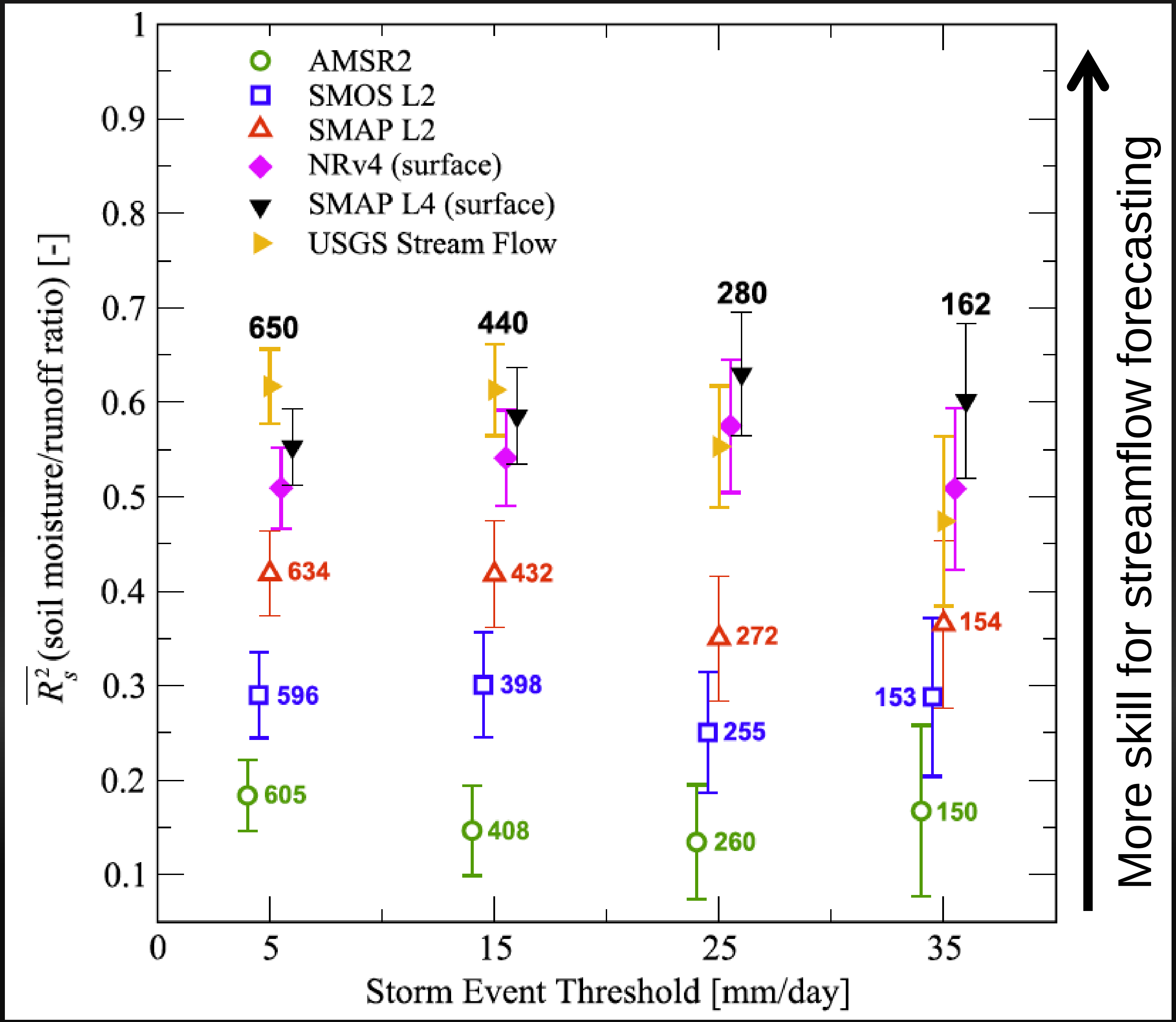
BL: Original model
OPT: Calibrated model
***-DA:** + assim. of SMAP Tb

Koster et al. (2017), *JHM*, submitted.

Can PMW observations improve flood forecasting?

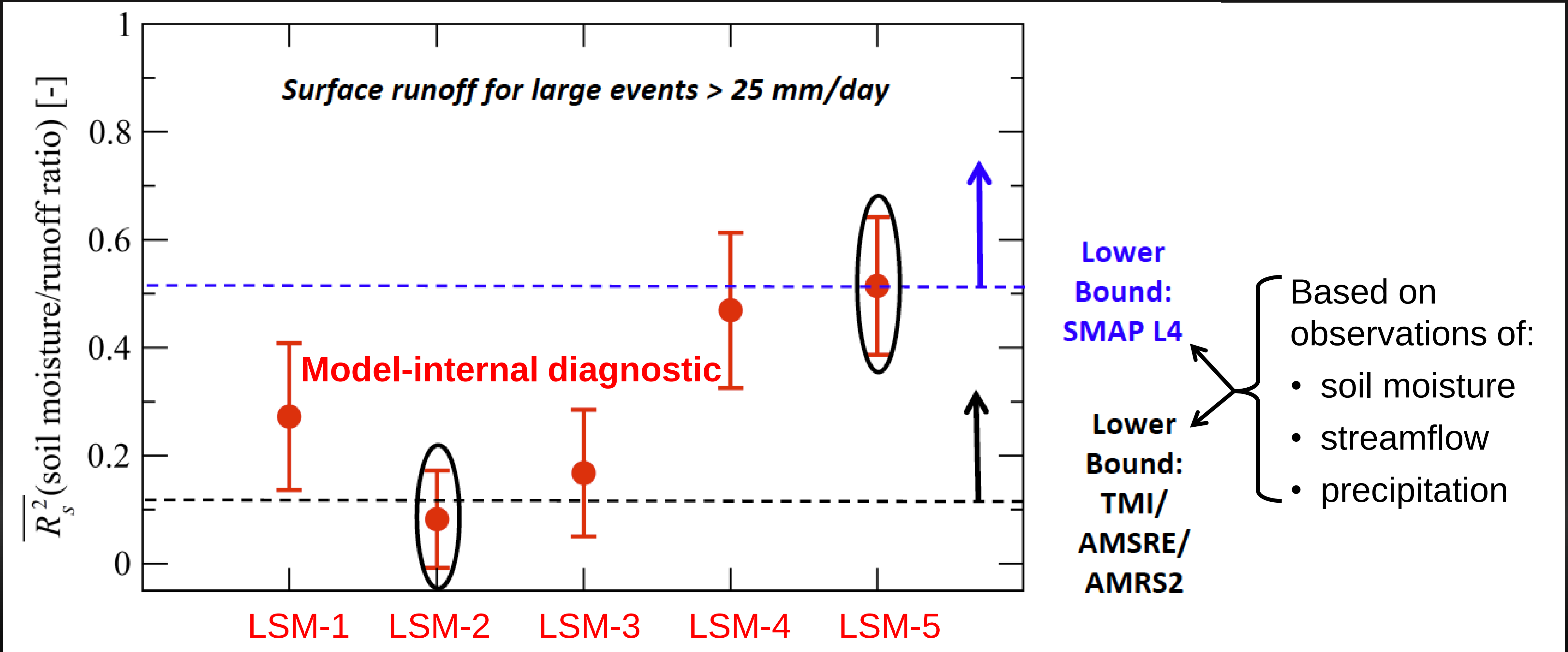
Assimilation of L-band data improves pre-storm soil moisture representation for flood forecasting.





Crow et al. (2017), *GRL*, doi:10.1002/2017GL073642.

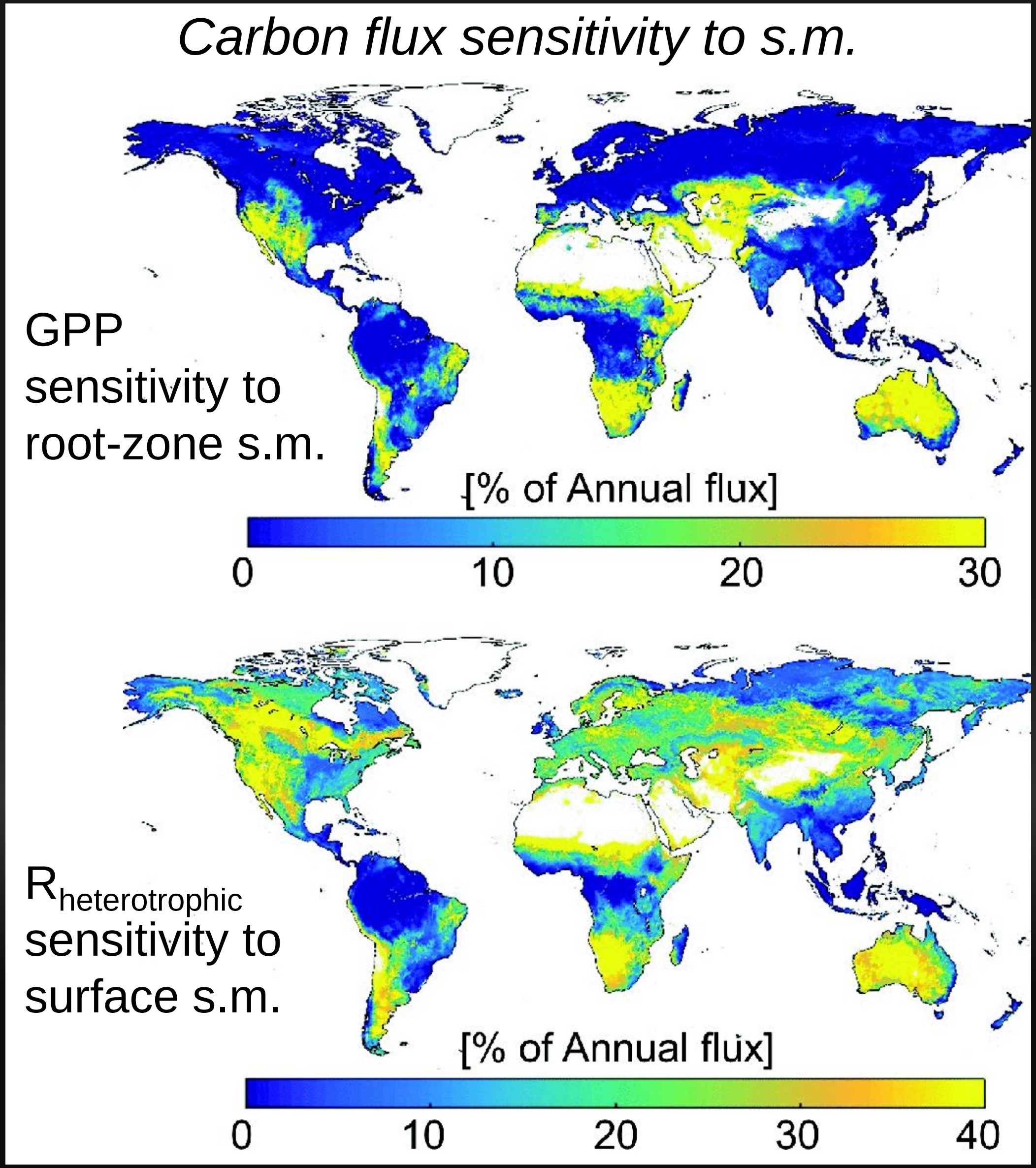
Can PMW observations be used to diagnose model processes (runoff)?



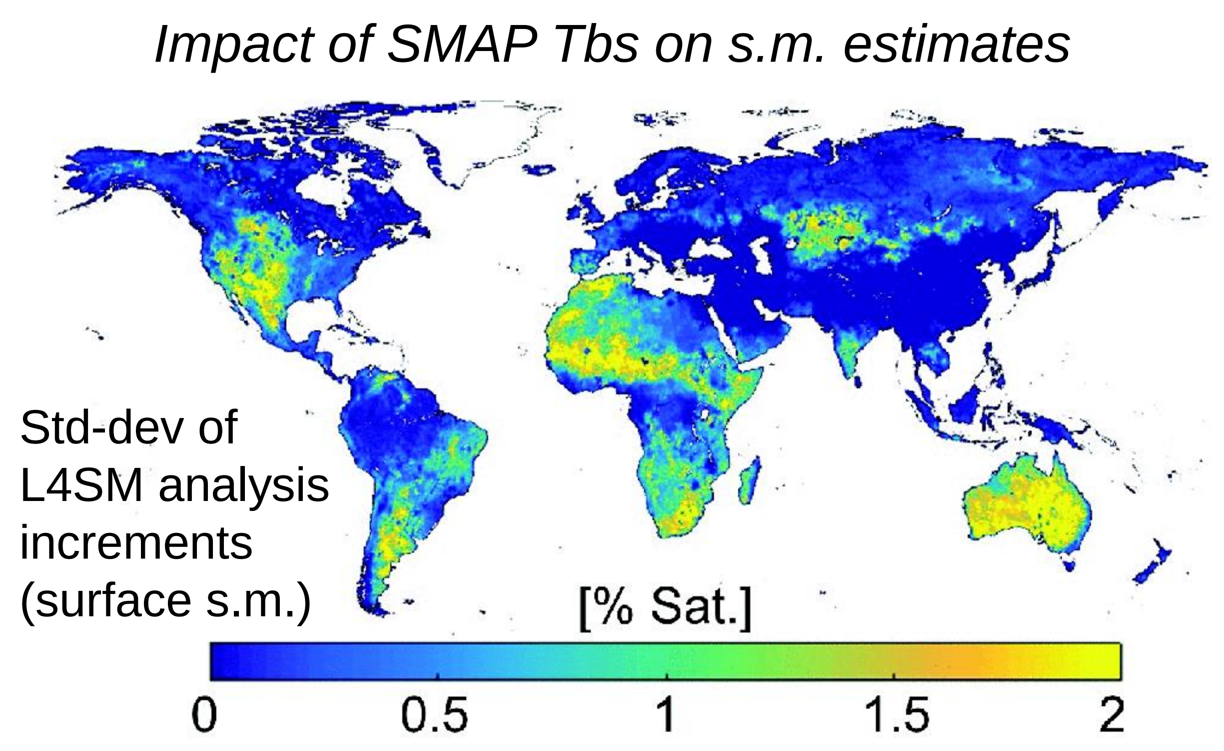
SMAP L4 soil moisture estimates reveal possible bias in the runoff response of land surface models.

Crow et al. (2017), *GRL*, submitted.

Can PMW observations constrain carbon fluxes?



SMAP Level-4 carbon product



Jones et al. (2017), *IEEE/TGARS*, doi:10.1109/TGRS.2017.2729343.

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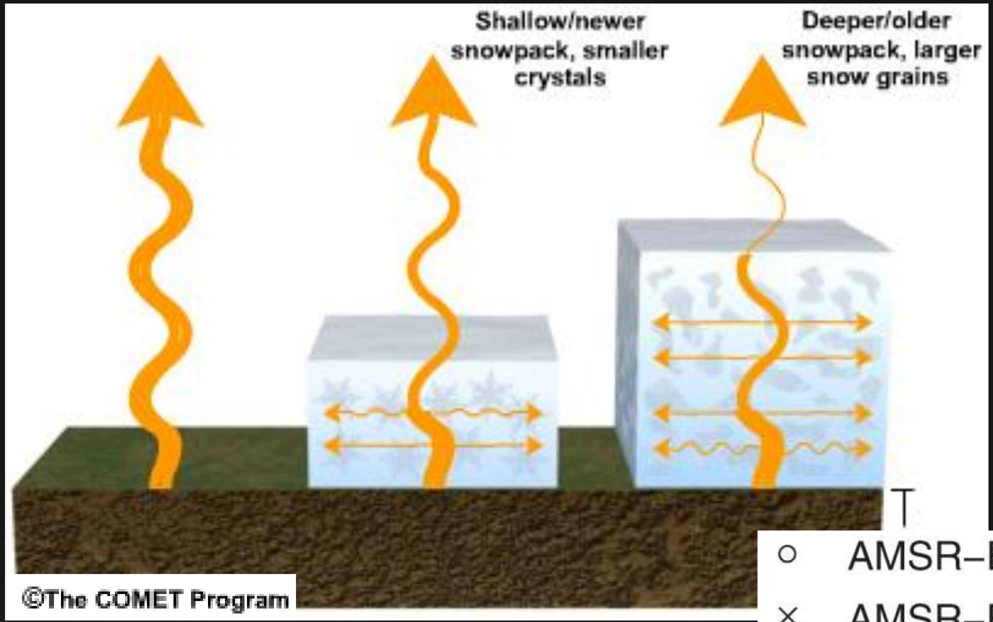
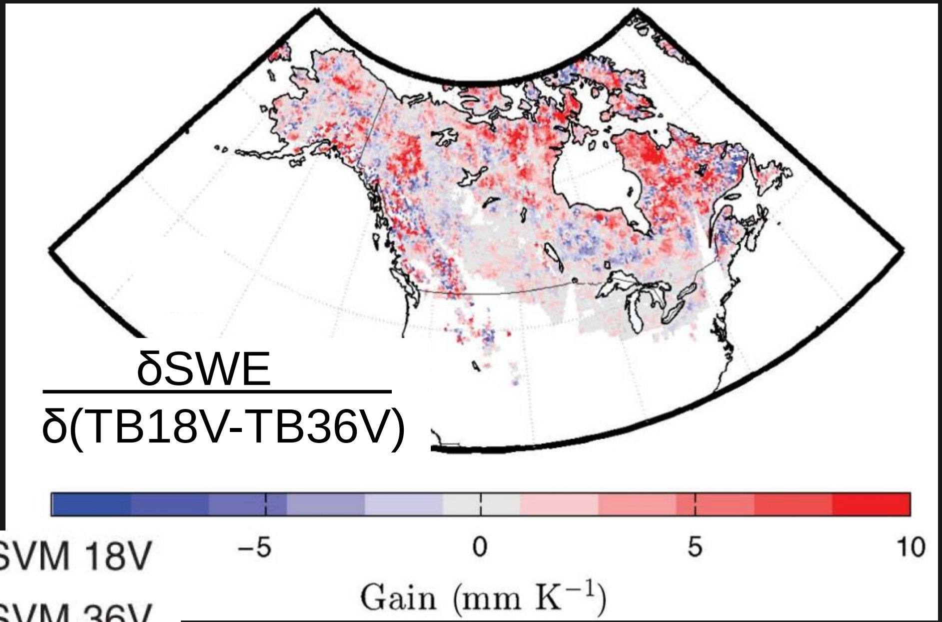
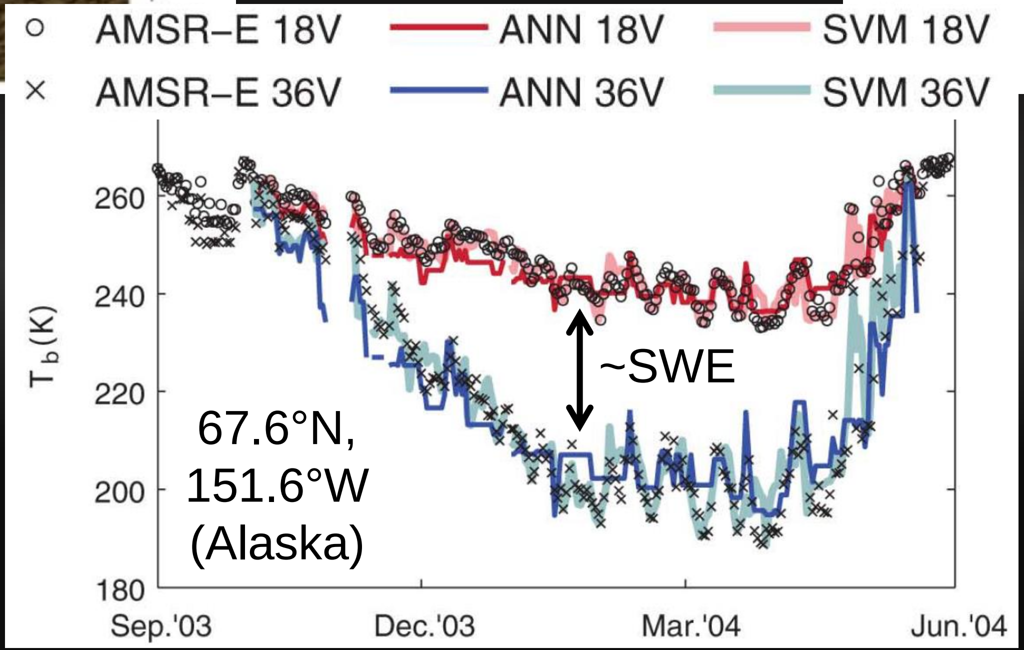






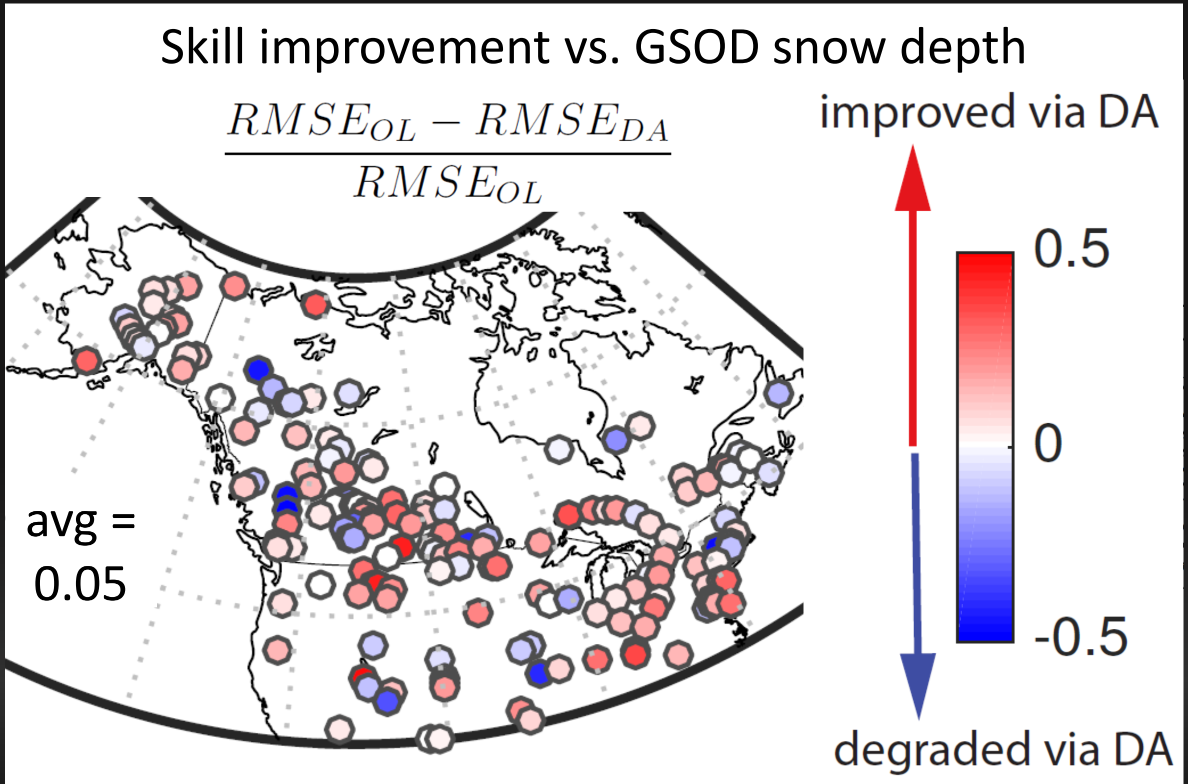
Physically-based snow radiative transfer modeling is difficult if not impossible with global land models.

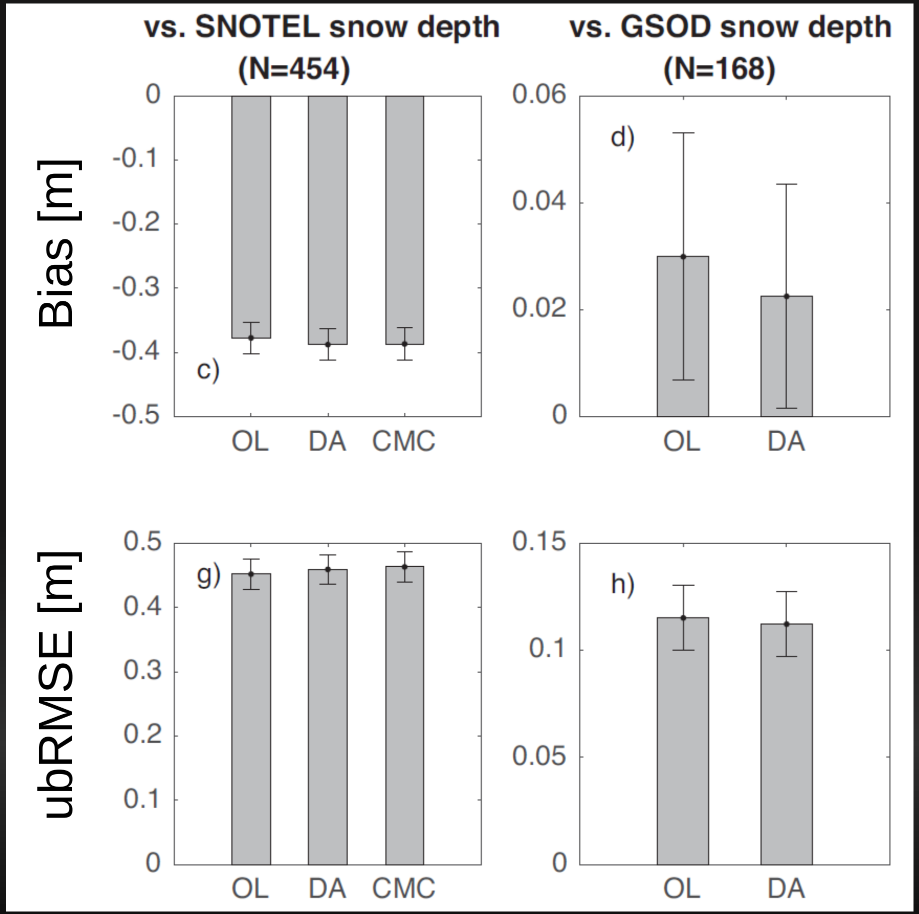
New observation operator based on machine learning.

ANN=artificial neural network
SVM=support vector machine

Forman and Reichle (2015), *IEEE/JSTARS*, doi:10.1109/JSTARS.2014.2325780.

Can PMW observations be used for snow assimilation?





Mixed result…

Xue et al. (2017), *WRR*, submitted.

Summary

- Low-frequency passive microwaves (PMWs) are sensitive to the terrestrial water cycle.
- Soil moisture
  - PMW observations useful for model diagnosis, calibration, and data assimilation.
  - PMW observations have potential to improve flood forecasts and carbon flux estimates.
  - L-band works better than C-band or X-band.
  - Assimilation provides estimates:
    - of dependent variables (incl. root-zone soil moisture)
    - with complete spatio-temporal coverage
    - at finer resolution.
  - Assimilate PMW observations together with active (radar) data.
  - Assimilate radiances and backscatter (rather than retrievals).
  - Model bias correction is still needed.
  - Uncertainty estimates are still rather imperfect.
- Snow assimilation showed mixed results.