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

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L-band (1.4 GHz) brightness temperatures ($T_b$) are sensitive to soil moisture and temperature in the surface layer (5 cm).
Tb increases with drier soil moisture (sfmc)

Tb increases with more vegetation ($\tau$)

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

**Lookup tables: per vegetation class**

- **SMAP L2**
- **SMOS IC**

**Calibrated: per grid cell**

- **SMAP L4**

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

- 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:**
- **Open water:**
  incl. open water reduces bias in Tb forward modeling

\[
Tb = f_{\text{land}}.Tb_{\text{land}} + f_{\text{SOW}}.Tb_{\text{SOW}} + f_{\text{DOW}}.Tb_{\text{DOW}}
\]

land + static (land mask) + dynamic open water (AMSR2)
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
    - \((\text{SM}, \text{VOD}) = f(Tb_{SMOS}, \text{MODIS LAI}, \text{ECMWF Ts}, \text{Tb}_{ECMWF \text{ notnominal}}, \text{RTM})\)
  - **SMOS-IC** (Fernandez-Moran et al., 2017)
    - homogenous pixels
    - \((\text{SM}, \text{VOD}) = f(Tb_{SMOS}, \text{ECMWF Ts}, \text{RTM})\)
  - **SMOS-LPRM** in ESA CCI
    - homogenous pixels
    - \(\text{VOD} = f(\text{MPDI}_{SMOS}^{\omega}), \text{and} \text{SM} = f(Tb_{SMOS}, \text{VOD}, \text{model Ts}, \text{RTM})\)

- **SMOS research products:** physically-based, neural network, various RTMs, ...
  - homogenous pixels
  - \(\text{VOD} = f(Tb_{SMOS}, \text{MERRA2 Ts, MERRA2 SM, RTM}), \text{or} \text{SM} = f(Tb_{SMOS}, \text{MERRA2 Ts, MERRA2 LAI, RTM})\)
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)
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 \( \tau \) retrievals
- Lit3 (fwd modeling) is inferior for retrievals
SMOS Data Assimilation
Data Assimilation

SMOS Obs (footprint) vs 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

*[K]

Conditioned on

Surface (0-5 cm)

"Root zone" (0-100 cm)
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
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Data Assimilation
- 3D EnKF
- bias mitigation*
- filter parameters*

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

⇒ * calibration using long-term SMOS record
Land Surface Modeling

Prognostic LSM

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

Input: Surface (0-5 cm)

Output: “Root zone” (0-100 cm)

Diagnostic RTM

- radiative transfer
- NN, regression
SM Data Assimilation

- 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

Innovations
(a) O-F Tb$_H$ [K]
(b) O-F Tb$_V$ [K]
(c) $\Delta$wtot [mm]
(d) $\Delta$tp1 [K]

Increments

Analysis
(e) sfmc [m$^3$.m$^{-3}$]
(f) rzmc [m$^3$.m$^{-3}$]
(g) tp1 [K]

(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 has a strong seasonal pattern

Example: at one location,
- at pentad 7, correct the observed $T_b^H$ for a bias of 237-241 K
- at pentad 36, correct the observed $T_b^H$ for a bias of 262-260 K
- at pentad ..., correct ...

model-SMOS $\langle T_b^H(40^o) \rangle \ [K]$, 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

\[
\text{std}(O-F/\sqrt{\sigma_{F}^2 + \sigma_{O}^2}),
\]

with \( \sigma_{F}^2 \) and \( \sigma_{O}^2 \) determined by DA design parameters (ensemble perturbations).

Target value = 1

\(< \text{ DA system } >\)

overestimates underestimates

actual uncertainty
**Δwtot Increments**

### Tb_7ang DA
1. **(a) m=0.46, s=0.11 [-]**
2. **(b) m=0.76, s=0.19 [-]**

### SM DA
1. **(c) m=6.86, s=3.65 [mm]**
2. **(d) m=4.17, s=1.93 [mm]**

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**Tb DA**

**SM DA**

- **N per day**
- **std(Δwtot)**
**Δwtot Increments**

**Tb_7ang DA**

(a) $m=0.46$, $s=0.11$ [-] 

(b) $m=0.76$, $s=0.19$ [-] 

**SM DA**

(c) $m=6.86$, $s=3.65$ [mm] 

(d) $m=4.17$, $s=1.93$ [mm]

Less Tb data than SM data assimilated

More increments than observations: spatial filter

N per day

0.2 0.4 0.6 0.8 1

0.2 0.4 0.6 0.8 1

std(Δwtot)

0 5 10 15

0 5 10 15
\( \Delta w_{tot} \) Increments

**Tb_7ang DA**

(a) \( m=0.46, s=0.11 \) [-]

(b) \( m=0.76, s=0.19 \) [-]

Less Tb data than SM data assimilated

More increments than observations: spatial filter

(c) \( m=6.86, s=3.65 \) [mm]

(d) \( m=4.17, s=1.93 \) [mm]

\( \text{std}(\Delta w_{tot}) \) for Tb DA larger than SM DA due to relatively higher Tb O-F, more info in Tb O-F
$\triangle wtot$ Increments (mm)

- unbiased system
- Tb DA introduces more large increments than SM DA
- $\sim$ 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

**Tb\_7ang DA**

(a) $\Delta \text{RMSD}_{ub} = -0.004 \, [m^3/m^3]$  
(153/187 improved)

(b) $\Delta \text{RMSD}_{ub} = -0.003 \, [m^3/m^3]$  
(143/187 improved)

(c) $\Delta \text{RMSD}_{ub} = -0.002 \, [m^3/m^3]$  
(125/187 improved)

(d) $\Delta \text{RMSD}_{ub} = -0.001 \, [m^3/m^3]$  
(121/187 improved)

**SM retrieval DA**

Surface s.m.

Root-zone s.m.

Blue=better  
Red=worse
In Situ Evaluation

a) Surface Soil Moisture

![Bar chart showing anomR for favorable and non-favorable areas with N=98(24) and N=83(22).]

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

b) Root-Zone Soil Moisture

![Bar chart showing anomR for favorable and non-favorable areas with N=98(24) and N=83(22).]

- open loop, Tb_7ang DA, Tb_fit DA, 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

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

- **Tb DA using RTM calib and lookup**

- **Conclusions**
  - 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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