Global Soil Moisture Estimation from L-Band Satellite Data: Impact of Radiative Transfer Modeling in Assimilation and Retrieval Systems

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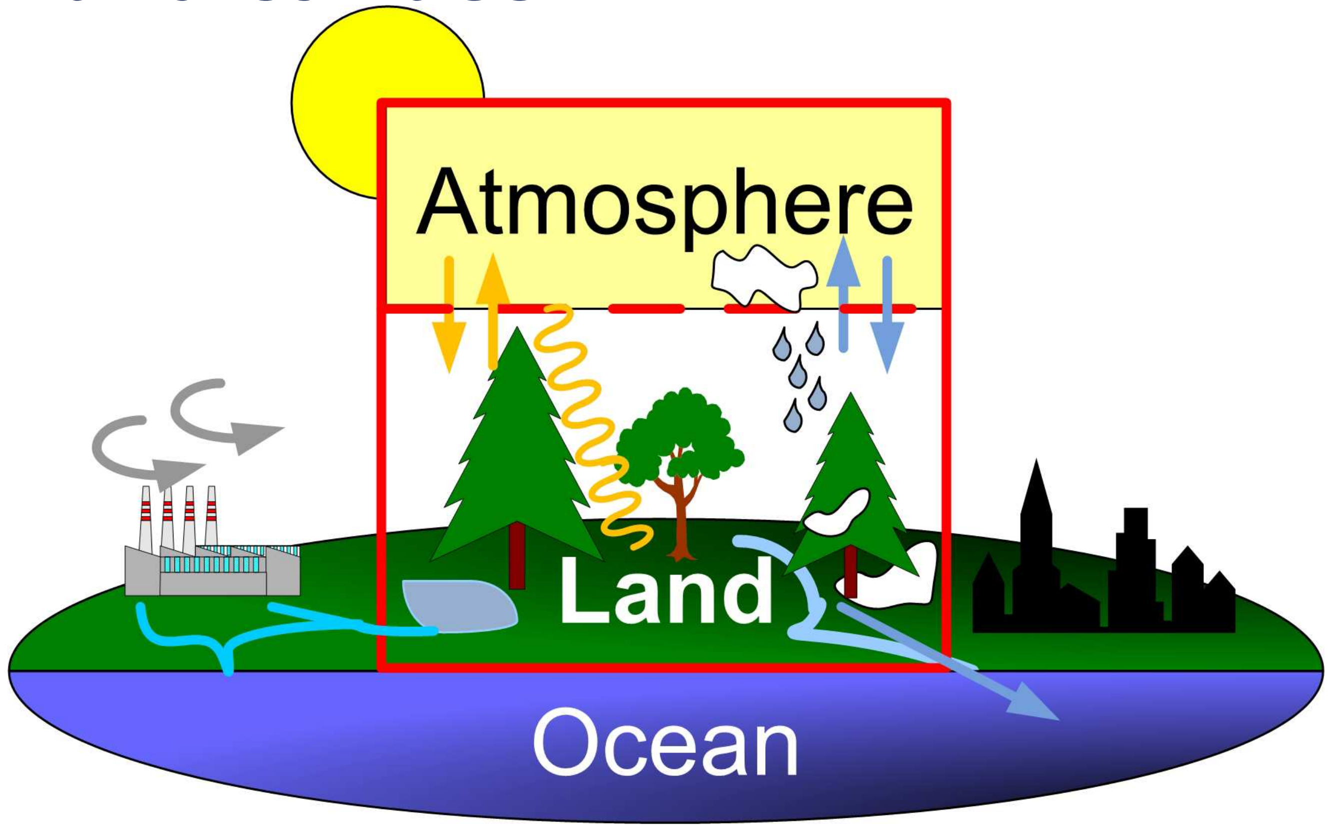
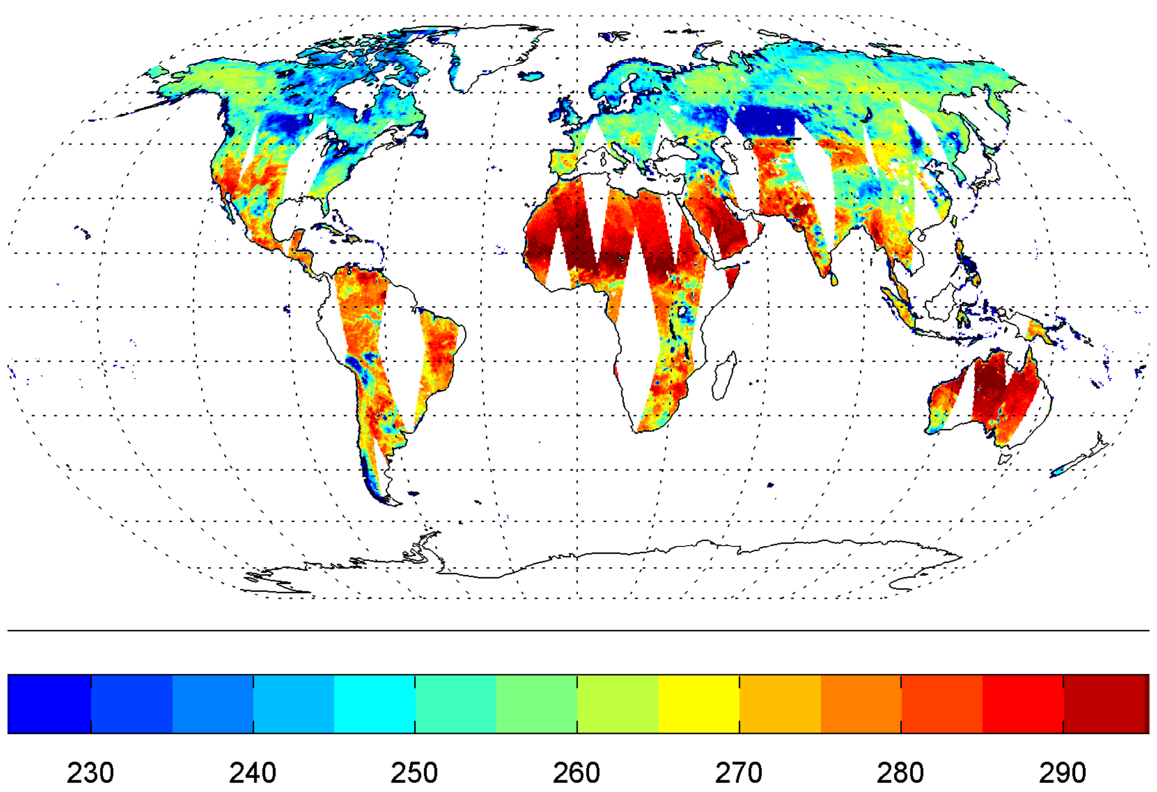
5 April 2018

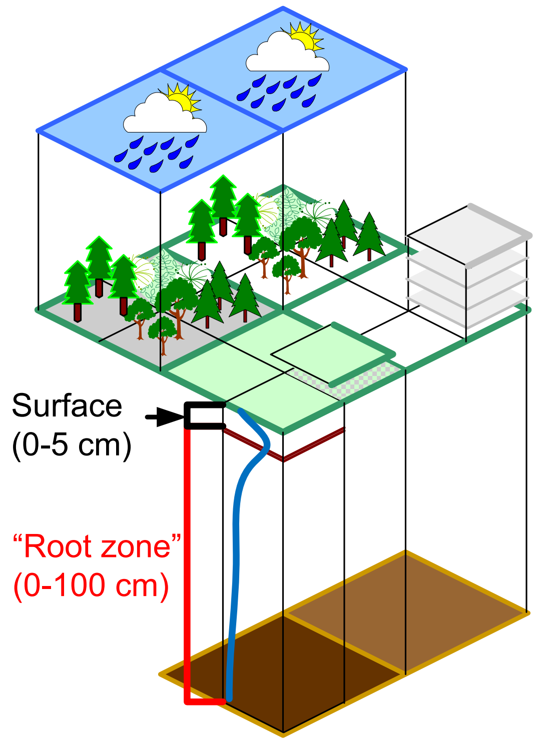
Land Surface System - HPC KU Leuven

Land surface:



Observing and modeling:

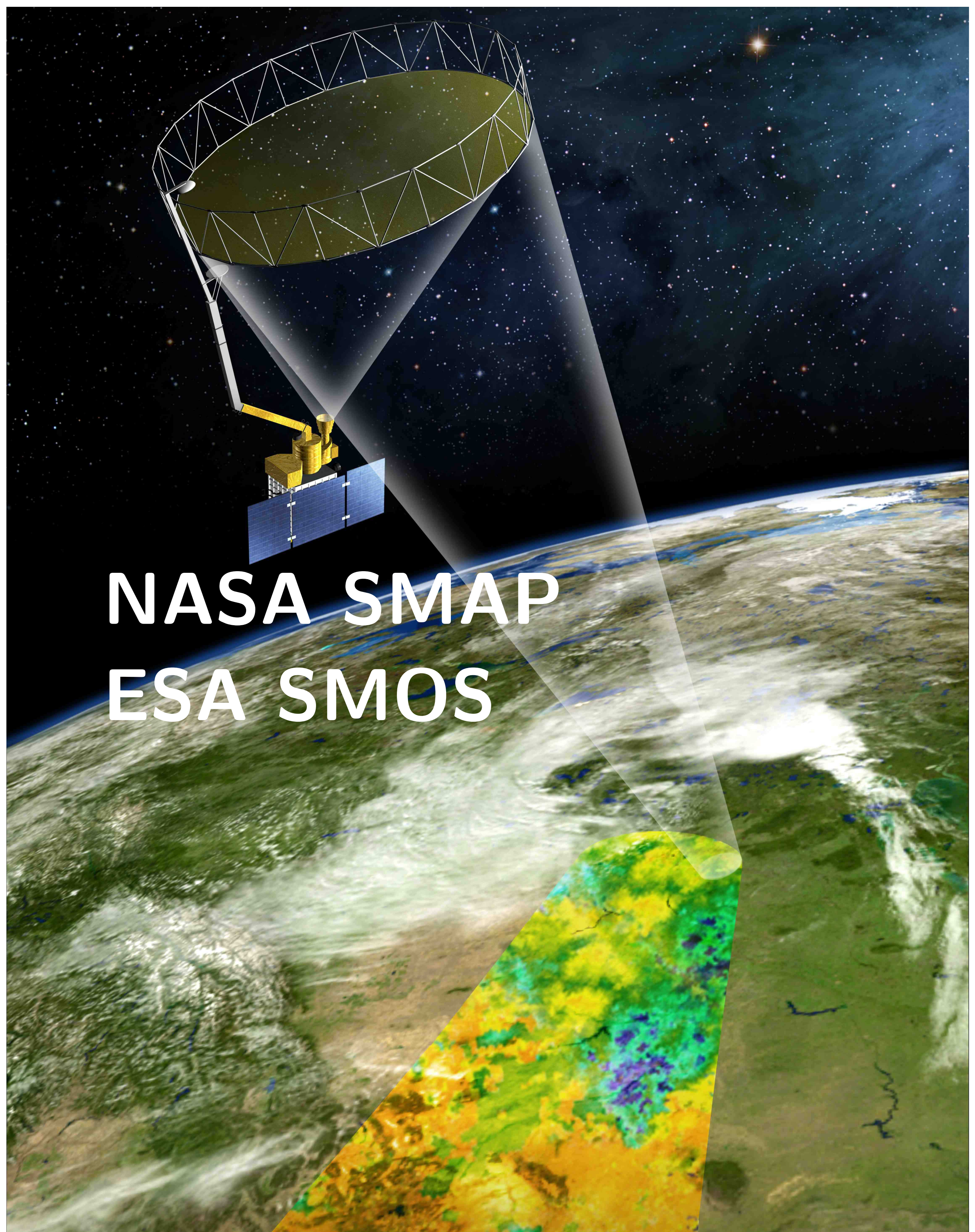




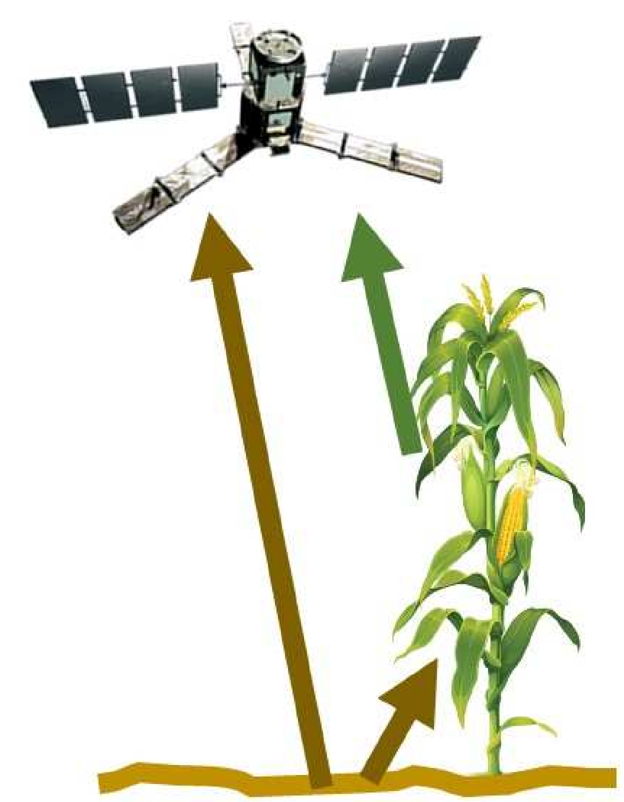
KU Leuven HPC Tier2:

L-Band Data

L-band (1.4 GHz) brightness temperatures (Tb) are sensitive to soil moisture and temperature in the surface layer (5 cm)



brightness temperature



} → RTM (parameters)

soil temperature

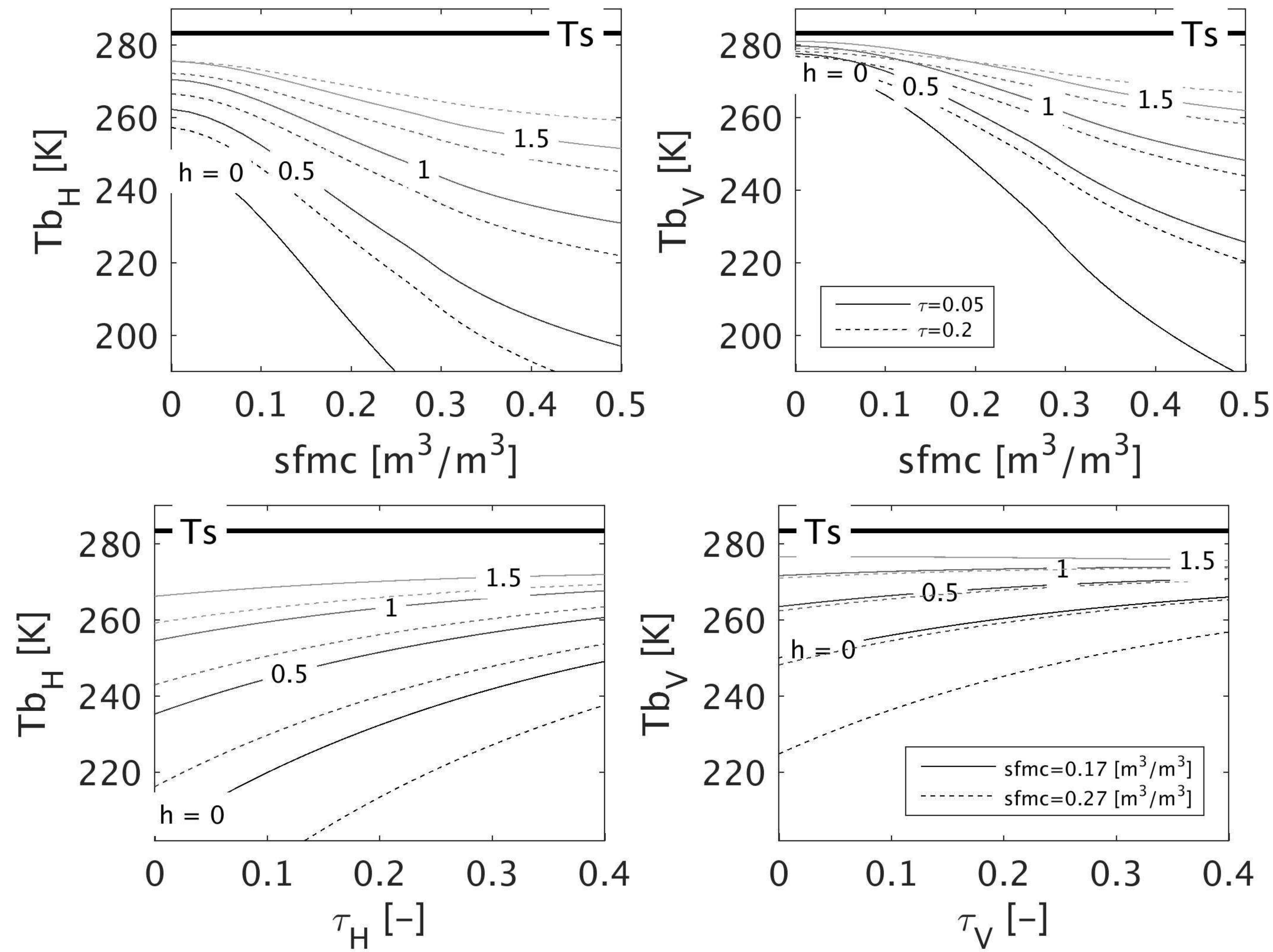
soil moisture

vegetation

forward (assimilation) ↑

inverse (retrieval) ↓

L-Band Radiative Transfer Modeling



Tb increases with drier soil moisture (sfmc)

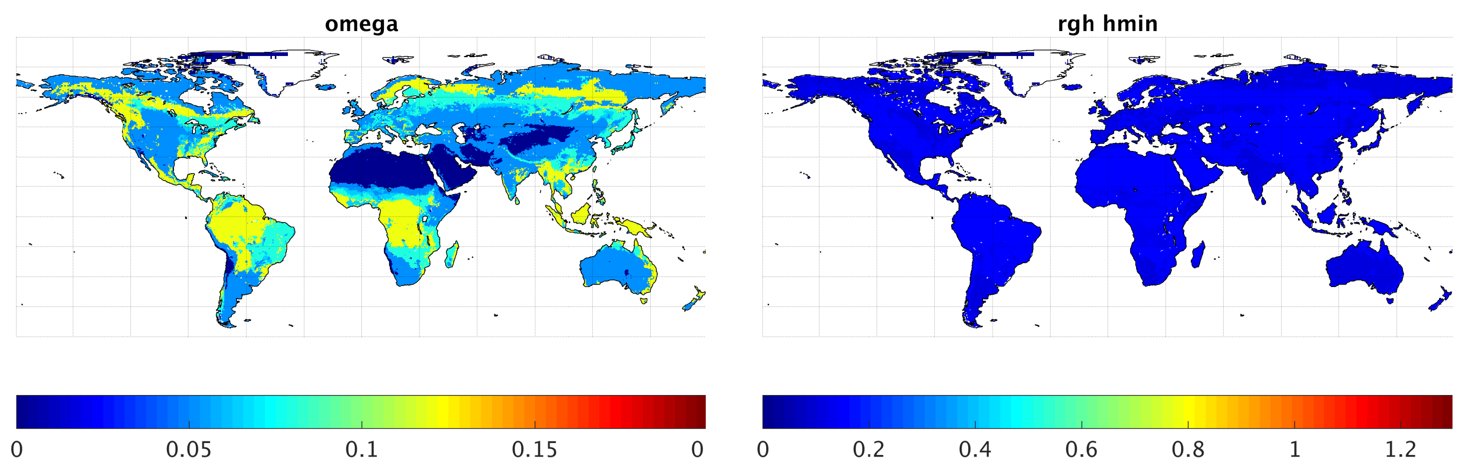
Tb increases with more vegetation (τ)

Tb strongly depends on parameters (e.g. h, roughness)

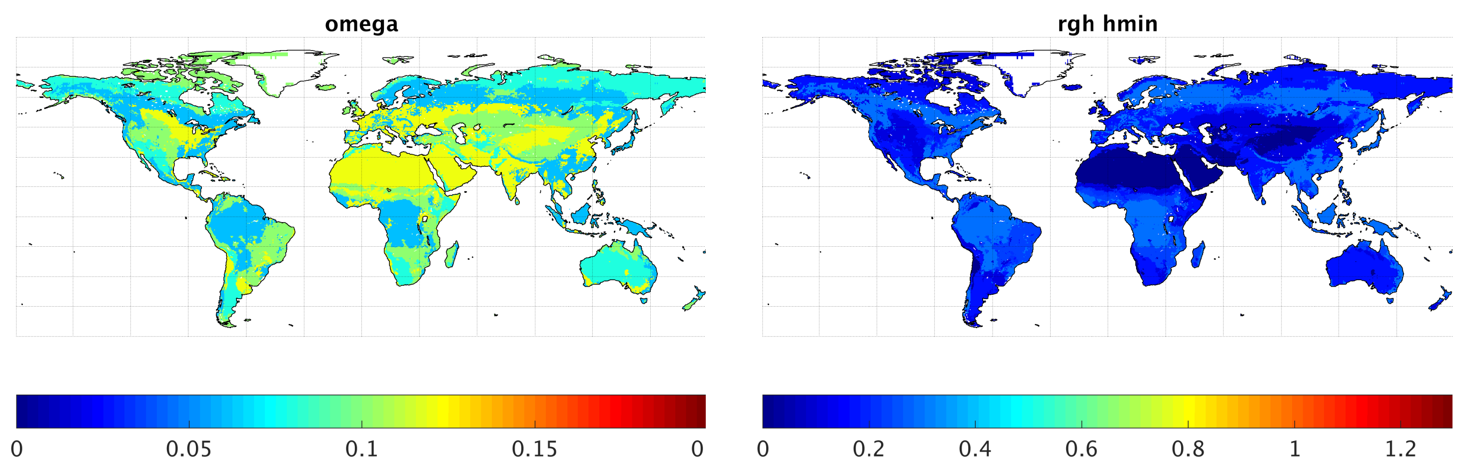
Parameter Estimation

Lookup tables: per vegetation class

SMAP L2



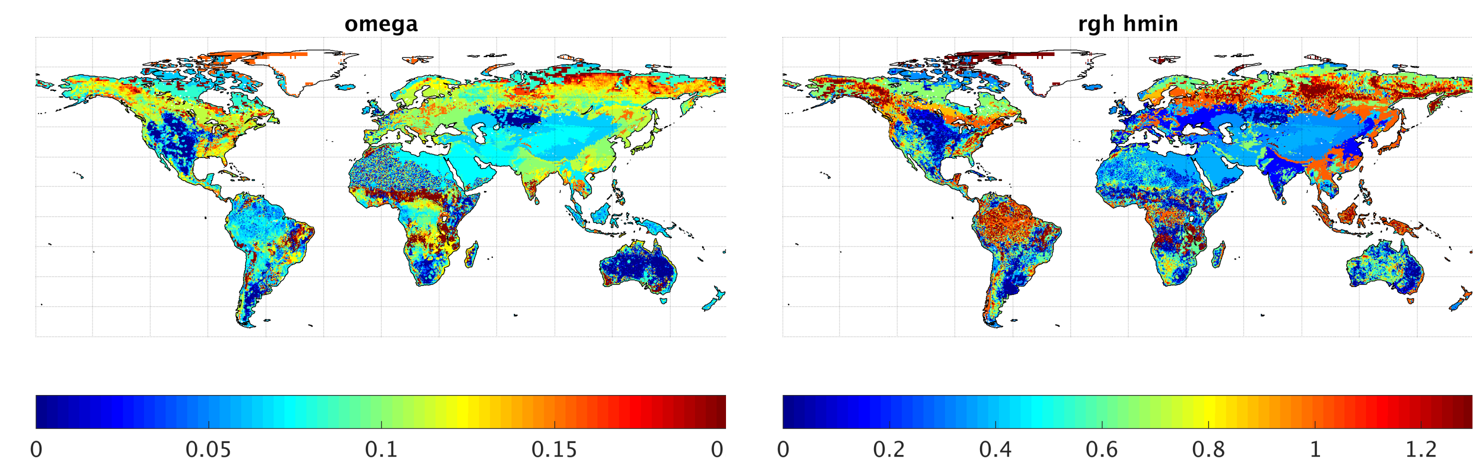
SMOS IC



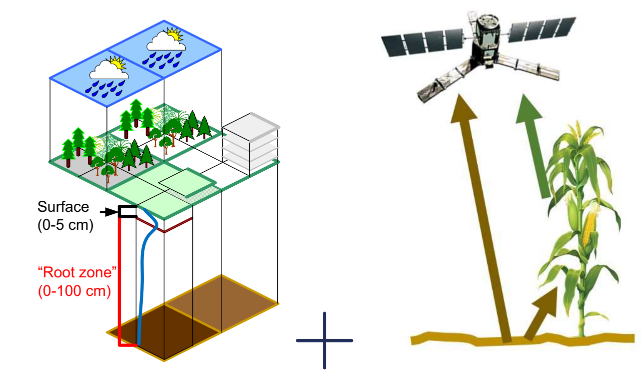
- Based on field experiments; optimizing retrievals vs in situ soil moisture
- Can this also be used for forward modeling (DA experiments)?

Calibrated: per grid cell

SMAP L4



- Based on optimizing SMOS Tb versus simulated Tb, using simulated soil moisture (De Lannoy et al., 2013, 2014)



- Can this also be used for inverse modeling (retrievals)?

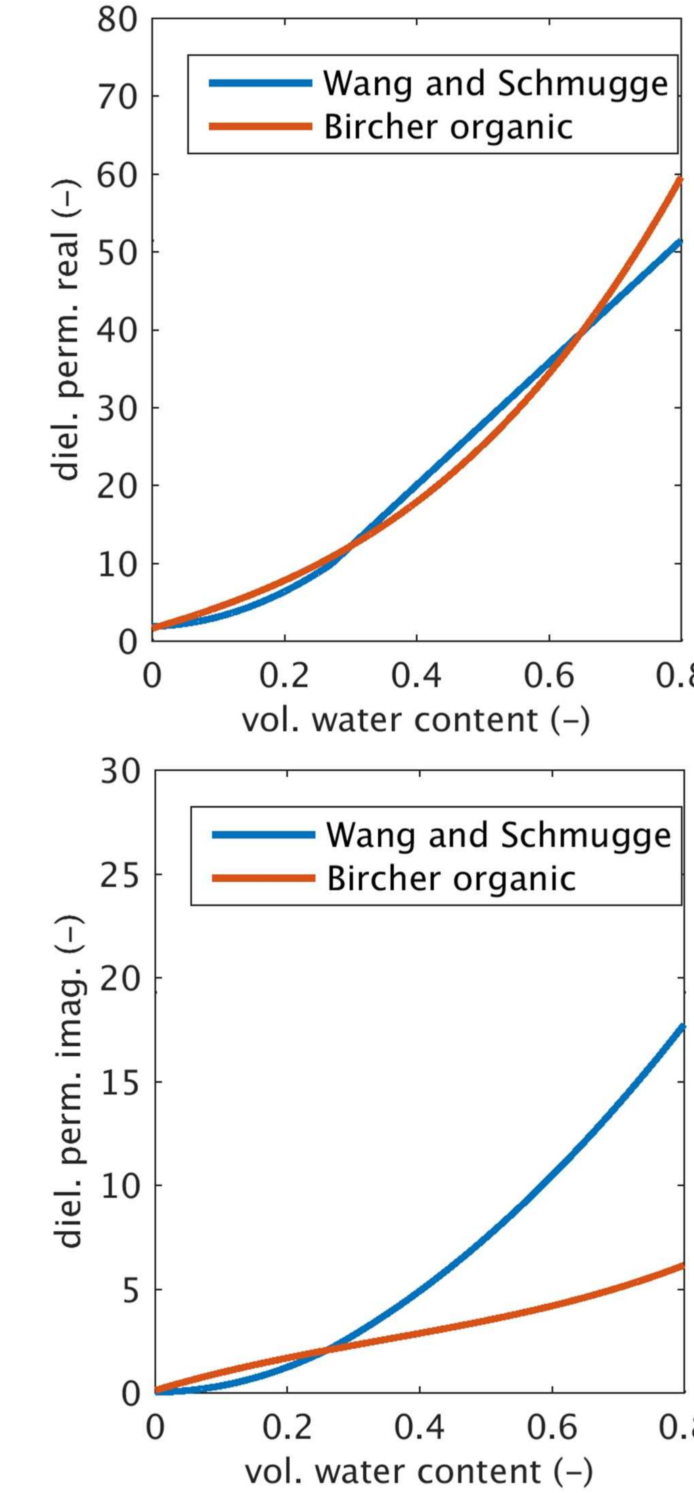
Complexities

Enhance the RTM for specific land cover types, e.g. peatlands:

- **Soil moisture dynamics:**
  improved physical processes in peatland
- **RTM w/ dielectric model:**
  Wang & Schmugge (1980) for mineral soils versus Bircher et al. (2016) for organic soils
- **Open water:**
  incl. open water reduces bias in Tb forward modeling

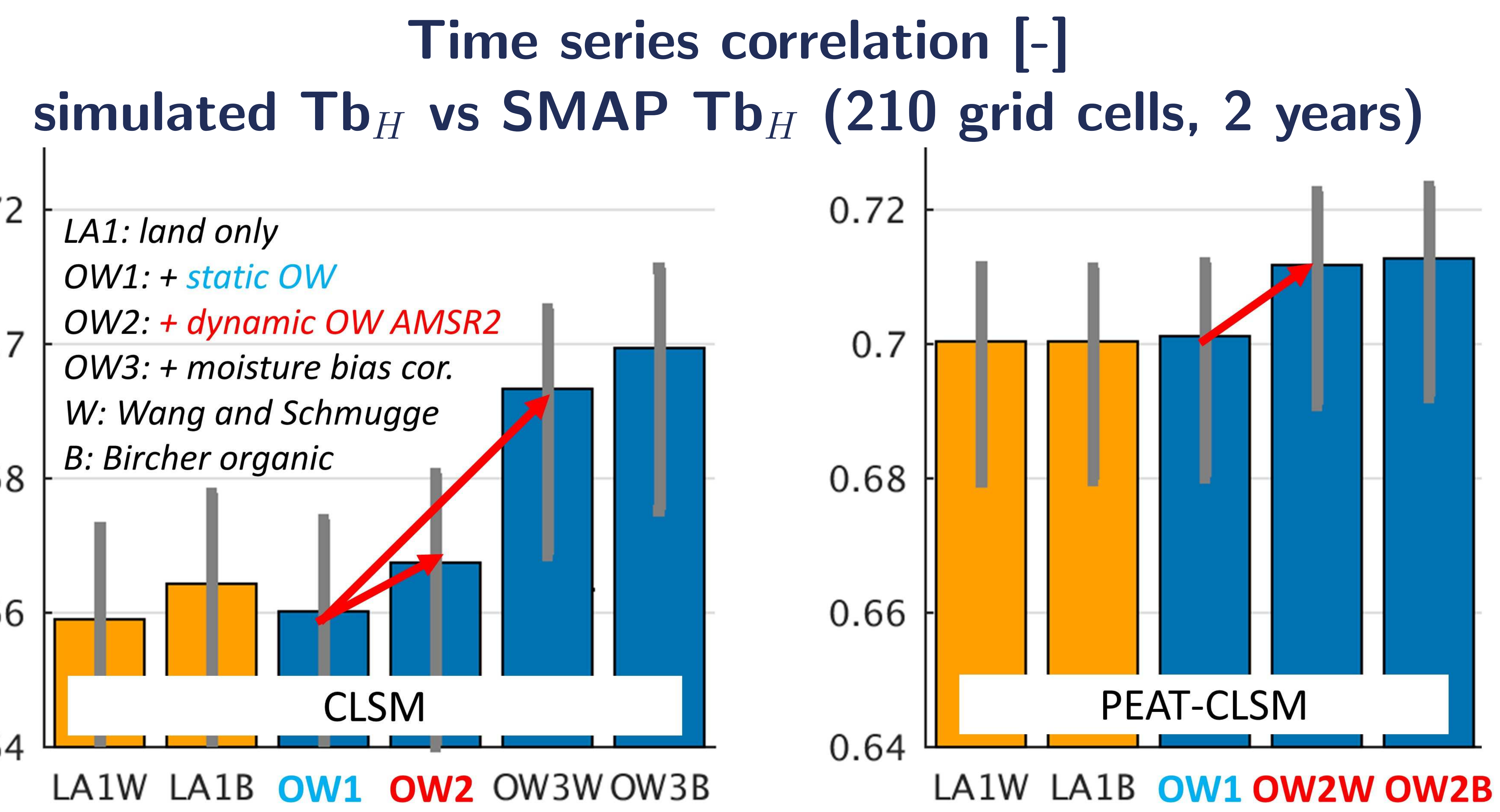
$$Tb = f_{land}.Tb_{land} + f_{SOW}.Tb_{SOW} + f_{DOW}.Tb_{DOW}$$

land + static (land mask) + dynamic open water (AMSR2)



(Michel Bechtold, Simon De Canniere)

Complexities



- Dielectric model only has minor impact (Bircher vs Wang & Schmugge)
- PEAT-CLSM outperforms CLSM for both soil moisture and Tb simulations
- Adding dynamic open water fraction further improves the results

(Michel Bechtold)

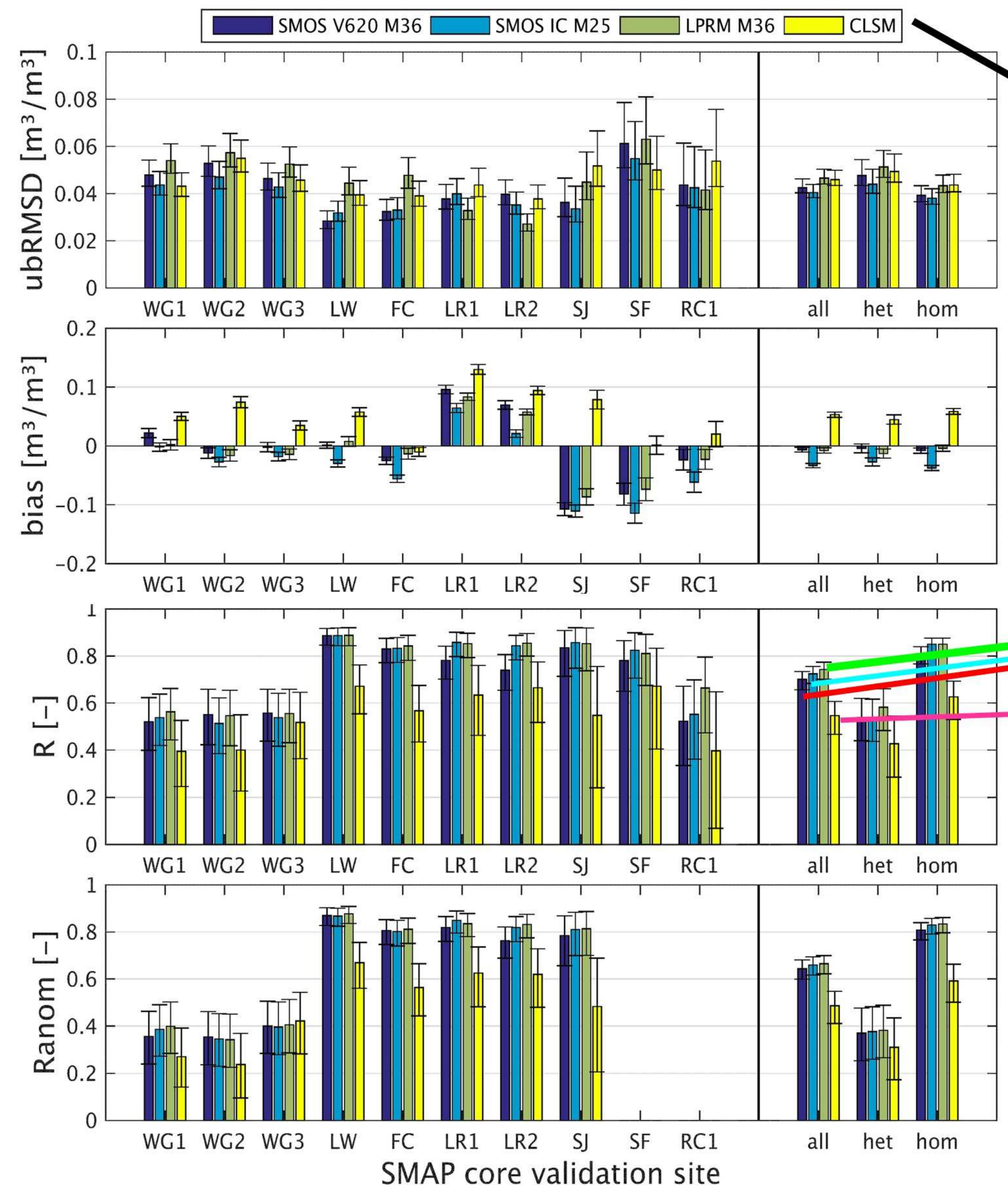
SMOS Retrievals

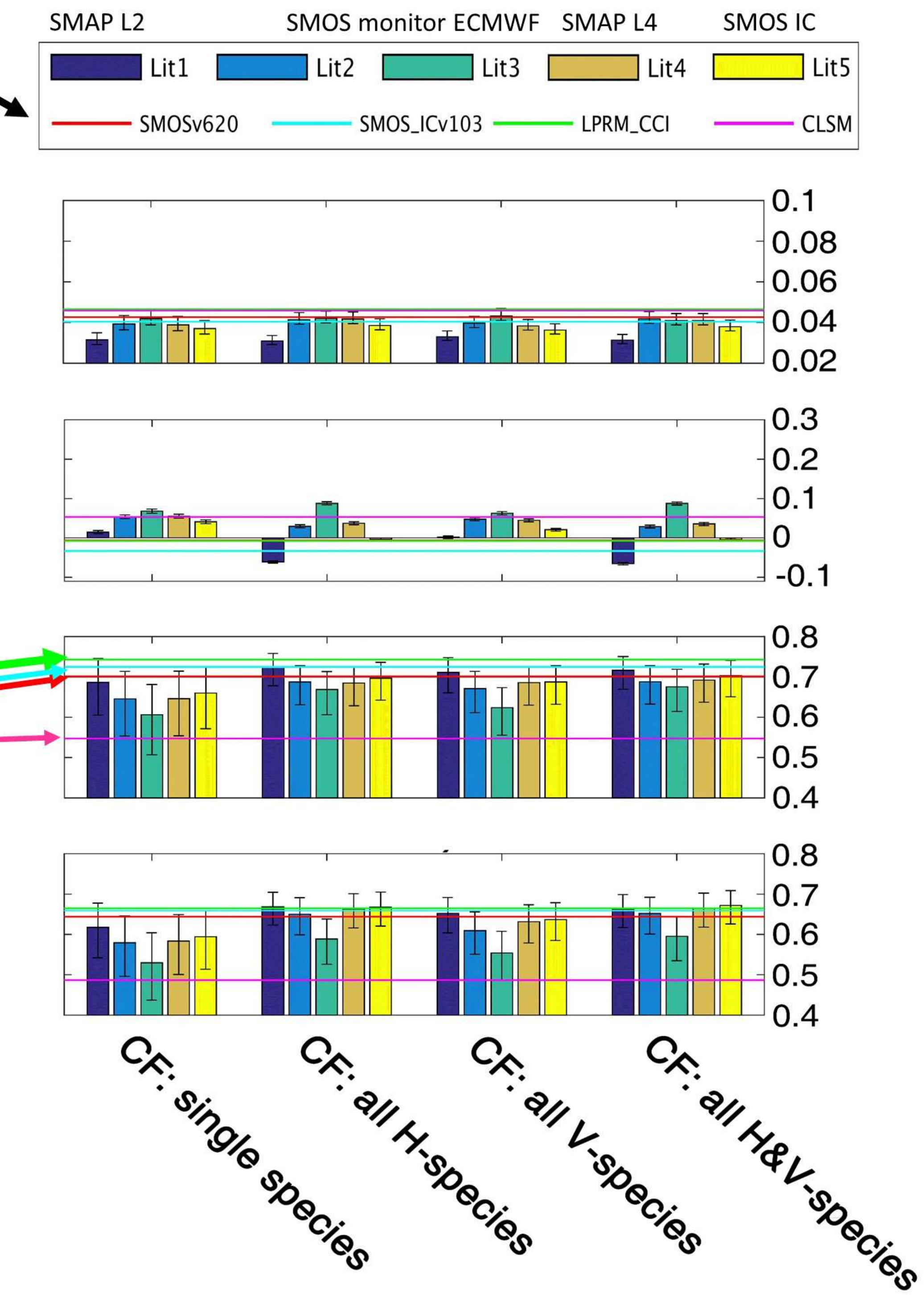
Global Soil Moisture (SM) and VOD Retrievals

- SMOS (quasi-)operational retrieval products:
  - **SMOS L2/L3**
    - only retrieval for nominal fraction, low vegetation/forest
    - (SM,VOD)=f(Tb^{SMOS}, MODIS LAI, ECMWF Ts, Tb$^{ECMWF}_{\mathrm{notnominal}}$, RTM)
  - **SMOS-IC** *(Fernandez-Moran et al., 2017)*
    - homogenous pixels
    - (SM,VOD)=f(Tb^{SMOS}, ECMWF Ts, RTM)
  - **SMOS-LPRM** in ESA CCI
    - homogenous pixels
    - VOD=f(MPDI^{SMOS},ω), and SM=f(Tb^{SMOS}, VOD, model Ts, RTM)
- **SMOS research products**: physically-based, neural network, various RTMs, ...
  - homogenous pixels
  - VOD=f(Tb^{SMOS}, MERRA2 Ts, MERRA2 SM, RTM), **or** SM=f(Tb^{SMOS}, MERRA2 Ts, MERRA2 LAI, RTM)

SM Retrievals

In situ validation (CalVal sites)



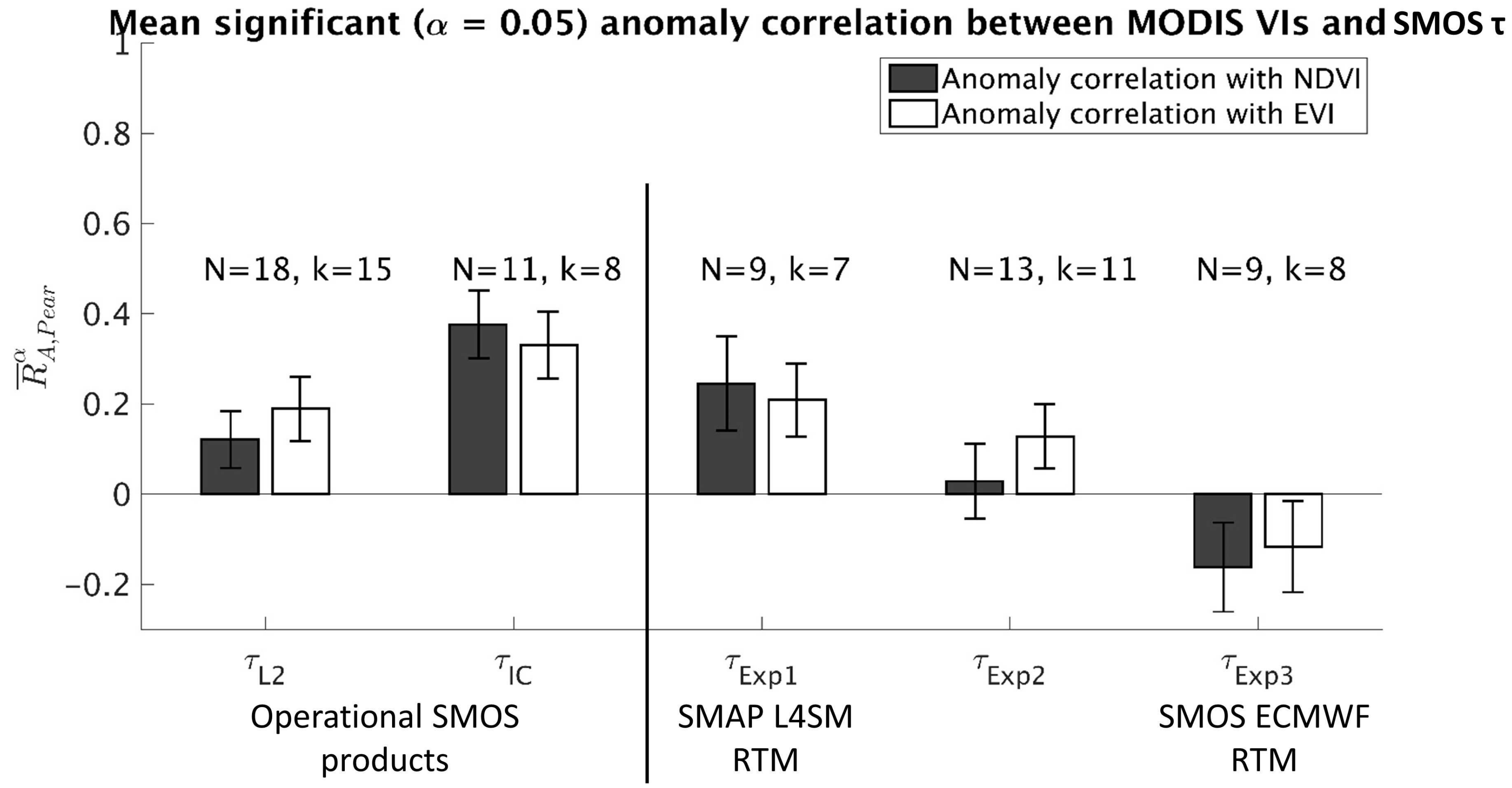


- all operational products do better than model simulations
- much simpler SMOS-IC product performs as good as complex SMOS L2
- RTM calibrated for forward modeling could serve for SM retrievals
- Lit3 (fwd modeling) is inferior for retrievals

(Jan Quets)

VOD Retrievals

Representative site evaluation (11 vegetation classes)



- limited (anomaly) correlations: L-band VOD contains other information than optical vegetation indices (VI)
- SMOS-IC performs better than operational SMOS L2 (anomaly R)
- RTM calibrated for forward modeling could serve for τ retrievals
- Lit3 (fwd modeling) is inferior for retrievals

(Michiel Van Gompel)

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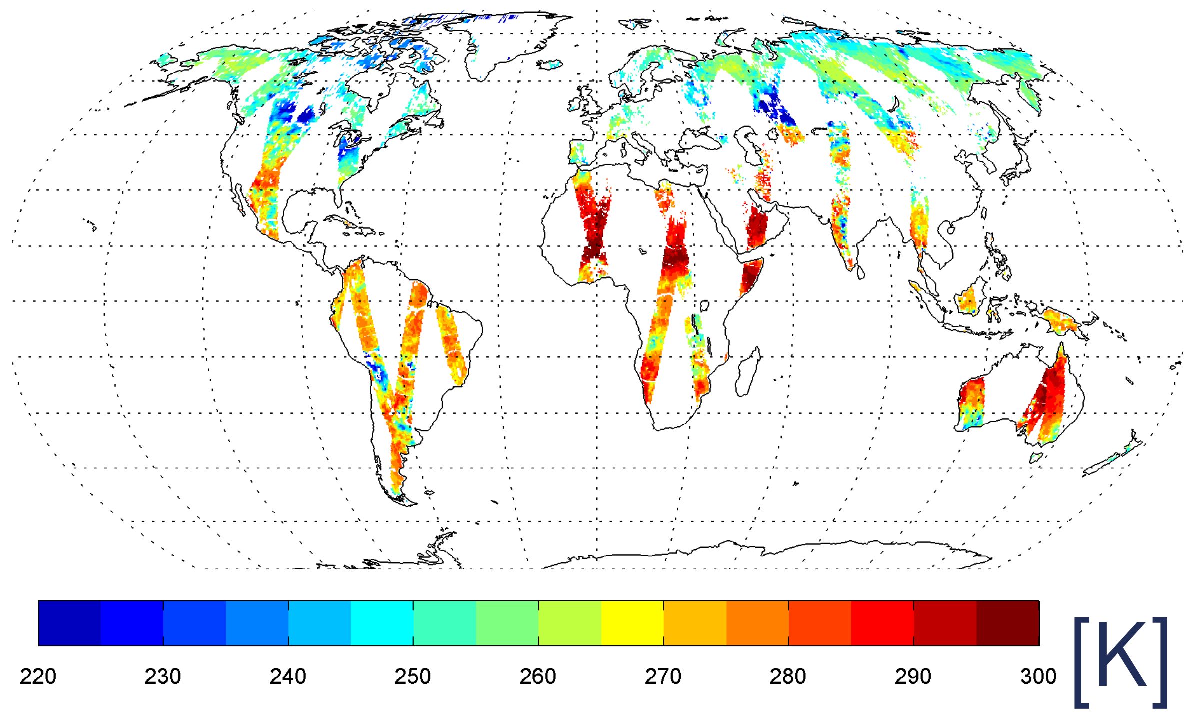
SMOS Data Assimilation

Data Assimilation

SMOS Obs (footprint)



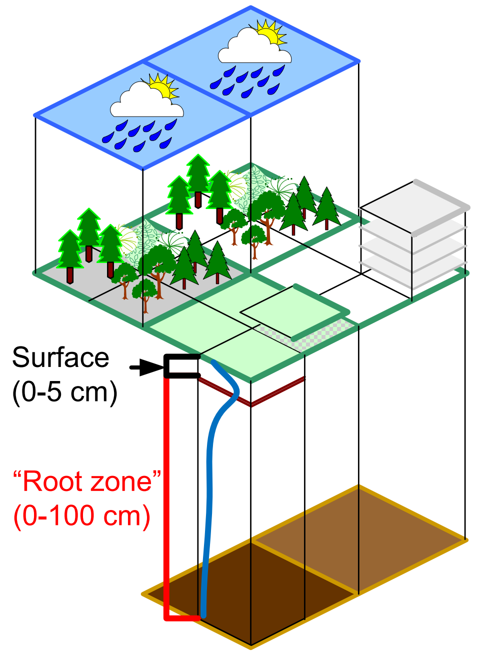
NASA GEOS-5 Land Surface Modeling (36 km)

- Catchment land surface model
- MERRA surface meteorology

Observation operator:

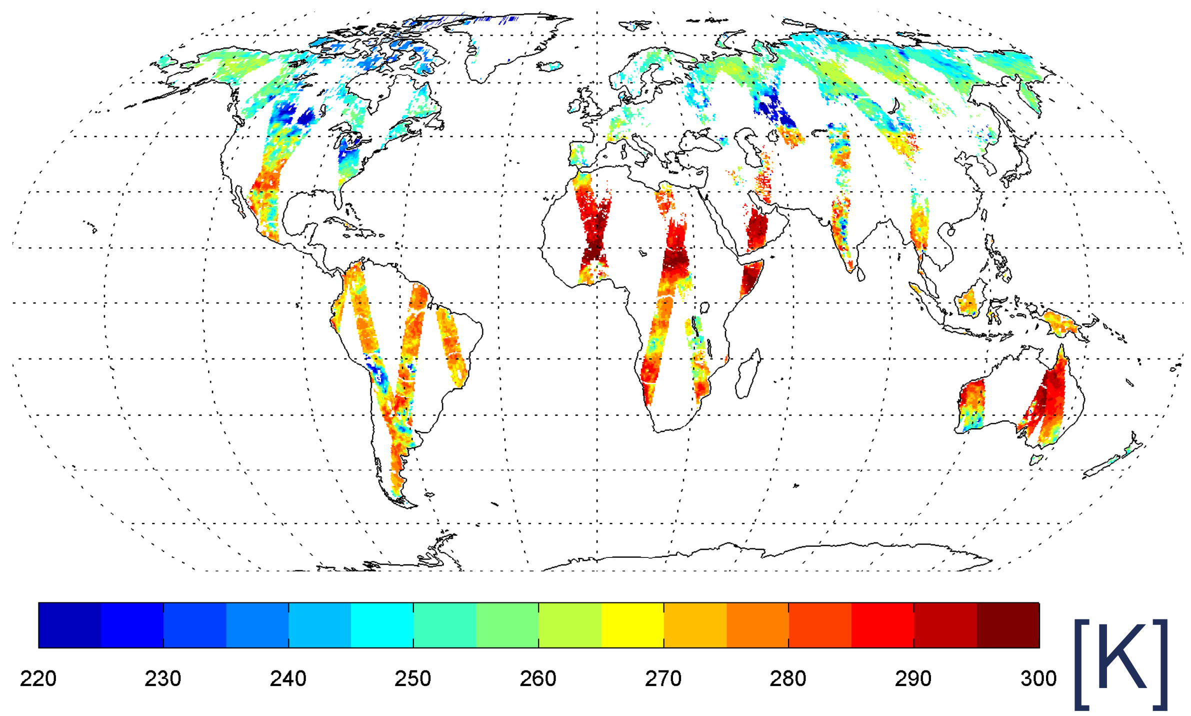
- spatial aggregation
- radiative transfer model*

    only in case of Tb assimilation



Data Assimilation

SMOS Obs (footprint)



NASA GEOS-5 Land Surface Modeling (36 km)

- Catchment land surface model
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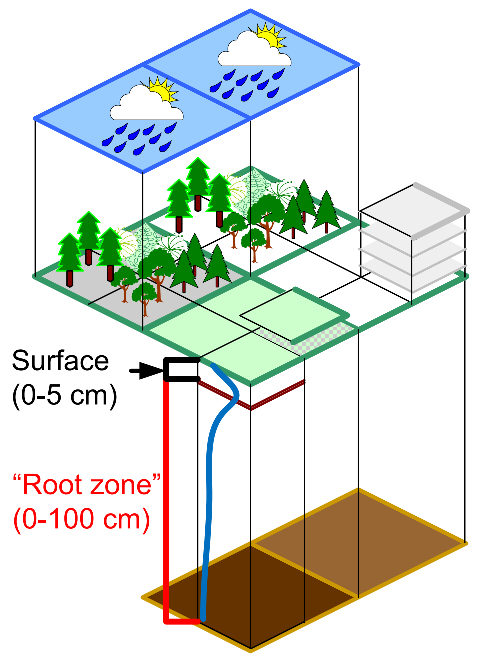


Observation operator:

- spatial aggregation
- radiative transfer model*
- only in case of Tb assimilation

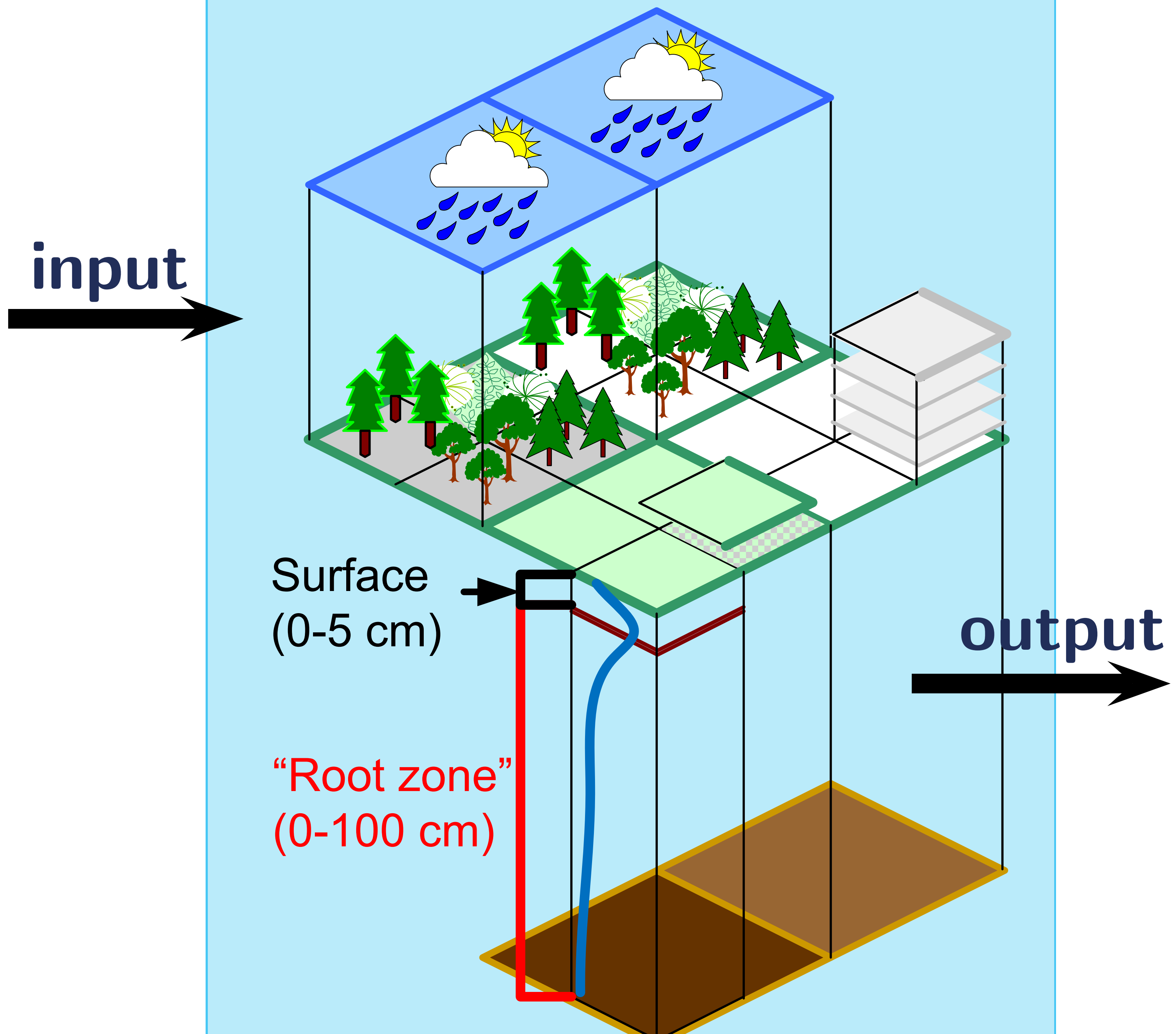
Data Assimilation
- 3D EnKF
- bias mitigation*
- filter parameters*

- Surface soil moisture ($\sim$ top 5 cm)
- Root zone soil moisture ($\sim$ top 1 m)
- Other consistent geophysical fields, with error estimates

$\Rightarrow$ * calibration using long-term SMOS record

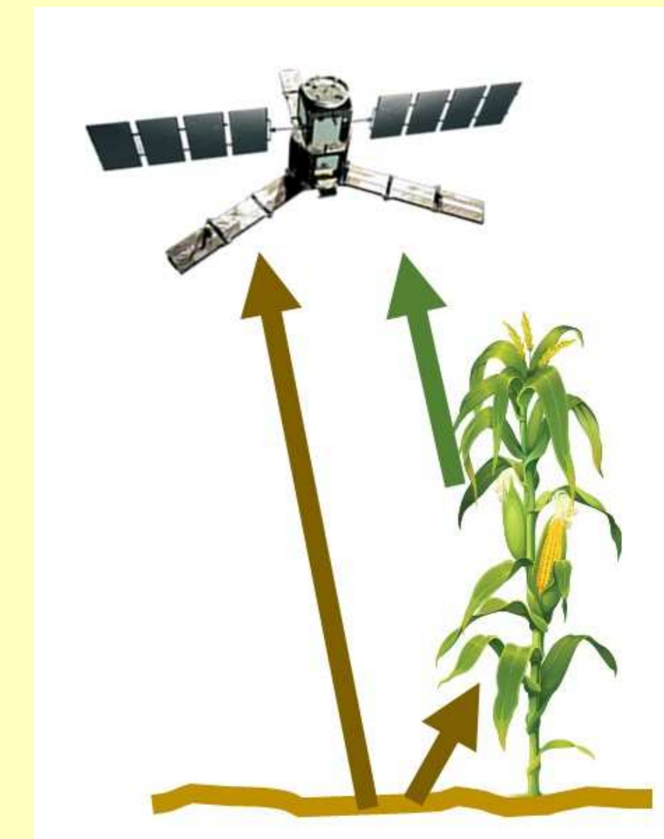
Land Surface Modeling

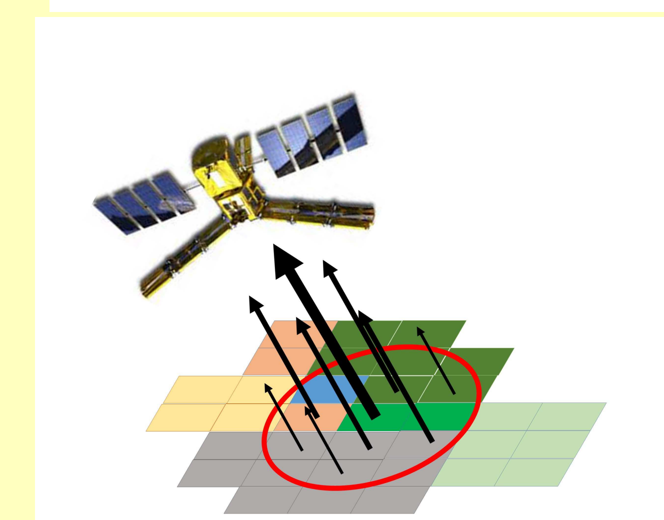
Prognostic LSM



- conservation mass and energy
- convection, diffusion
- Richards equation

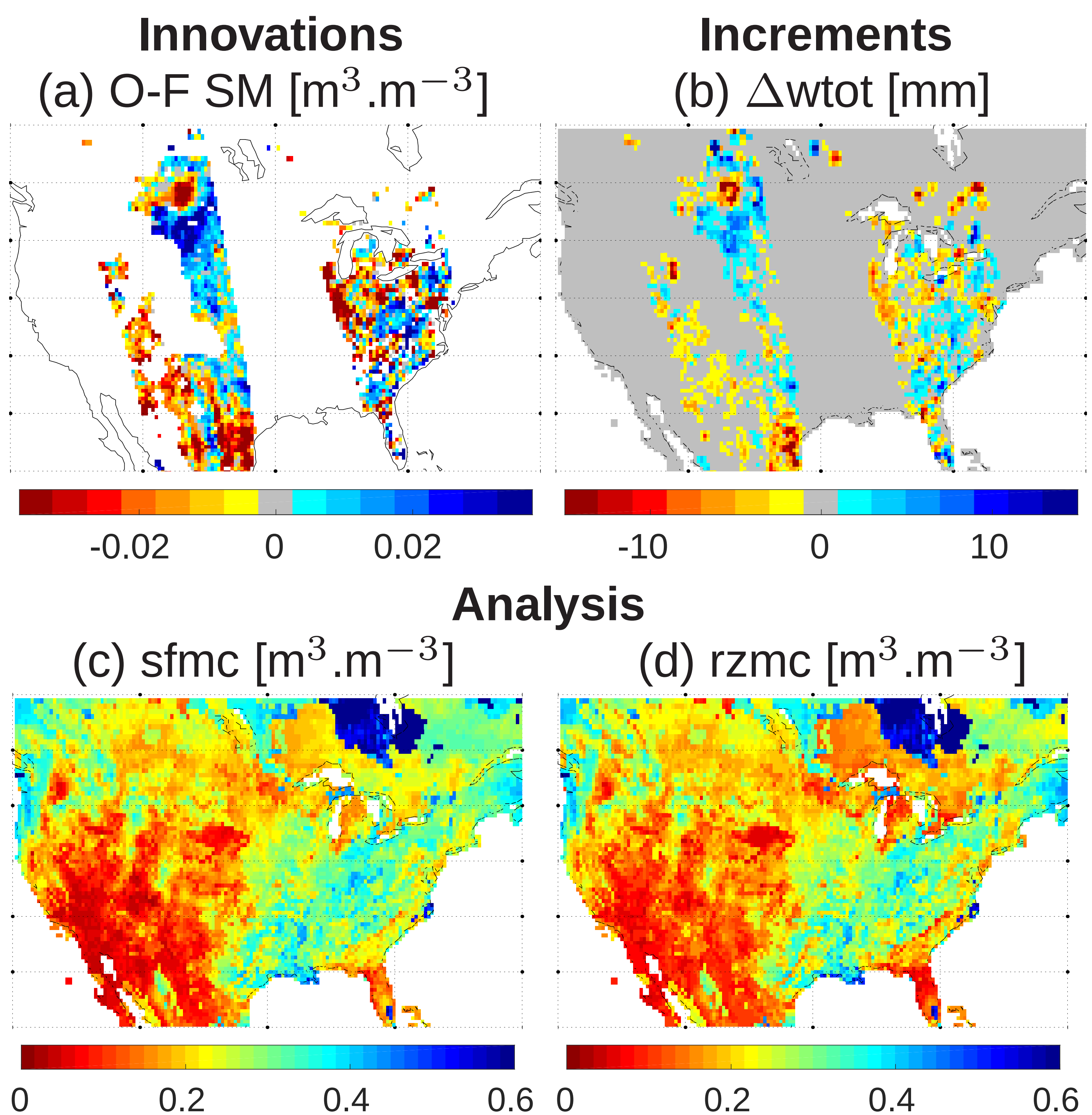
Diagnostic RTM





- radiative transfer
- NN, regression

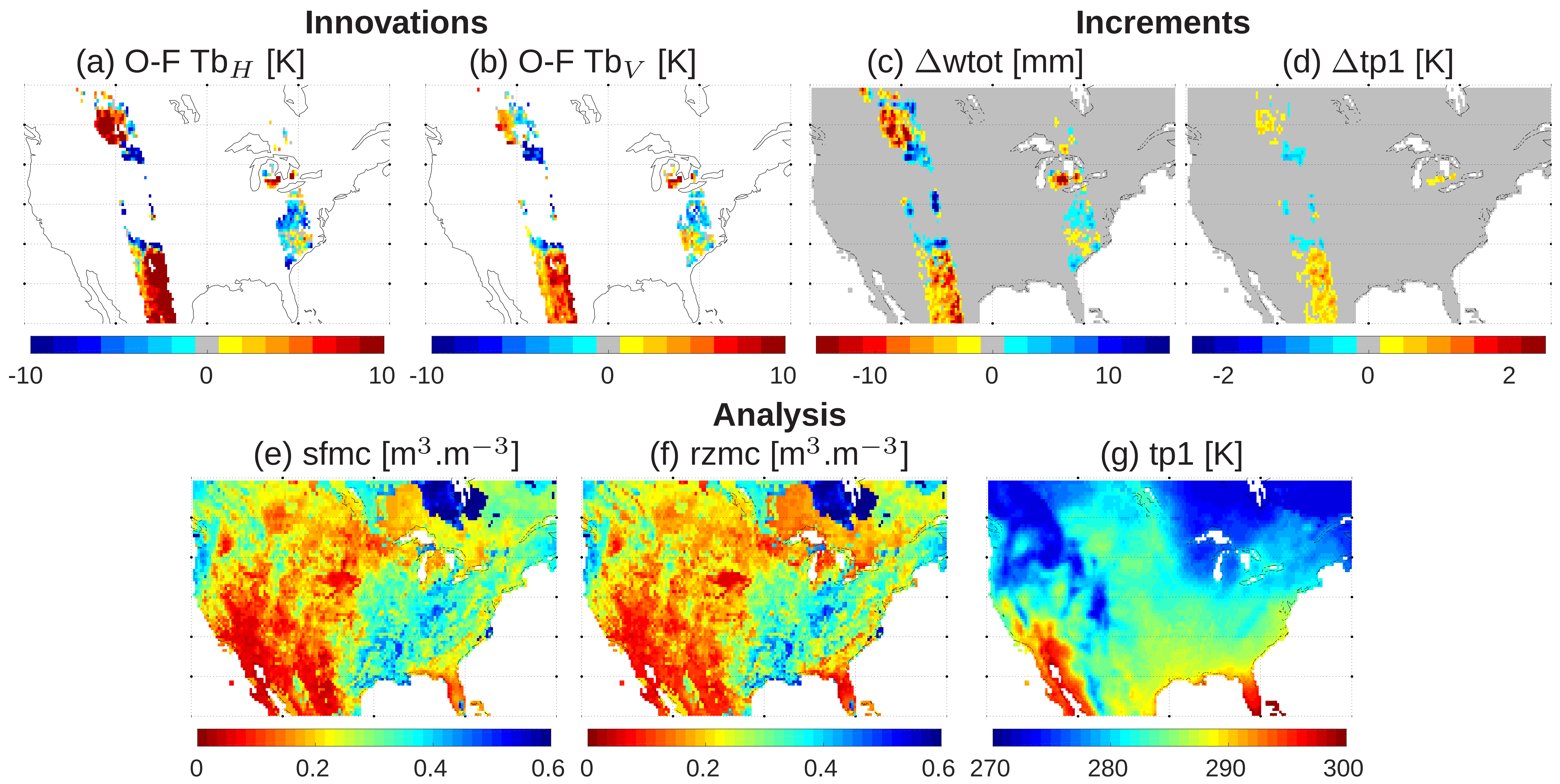
SM Data Assimilation



(30 April 2015, 12 UTC)

- Observation-minus-forecast (O-F, innovation), footprint-scale
- Increment, model grid
- Analysis, model grid
- 3D EnKF: smooth transitions, no swath edges in analysis

Tb Data Assimilation



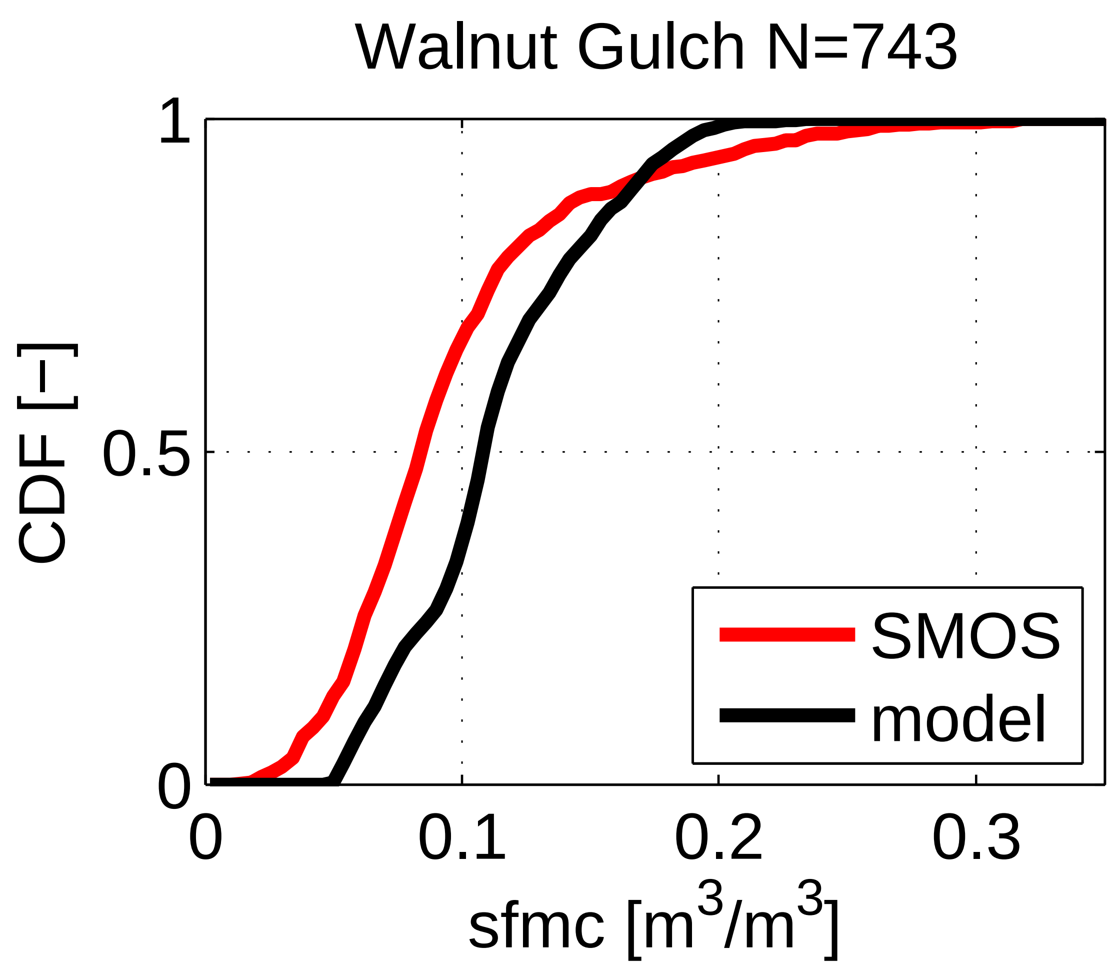
(30 April 2015, 12 UTC)

SM Observation or Innovation Bias

SM is relatively stationary

Example: at one location,

- **at any time**, replace an observed SM of 0.08 m^3/m^3 with a value of 0.10 m^3/m^3



- CDF based on 5 years, all seasons
- separate rescaling for ascending (6 am) and descending (6 pm) times

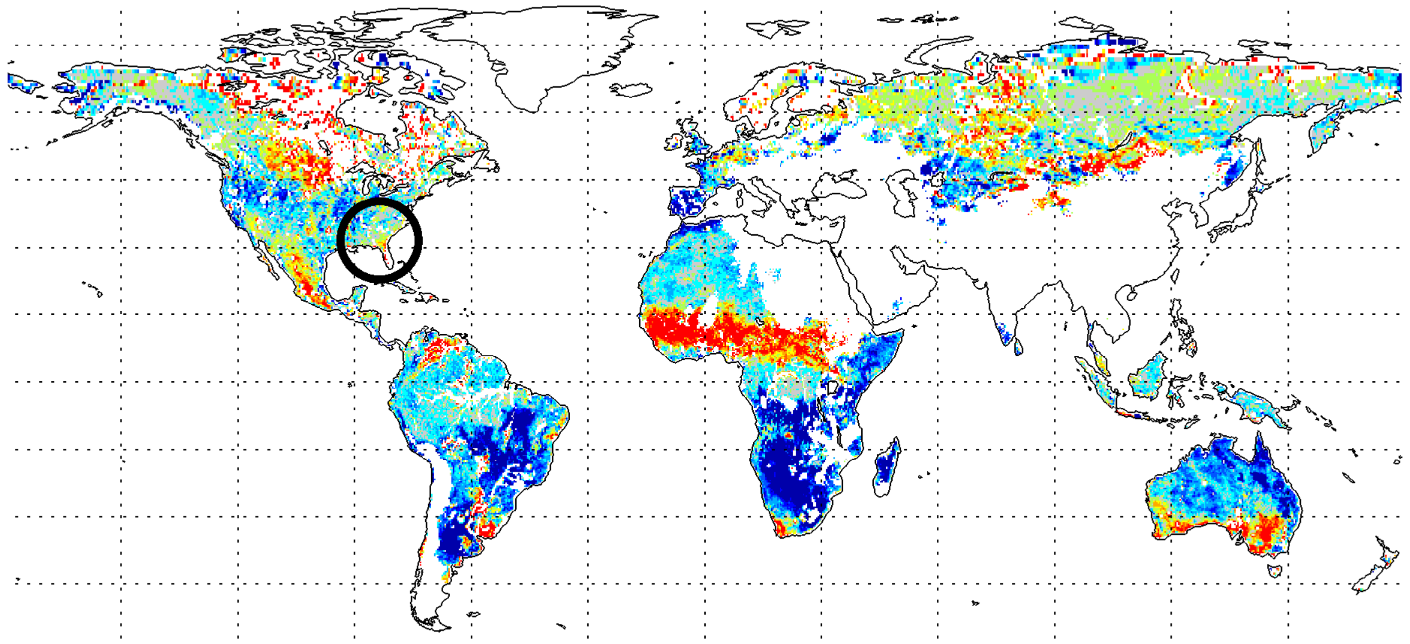
Tb Observation or Innovation Bias

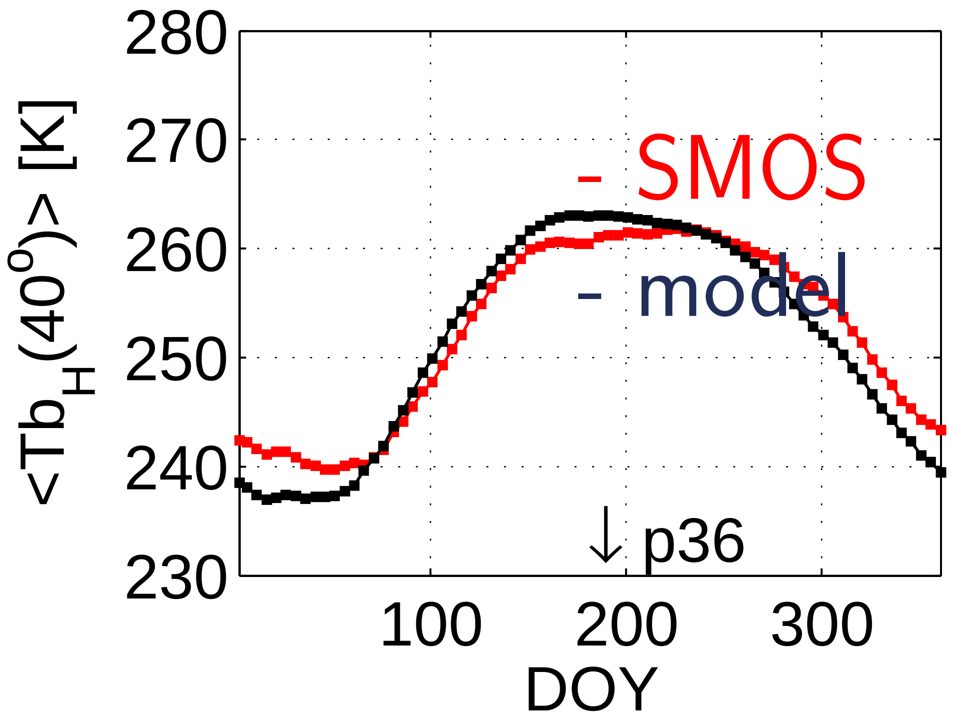
Tb has a strong seasonal pattern

Example: at one location,

- **at pentad 7**, correct the observed Tb_H for a bias of 237-241 K
- **at pentad 36**, correct the observed Tb_H for a bias of 262-260 K
- **at pentad ...**, correct ...

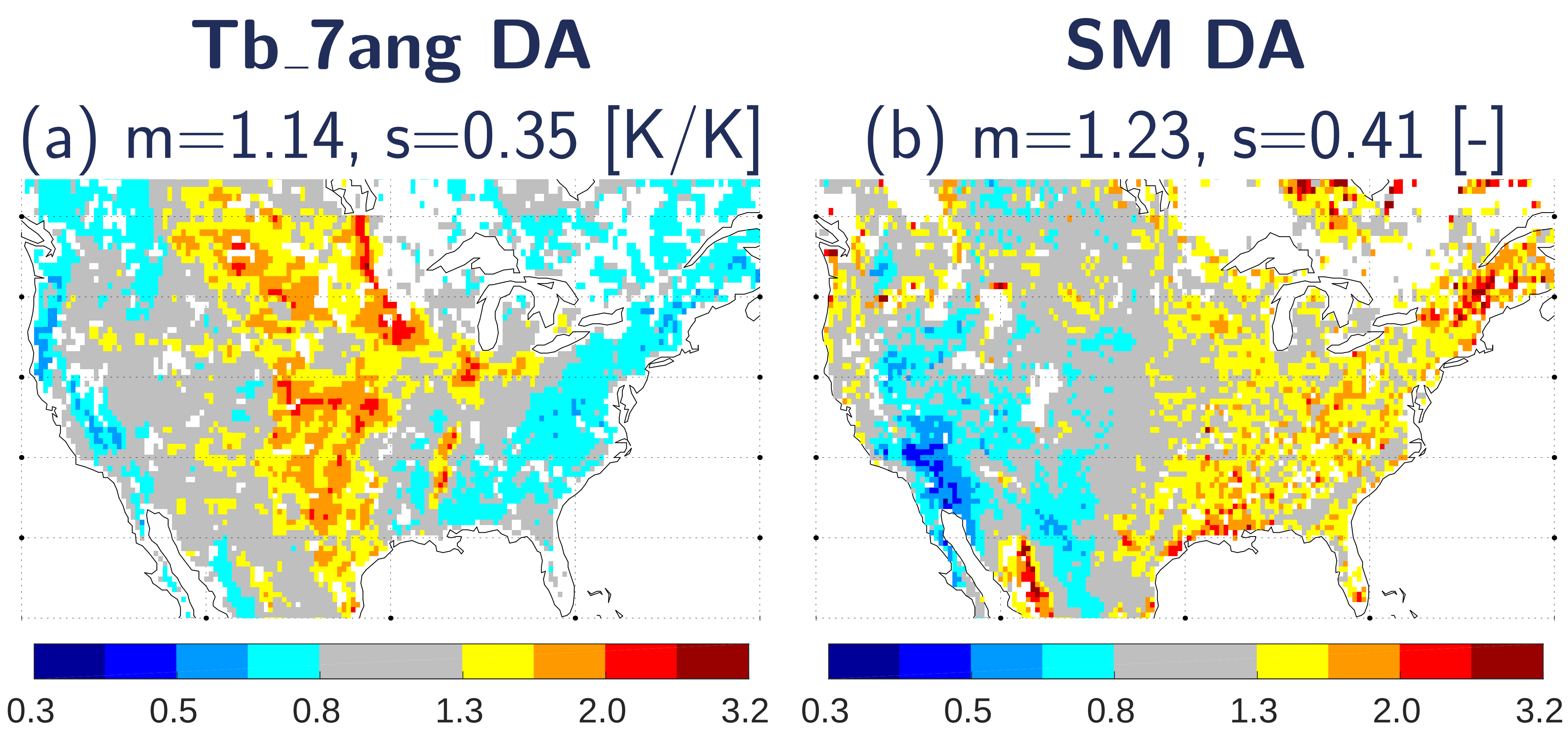
model-SMOS $<$**Tb**$_H$**(40**^{o}**)**$>$ **[K], Asc, pentad 36** Little River





- mean-only, 5 year-average, per pentad
- separate rescaling for ascending (6 am) and descending (6 pm), 7 angles, 2 polarizations

Normalized Tb or SM Innovations



std(O-F/$\sqrt{\sigma_F^2 + \sigma_O^2}$),

with σ_F^2 and σ_O^2 determined by DA design parameters (ensemble perturbations).

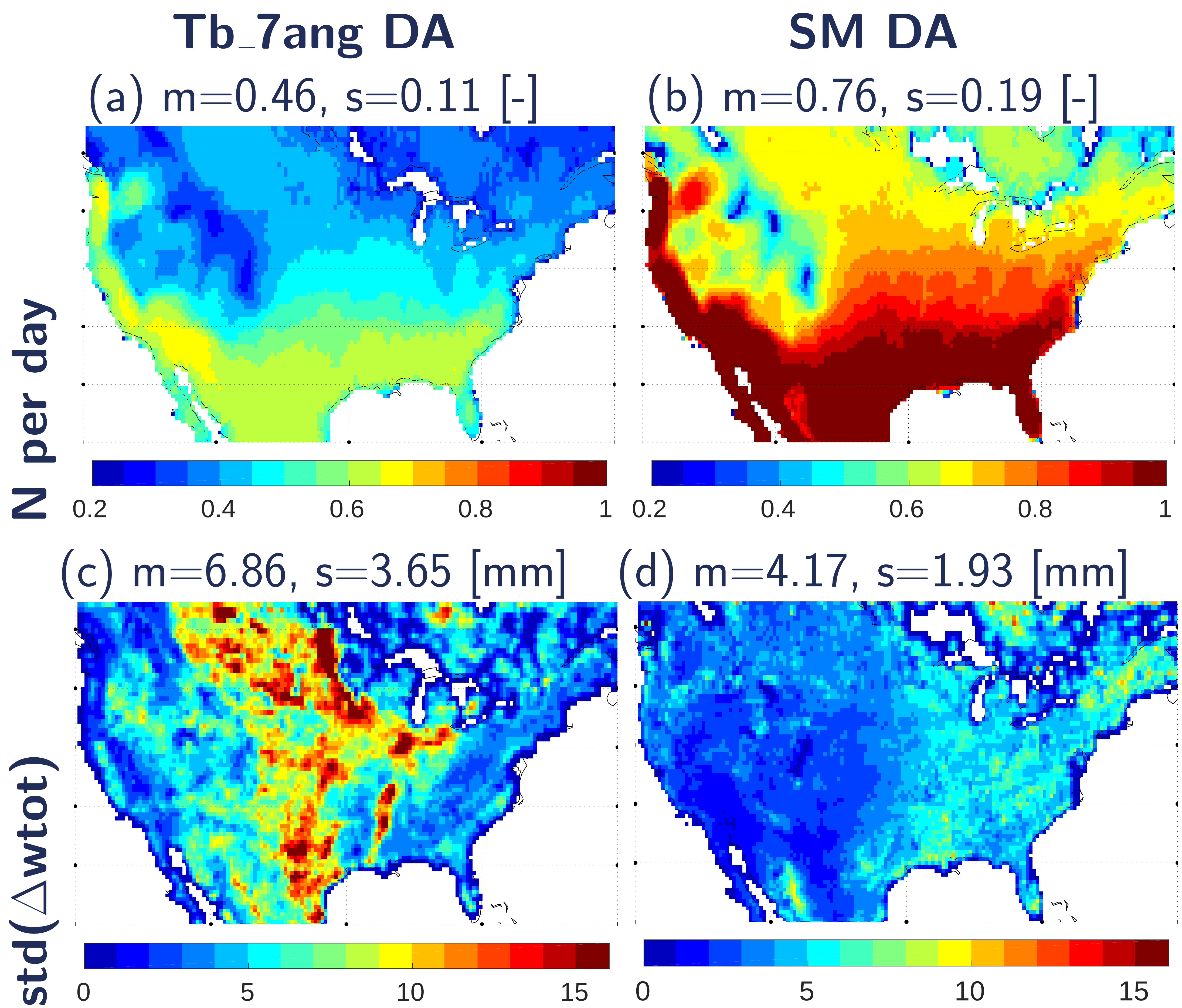
Target value = 1

< −− **DA system** −− >

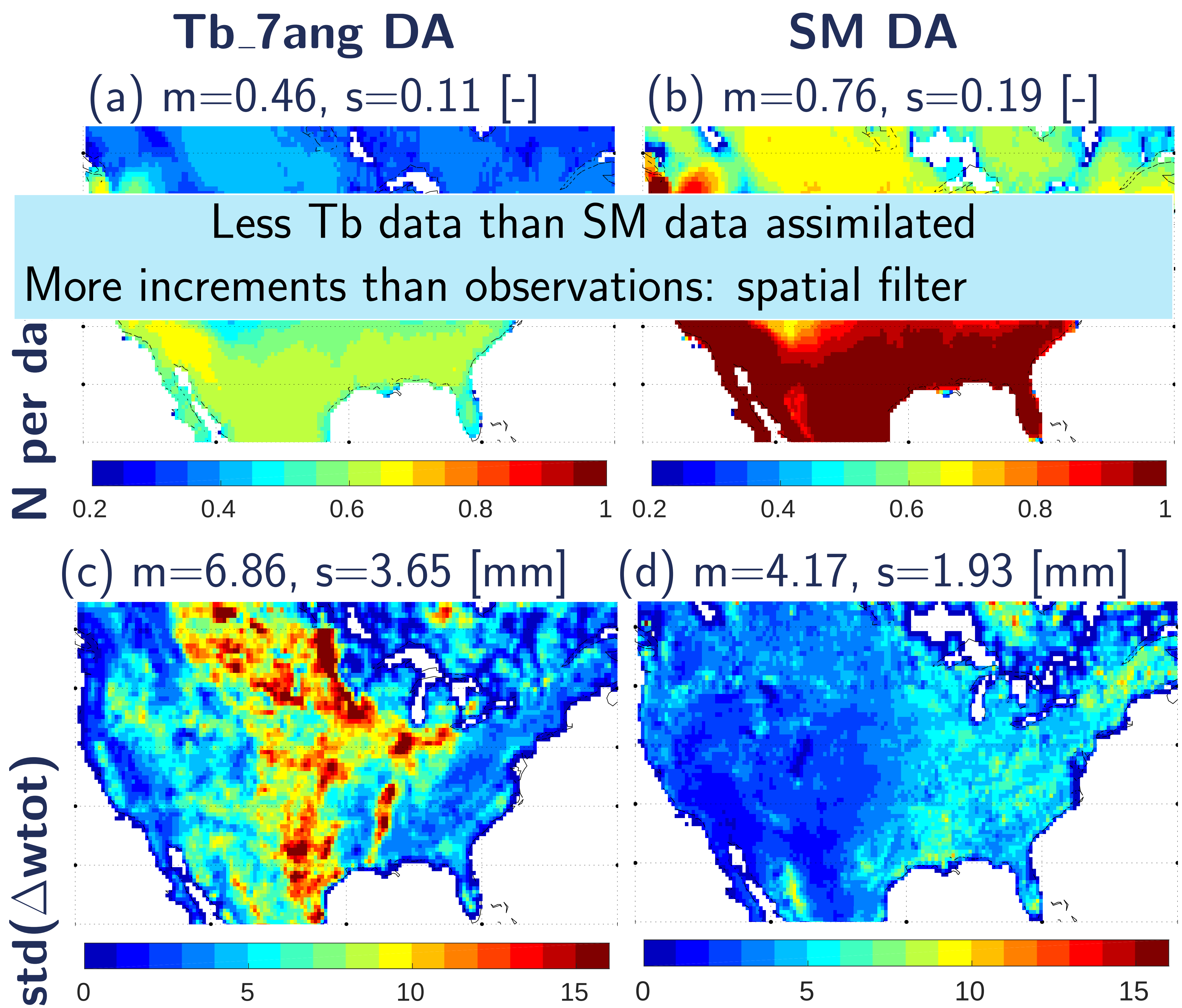
overestimates **under**estimates

actual uncertainty

Δwtot Increments



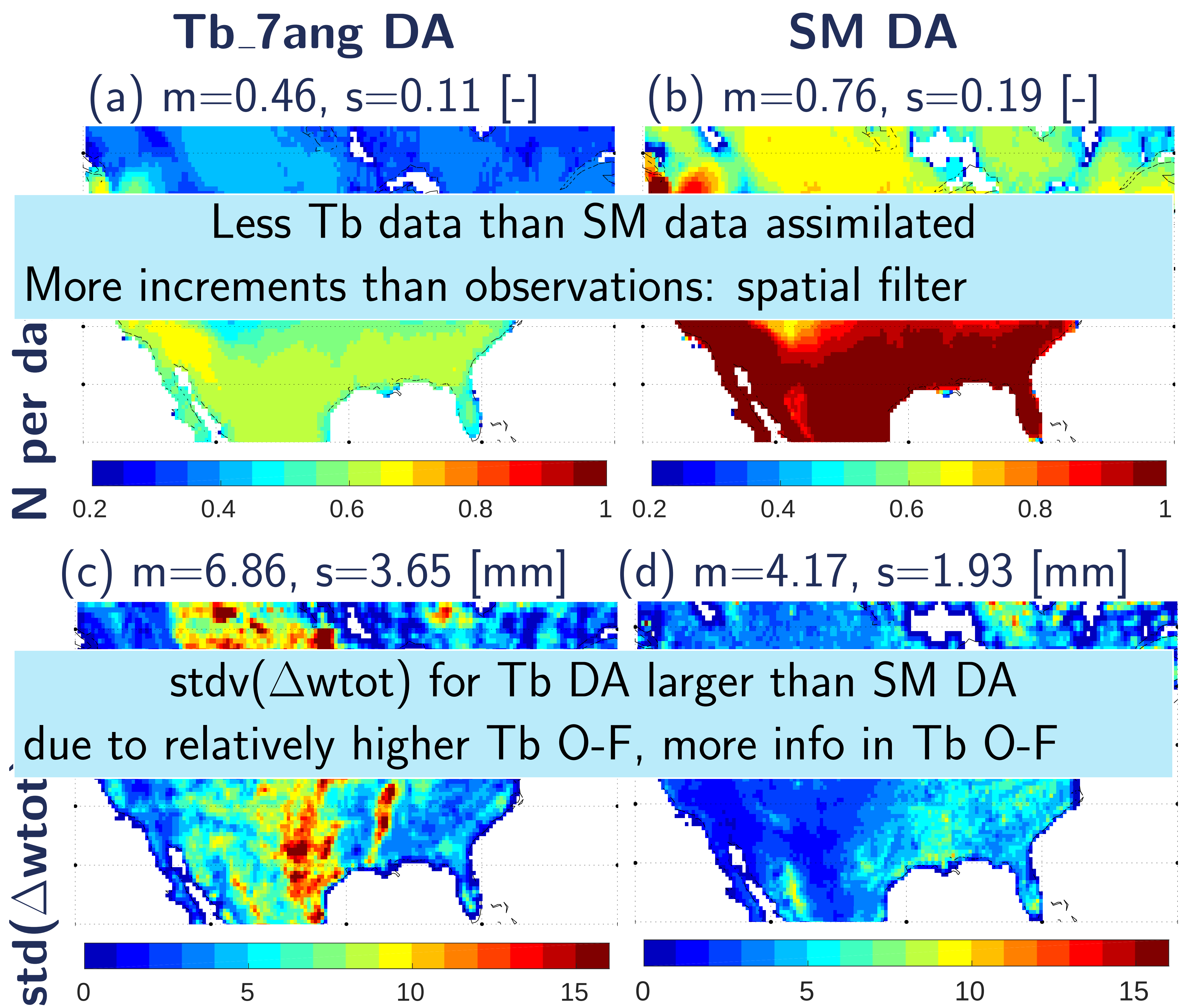
∆wtot Increments



Less Tb data than SM data assimilated

More increments than observations: spatial filter

∆wtot Increments



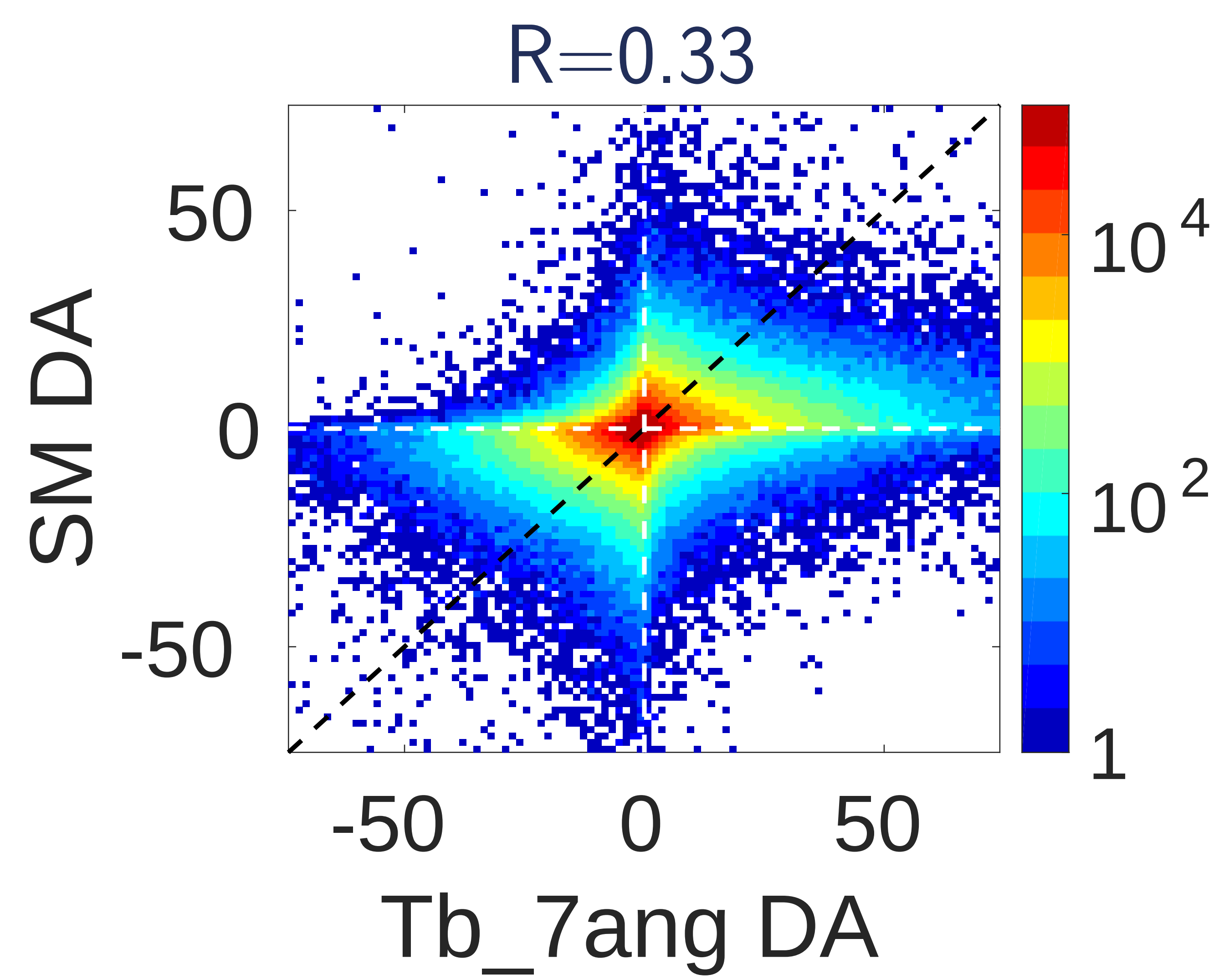
Less Tb data than SM data assimilated

More increments than observations: spatial filter

stdv(∆wtot) for Tb DA larger than SM DA

due to relatively higher Tb O-F, more info in Tb O-F

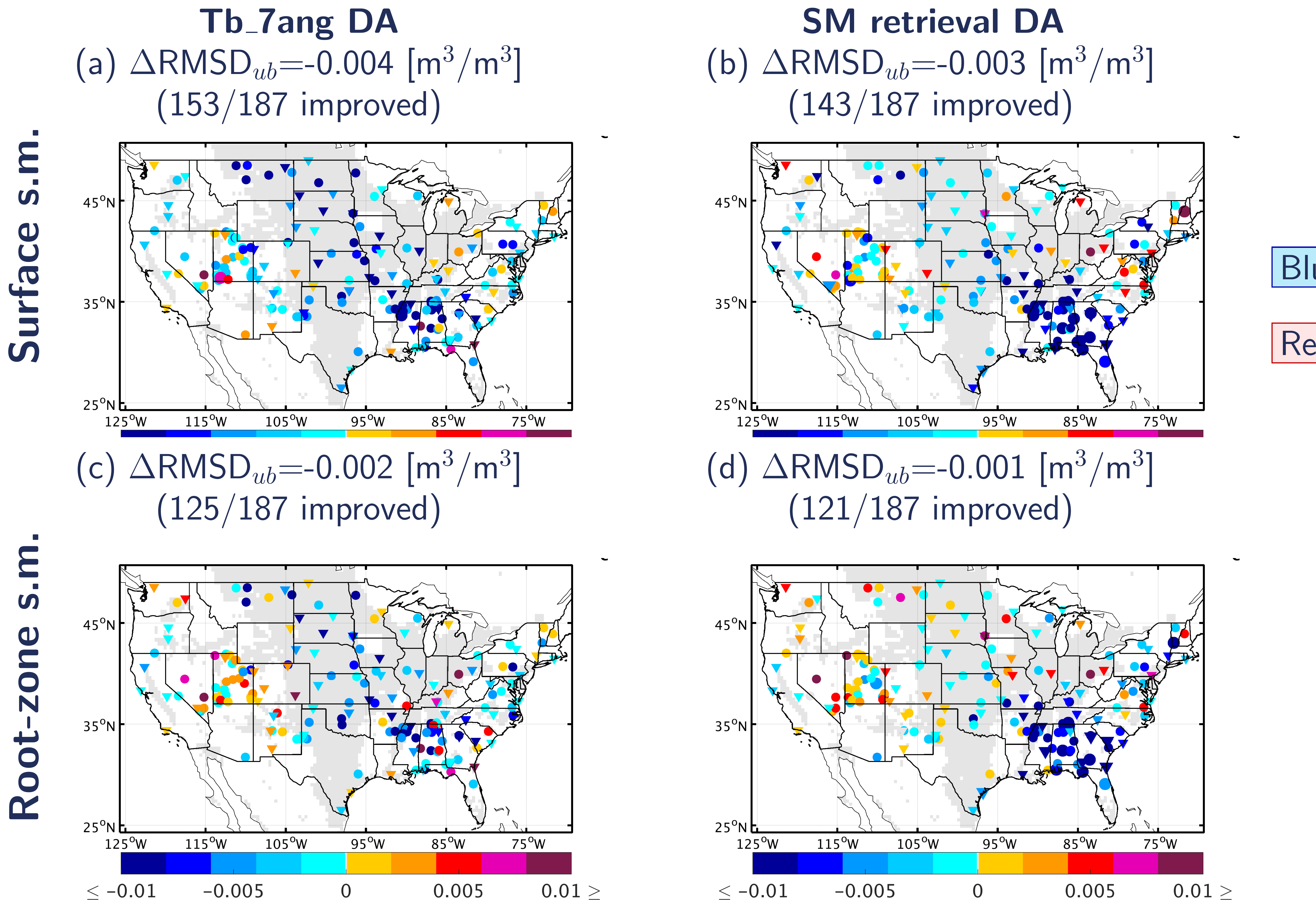
∆wtot Increments (mm)



- unbiased system
- Tb DA introduces more large increments than SM DA
  ∼ Tb DA has larger innovations than SM DA
- different information extracted during Tb DA and SM retrieval process?

(De Lannoy and Reichle, 2016, HESS)

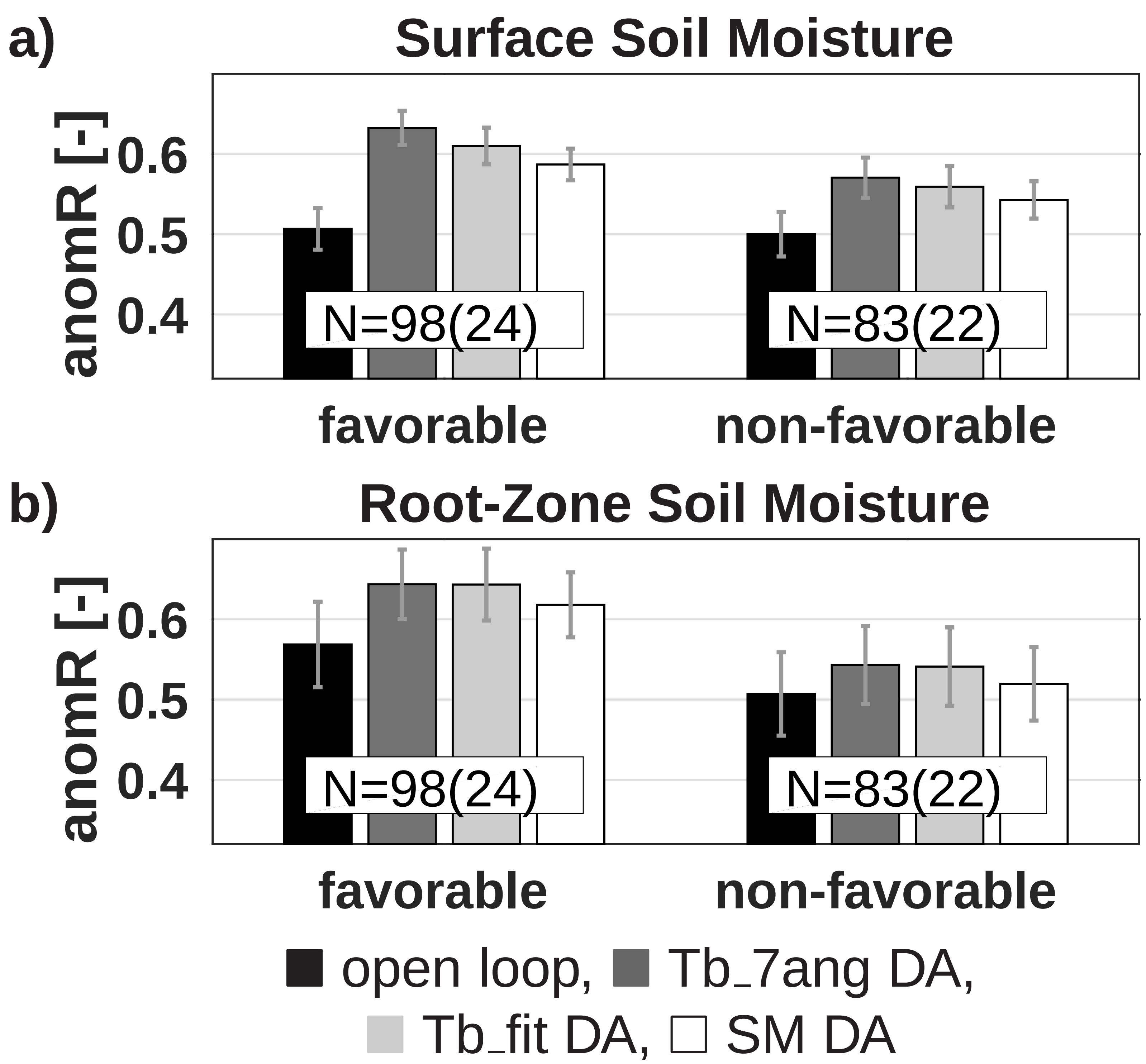
In Situ Evaluation



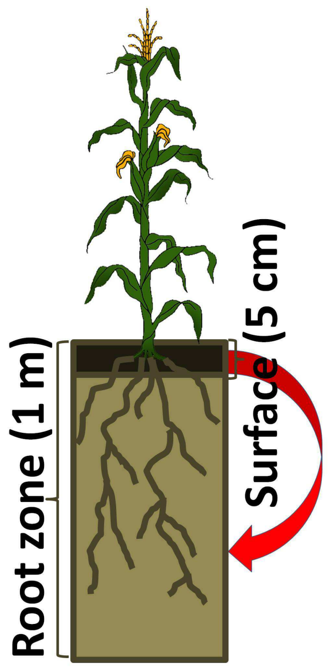
Blue=better

Red=worse

In Situ Evaluation



- largest soil moisture improvements in favorable areas
- similar averaged skill statistics for Tb and SM DA

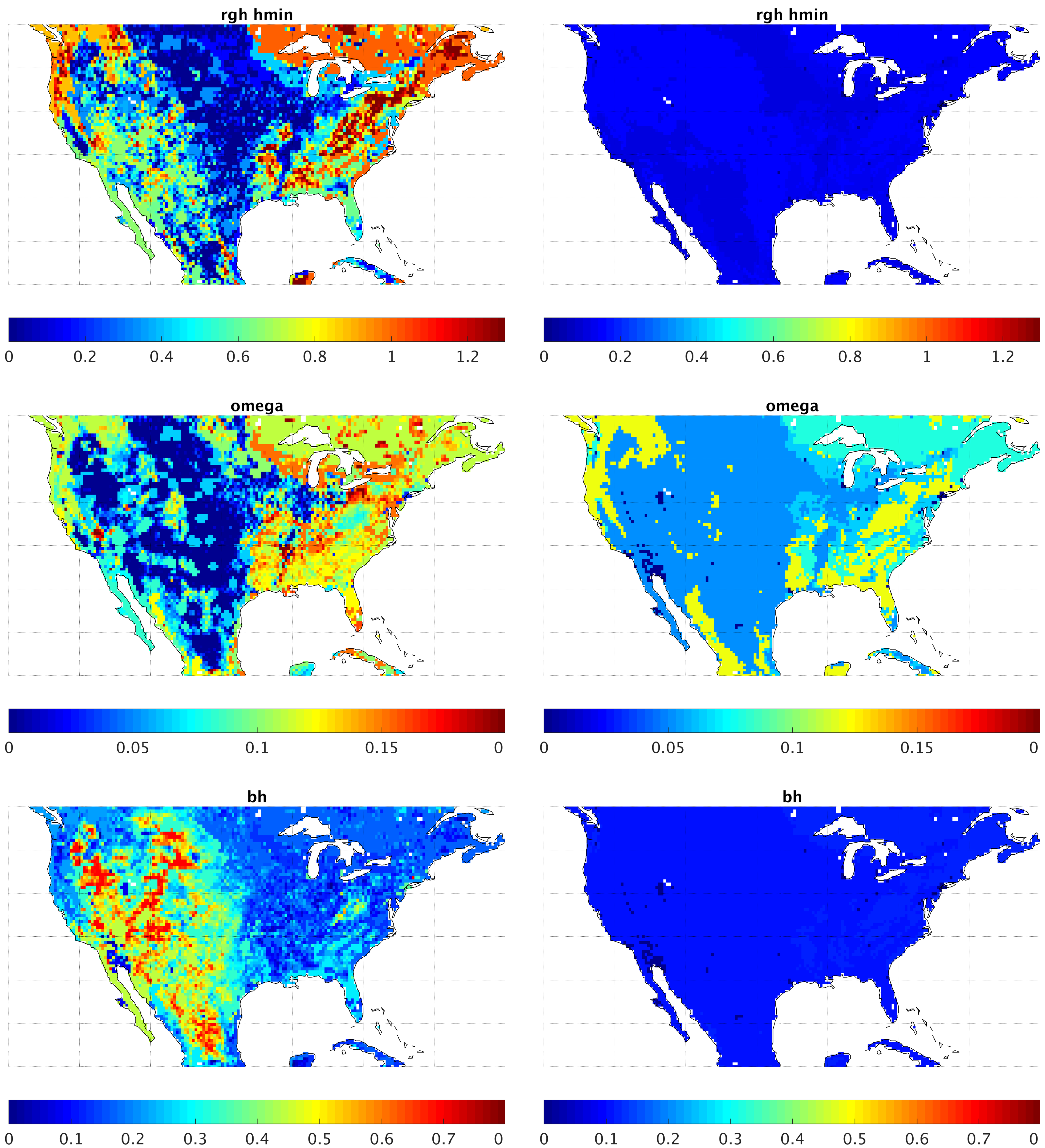


(De Lannoy and Reichle, 2016)

Effect of RTM on Tb DA

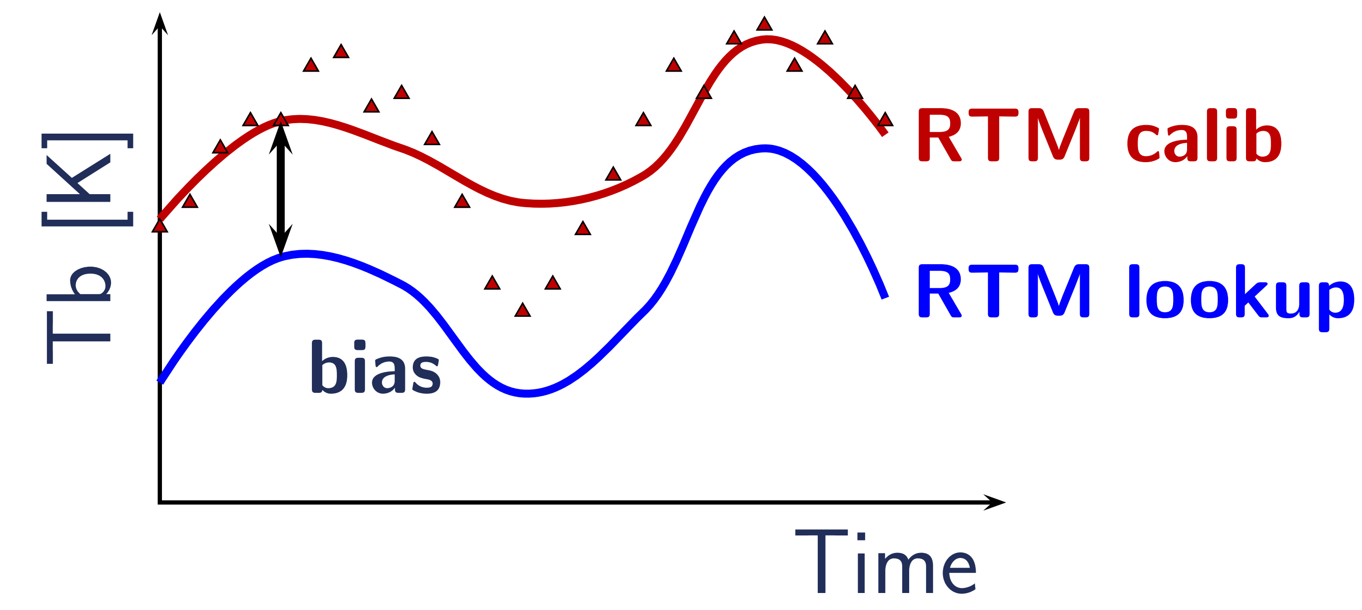
Repeat the Tb_7ang DA experiment, but with lookup table RTM parameters:

Calibrated *Lookup (SMAP L2)*



Effect on Tb obs predictions:

- primary: different seasonal bias
  → Tb rescaling
- secondary: different anomalies?



(Alexander Gruber)

Effect of RTM on Tb DA

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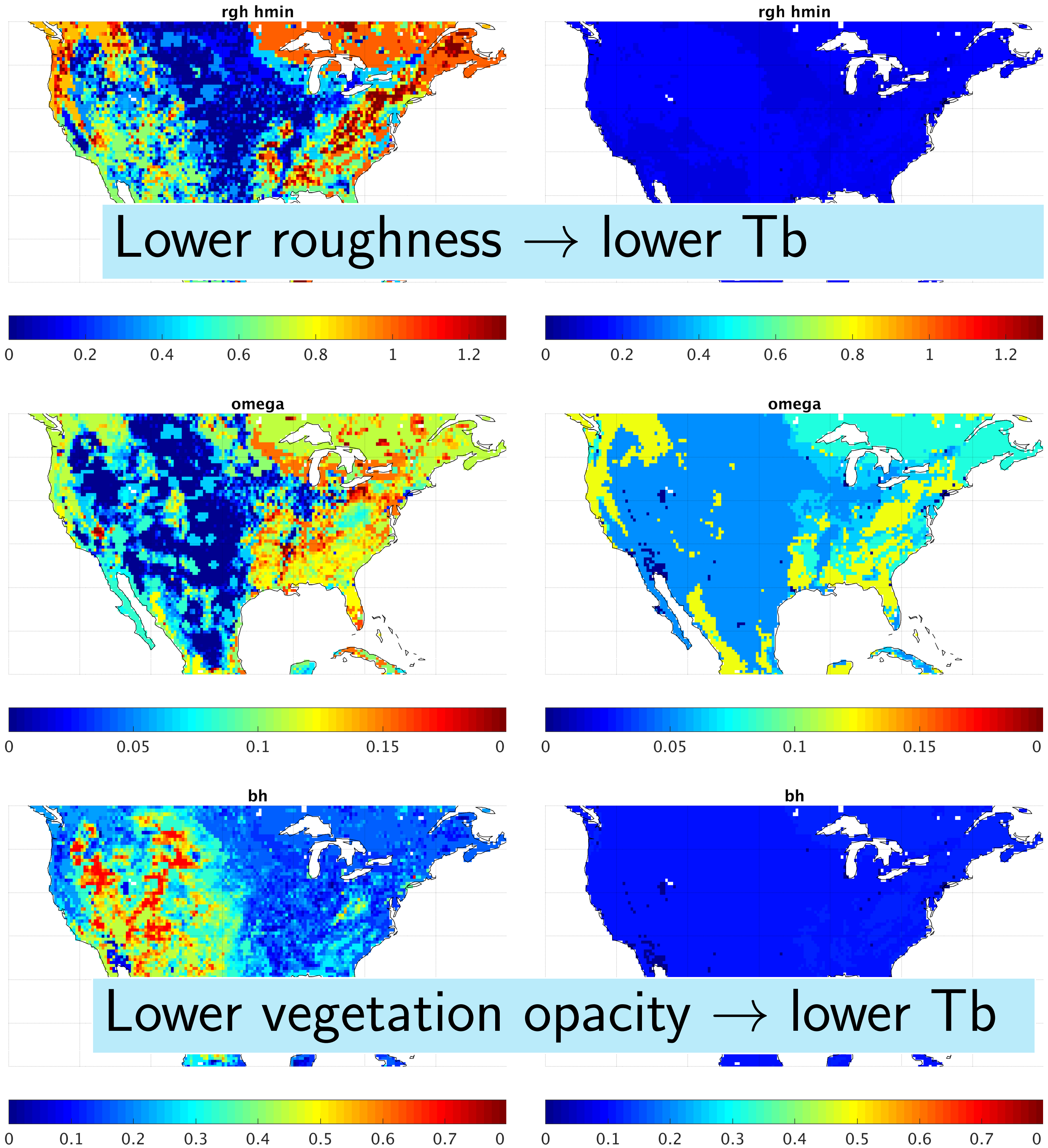
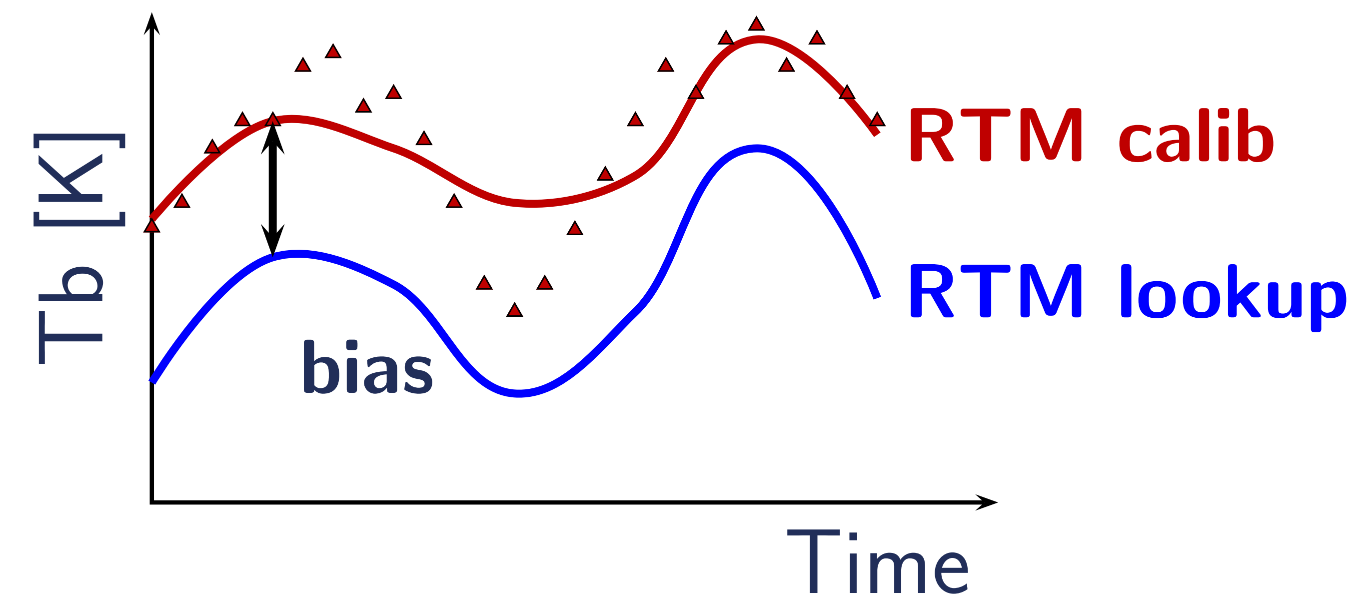


Lower roughness → lower Tb

Lower vegetation opacity → lower Tb

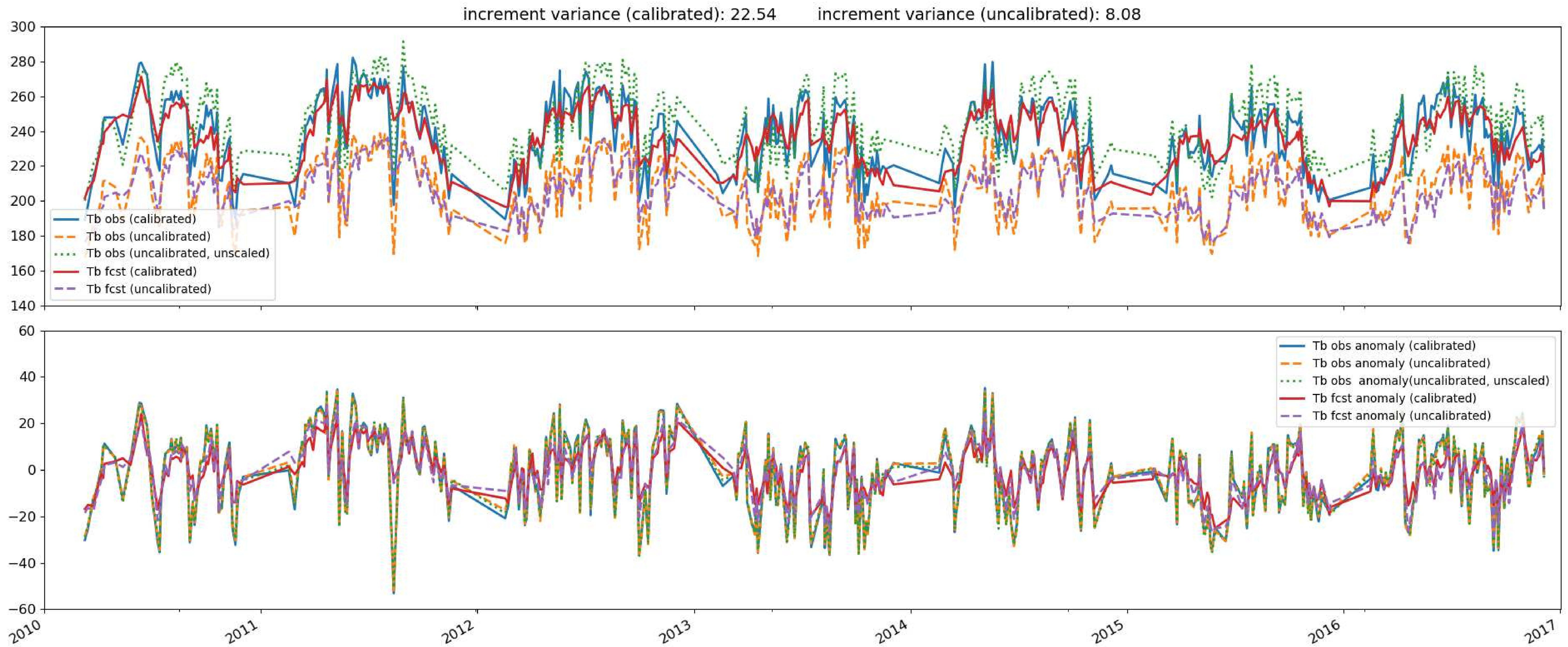
Effect on Tb obs predictions:

- primary: different seasonal bias → Tb rescaling
- secondary: different anomalies?



(Alexander Gruber)

Tb Innovations

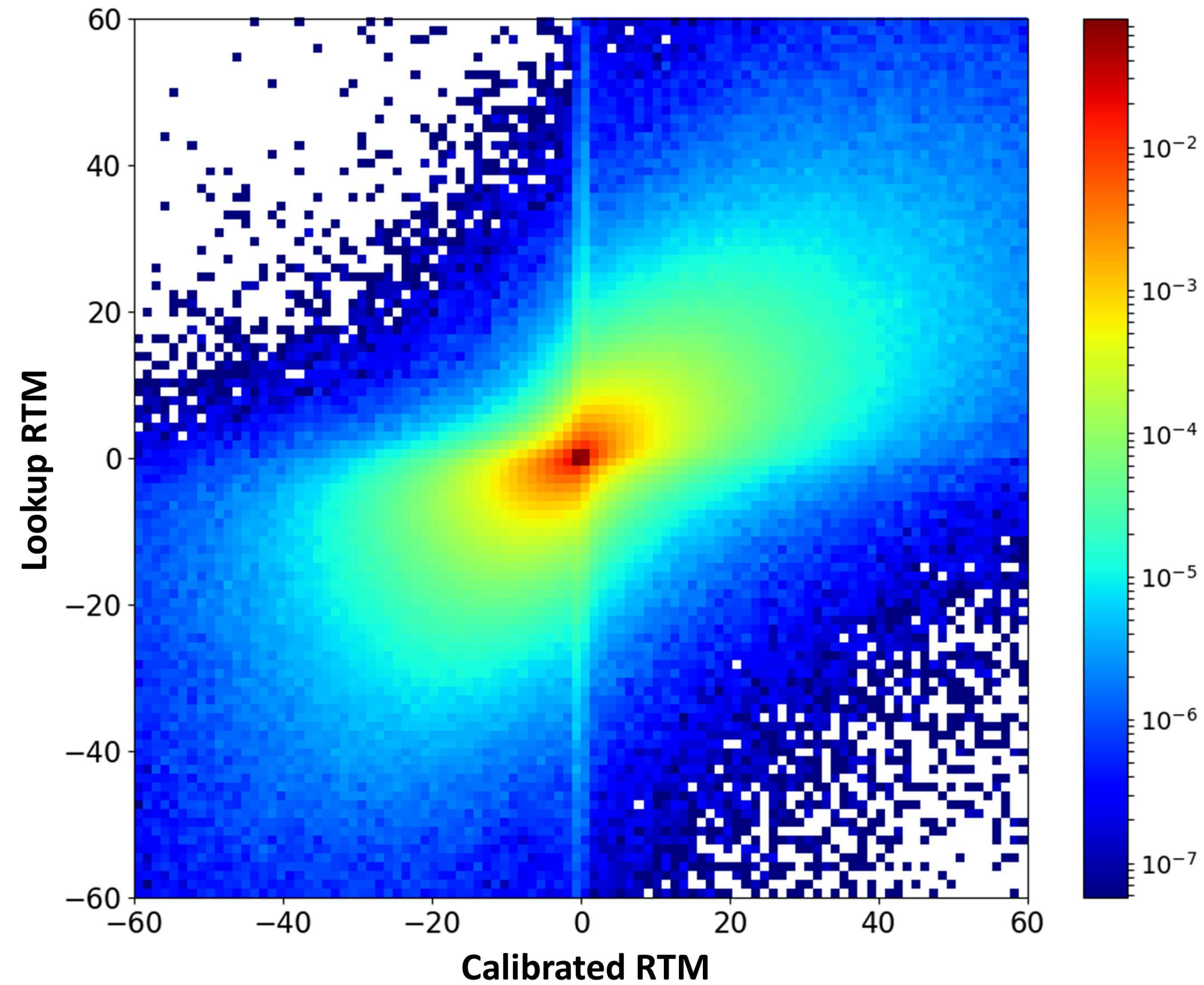


- obvious seasonal bias RTM calib vs lookup
- after rescaling: similar Tb anomalies for RTM calib and lookup
- different variance in Tb obs and Tb fct anomalies (for both RTM calib and lookup)
- Tb anomaly innov variance is slightly larger for RTM calib (not over forests)

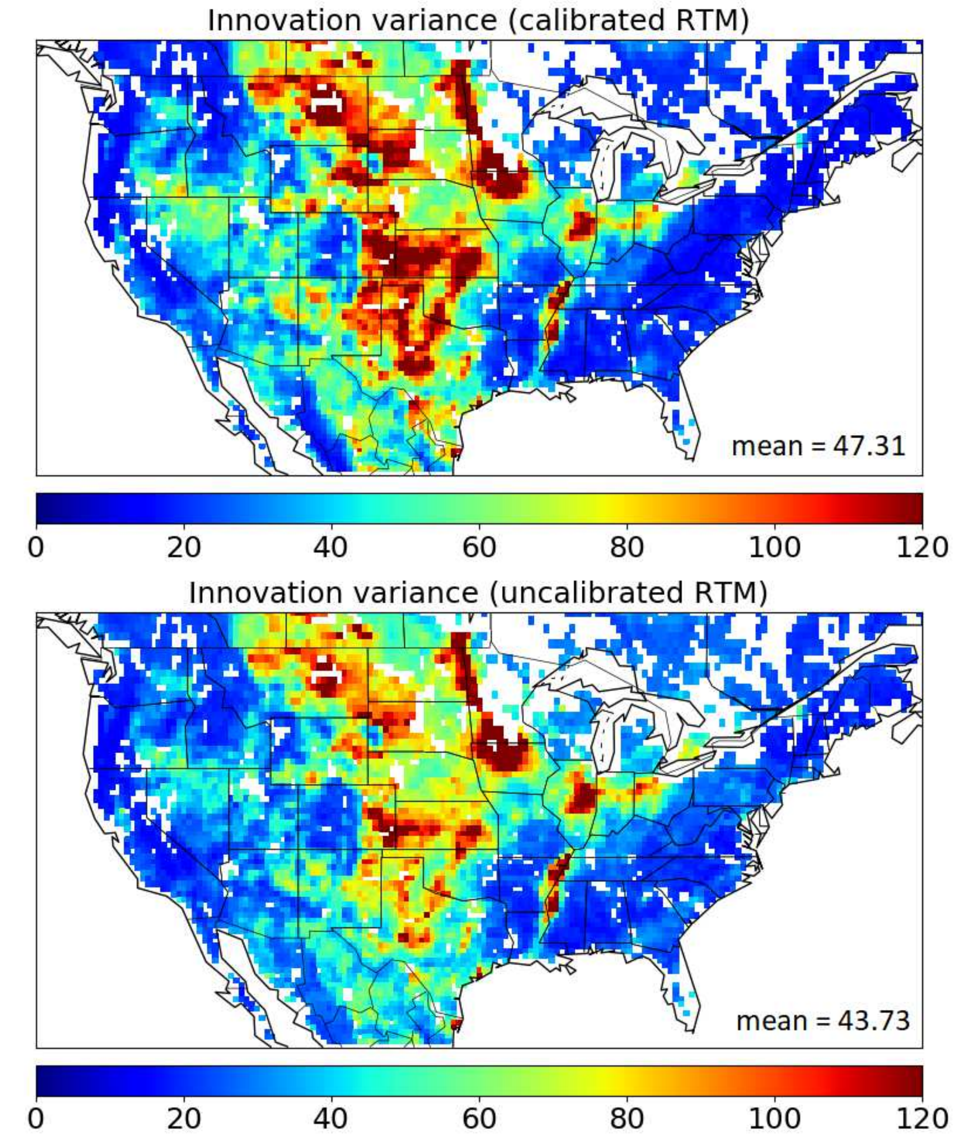
(Alexander Gruber)

Δwtot Increments

Increments [mm]



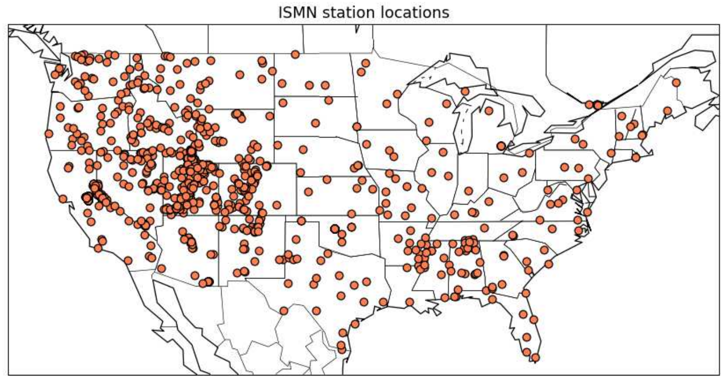
Innovations [K^2]

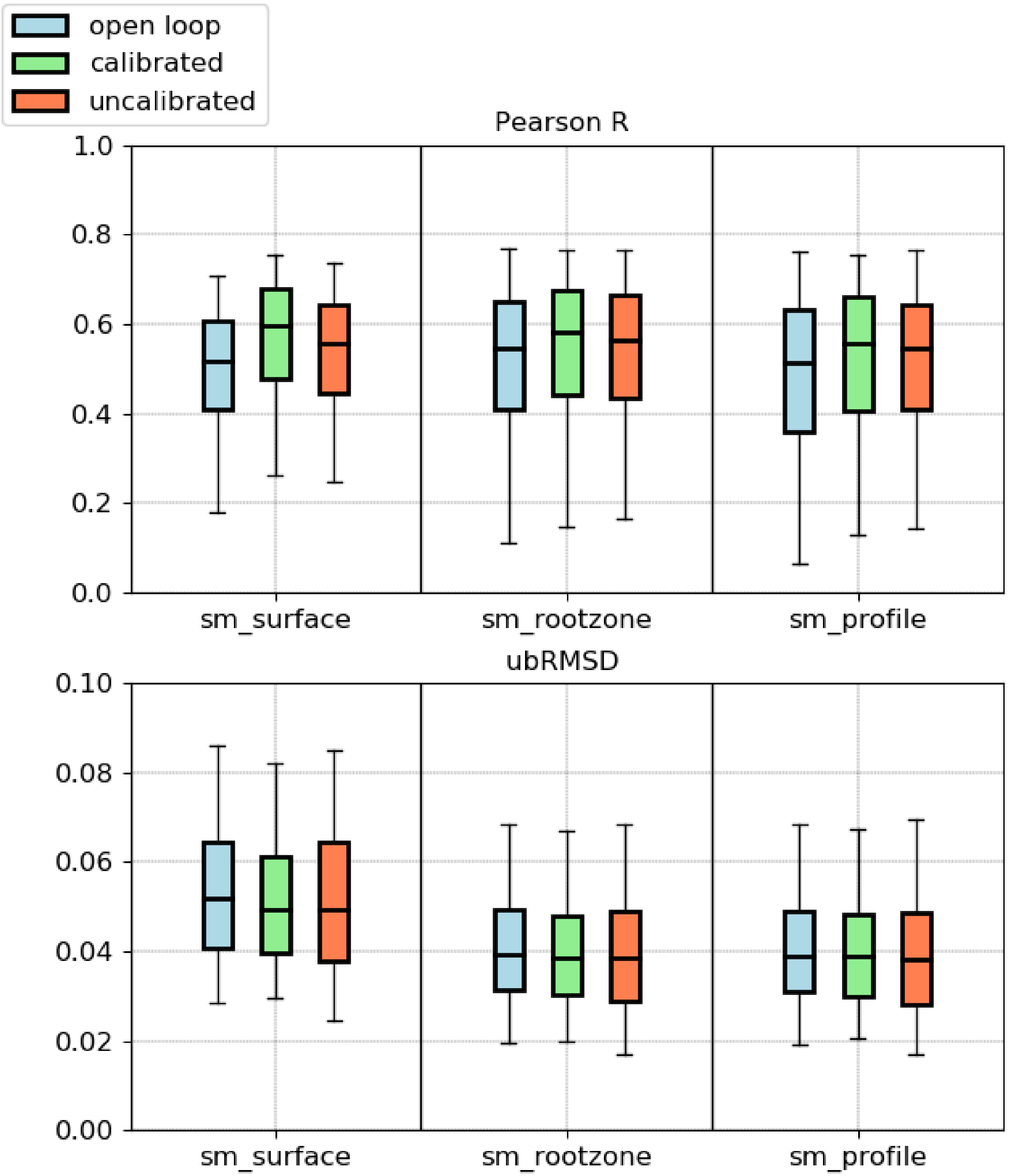


- unbiased system
- both Tb DA schemes correct soil moisture trajectories similarly
- calibrated RTM introduces more large increments than lookup RTM
  $\sim$ Tb (anomaly) innovation variance

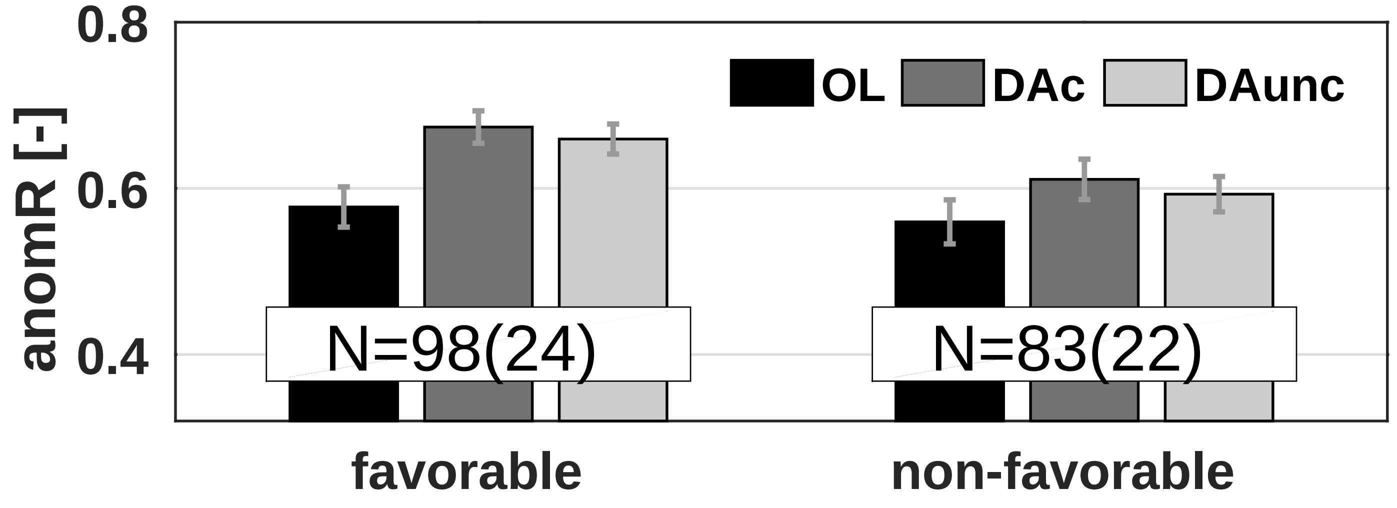
In Situ Evaluation

In situ surface and root-zone soil moisture (ISMN, not strictly QC-ed)





In situ surface soil moisture (SCAN+USCRN, strictly QC-ed)



- DA always performs better than OL (even when forced with qualitative MERRA2)
- similar averaged skill statistics for Tb DA using RTM calib and lookup

(Alexander Gruber)

Conclusions

SMOS (or SMAP) Tb to soil moisture via radiative transfer modeling

- very different RTM parameterizations available for forward and inverse modeling
  - optimized parameters for retrievals work for data assimilation (fwd RTM)
  - optimized parameters for fwd modeling work for retrievals (inverse RTM)
- Tb estimates much improved when accounting for open water in RTM

Data assimilation:

- SM DA and Tb DA both improve surface and root-zone soil moisture
- SM DA and Tb DA add different increments to products
- seasonal bias mitigation in Tb DA effectively overcomes shortcomings in RTM parameterization (calibrated or not)
- to do: spatio-temporal optimization of Tb (obs and forecast) errors

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